GLASSDB: Practical Verifiable Ledger Database Through Transparency

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ABSTRACT
Verifiable ledger databases protect data history against malicious tampering. Existing systems, such as blockchains and certificate transparency, are based on transparency logs — a simple abstraction allowing users to verify that a log maintained by an untrusted server is append-only. They expose a simple key-value interface. Building a practical database from transparency logs, on the other hand, remains a challenge.

In this paper, we explore the design space of verifiable ledger databases along three dimensions: abstraction, threat model, and performance. We survey existing systems and identify their two limitations, namely, the lack of transaction support and the inferior efficiency. We then present GLASSDB, a distributed database that addresses these limitations under a practical threat model. GLASSDB inherits the verifiability of transparency logs, but supports transactions and offers high performance. It extends a ledger-like key-value store with a data structure for efficient proofs, and adds a concurrency control mechanism for transactions. GLASSDB batches independent operations from concurrent transactions when updating the core data structures. In addition, we design a new benchmark for evaluating verifiable ledger databases, by extending YCSB and TPC-C benchmarks. Using this benchmark, we compare GLASSDB against three baselines: reimplemented versions of two verifiable databases, and a verifiable map backed by a transparency log. Experimental results demonstrate that GLASSDB is an efficient, transactional, and verifiable ledger database.

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1 INTRODUCTION
A verifiable database protects the integrity of user data and query execution on untrusted database providers. Until recently, the focus has been on protecting the integrity of query execution [18, 24, 34]. In this context, users upload the data to an untrusted provider which executes queries and returns proofs that certify the correctness of the results. However, such OLAP-style verifiable databases rely on complex cryptographic primitives that limit the performance or the range of possible queries.

We observe a renewed interest in verifiable databases, with a focus on OLTP-style systems. In particular, there emerges a new class of systems, called verifiable ledger databases, whose goal is to protect the integrity of the data history. In particular, the data is maintained by an untrusted provider that executes read and update queries. The provider produces integrity proofs about the data content and its entire evolution history.

An example of verifiable ledger databases is the blockchain [4, 9, 29]. The blockchain maintains a replicated append-only log in a decentralized setting. It protects the integrity of the log against Byzantine attackers, by running a distributed consensus protocol among the participants. The integrity proof (in a permissioned blockchain) consists of signed statements from a number of participants. Another example is a certificate transparency log [14, 21], in which a centralized server maintains a tamper-evident, append-only log of public key certificates. The server regularly publishes summaries of the log which are then checked for consistency by a set of trusted auditors. The integrity proof generated by the server can be verified against the published and audited summaries. The third example is Amazon’s Quantum Ledger Database (QLDB) service [2], which maintains an append-only log similar to that of certificate transparency. QLDB uses the log to record data operations that are then applied to another backend database.

Our goal is to build a practical verifiable ledger database. We observe that the three examples above are built from a common abstraction, namely a transparency log, which provides two important security properties. First, users can verify that the log is append-only, namely, any successful update operations will not be reverted. Second, users can verify that the log is linear, that is, there is no fork in history. Blockchains enforce these properties by replicating the log and running consensus protocol among the participants. Certificate transparency log and QLDB rely on auditors or users
to detect violations of the properties. Despite useful security properties, transparency logs are inadequate as databases. In fact, we identify three challenges in building a practical verifiable ledger database on top of this abstraction.

The first challenge is the lack of a unified framework for comparing verifiable ledger databases. In particular, we note that the three systems above have roots from three distinct fields of computer science: blockchains are from distributed computing, certificate transparency is from security, and QLDB is from database. As a consequence, there is no framework within which they can be compared fairly. The second challenge is the lack of database abstraction, that is, transactions. The transparency logs used in existing systems expose a key-value interface. For example, blockchains maintain the states in a key-value storage, certificate transparency and QLDB store the hashes of the certificates and the operations in the log, respectively. This key-value model is too low-level to support general OLTP database workloads. The third challenge is how to achieve high performance while retaining security. Blockchains, for instance, suffer from poor performance due to the consensus bottleneck. Certificate transparency has low performance because of expensive disk-based operations, while QLDB generates inefficient integrity proofs for verifying the latest data.

We address the first challenge by establishing the design space of verifiable ledger databases. The space consists of three dimensions. The abstraction dimension captures the interface exposed to the users, which can be either key-value or general transactions. The threat model dimension includes different security assumptions. The performance dimension includes design choices that affect the integrity proof sizes and the overall throughput. In addition to the design space, we propose a benchmark for comparing the performance of different verifiable ledger databases. Specifically, we extend traditional database benchmarks, namely YCSB and TPC-C, with additional workloads containing verification requests on the latest or historical data.

We address the second and third challenges by designing and implementing GlassDB, a new distributed verifiable ledger database that overcomes the limitations of existing systems. GlassDB supports distributed transactions and has efficient proof sizes. It relies on auditing and user gossiping for security. It achieves high throughput by building on top of a novel data structure: a two-level Merkle-like tree. This data structure protects the data indexes, which enables secure and efficient verification. Furthermore, it is built over the states, as opposed to over transactions, which enables efficient lookup and proof generation while reducing the storage overhead. GlassDB partitions data over multiple nodes, where each node maintains a separate ledger, and uses the classic two-phase commit protocol to achieve transaction semantics. Each node of GlassDB has multiple threads for processing transactions and generating proofs in parallel, and a single thread for updating the ledger storage. GlassDB uses optimistic concurrency control to resolve conflicts in transactions, and batching to reduce the cost of updating and persisting the core data structure. We conduct an extensive evaluation of GlassDB, and benchmark it against three baselines: reimplemented versions of two verifiable databases, and a key-value store based on the transparency log.

In summary, we make the following contributions.

- We present the design space of verifiable ledger databases, consisting of three dimensions: abstraction, threat model, and performance. We discuss how existing systems fit into this design space.
- We design and implement GlassDB, a distributed verifiable ledger database that addresses the limitations of existing works. In particular, GlassDB supports distributed transactions with high performance, under a practical threat model.
- We design new benchmarks for evaluating and comparing verifiable ledger databases. The benchmarks extend YCSB and TPC-C with workloads that stress test the performance of proof generation and historical data access.
- We conduct detailed performance analysis of GlassDB, and compare it against two verifiable databases, namely QLDB [2] and LedgerDB [31], and a key-value store based on transparency log, Trillian [15]. The results show that GlassDB consistently outperforms the three baselines across all workloads.

### 2 VERIFIABLE LEDGER DATABASES

#### 2.1 What A Verifiable Ledger Database Is

A verifiable database is a database that ensures the integrity of both the data and query execution. It is useful in outsourced settings, in which the data is managed by an untrusted third party whose misbehavior can be reliably detected. Until recently, verifiable databases have focused on ensuring the integrity of query execution, particularly on the performance and expressiveness of analytical queries that can be verified [18, 24, 34].

A verifiable ledger database is one instance of verifiable database, which focuses on protecting the integrity of both the data content and data history. A user issues a read or update operation (OLTP query) to the database server (or server), which then executes the operation and appends it to a history log $H$. The database returns integrity proofs showing that (1) the operation is executed correctly on the states derived from $H$, and (2) the operation is appended to $H$, and $H$ is append-only. These proofs ensure that malicious tampering such as changing the data content, back-dating operations, forking the history log, are detected. Existing works on authenticated data structure [18], for example, only meet the first condition.

More formally, a verifiable ledger database $D$ consists of four main operations.

- $(\text{digest}_{S, H'}, \pi, R, S', H') \leftarrow \text{Execute}(S, H, op)$: this is run by the database server. It takes as input the current state $S$ and history log $H$, and the user operation $op$. It executes $op$, updates the states $S$ accordingly, and appends $op$ to $H$. It returns the updated states $S'$, updated history $H'$, a digest value $\text{digest}_{S, H'}$ computed over the new state and history, an execution result $R$, and a proof $\pi$.
- $\pi \leftarrow \text{ProveAppend}(\text{digest}_{S, H}, \text{digest}_{S', H'})$: this is run by the server. It takes as input two digest values corresponding to two different history logs. It returns a proof $\pi$.
- $(0, 1) \leftarrow \text{VerifyOp}(op, R, \pi, \text{digest}_{S, H}, \text{digest}_{S', H'})$: this is run by the user. It takes as input the user operation $op$, the execution result $R$, the proof $\pi$, and $\text{digest}_{S, H}, \text{digest}_{S', H'}$ that correspond to the history and state before and after $op$ is executed. It returns 1 if the proof is valid, and 0 otherwise.
We now give a definition for secure ledger databases (a more formal definition in the extended version of the paper).

**Definition 1.** A verifiable ledger database is secure if it satisfies the following properties.

1. **Integrity:** the database server cannot tamper with the user operation without being detected. More precisely, given a proof \( \pi \) corresponding to \( R \) such that \( \text{VerifyOp} \) returns 1, the server cannot find \( \pi', R' \) such that \( \text{VerifyOp} \) returns 1 and \( R \neq R' \).
2. **Append-only:** the database server cannot fork the history log without being detected. More precisely, given a proof \( \pi \) for an op that results in a log \( H \), such that \( \text{VerifyOp} \) returns 1, the server cannot find \( \pi', \) op’ that results in another log \( H' \) such that \( \text{VerifyOp} \) returns 1, \( \text{VerifyAppend} \) for \( H, H' \) return 1, but \( H \) is not a prefix of \( H' \).

**Example.** Suppose the current history at the database \( D \) is \( H_1 \), corresponding to the state \( S_1 = \{ a = 1, b = 2 \} \). Starting from the same \( H_1 \), one user \( A \) issues a sequence of operations \( \langle \text{add}(c, 3), \text{remove}(c), \text{add}(d, 4) \rangle \), while another user \( B \) issues \( \langle \text{add}(d, 4) \rangle \). This scenario can happen due to concurrency, or because the server acts maliciously. For user \( A \)'s last operation, the server returns \( \text{digest}_{S_1} H_1, \pi, R_1 \). For user \( B \)'s operation, it returns \( \text{digest}_{S_1} H_1, \pi', R_2 \). The append-only property means that for \( \pi \leftarrow \text{ProveAppend}(\text{digest}_{S_1} H_1, \text{digest}_{S_1} H_4) \), \( \text{VerifyAppend}(\text{digest}_{S_1} H_1, \text{digest}_{S_1} H_4, \pi) = 0 \). In other words, the server cannot fork the history, even if the two branches result in the same state.

### 2.2 Design Space

Definition 1 admits a simple, naive design in which the proof consists of the query result and complete history \( H \) (signed with the provider’s cryptographic key). The users replay all operations in \( H \) to verify the correctness of \( H \), and they broadcast messages among each other to detect any inconsistent behavior, e.g., the database signed different histories that were not linear. However, this design incurs significant communication and computation costs for the users. A more practical design would need to reduce these costs. To enable a principled comparison of different verifiable ledger databases, we propose to explore the design space along three dimensions: abstraction, threat model, and performance.

**Abstraction.** This refers to the programming interface supported by the database, which has a trade-off between flexibility and expressiveness. At one end of the spectrum is the simple key-value storage that exposes simple `Put` and `Get` operations. At the other end is the full-fledged transactional system that supports serializable (ACID) transactions. The key-value abstraction is more flexible and easier to scale, whereas transactions are easier to use and reason about. There are other design choices between pure key-value and ACID transactions. In particular, some database systems support serializable transactions over small sets of related keys [8, 11], or keys within the same partitions [17]. Some other databases support transactions with weaker isolation levels, such as snapshot isolation [22]. These design choices can deliver higher performance than the design with serializable transactions, but they suffer from anomalies. We note that in the context of verifiable ledger databases, such anomalies can happen due to the server acting maliciously to cause conflict during execution, instead of due to real concurrency. As a consequence, the application needs to handle a potentially large number of anomalies, which increases complexity and performance overhead. For the rest of the paper, we use the term transactions to refer to serializable transactions.

**Threat model.** The security of a verifiable ledger database is defined as having integrity proofs that satisfy the two conditions in Definition 1 under a specific threat model. All threat models share common assumptions that the attacker cannot break cryptographic primitives or mount denial of service attacks.

There are three main threat models in the context of verifiable ledger databases. The most common model involves a single untrusted database provider that behaves in a Byzantine manner. It has been shown that in this setting, it is only possible to achieve fork consistency [19], i.e., users cannot prevent misbehavior but can only detect it by communicating with each other. As a result, this model assumes that users engage in gossiping, and that the attacker cannot permanently partition the network. To further reduce the cost on the users, the model can be extended by introducing a set of trusted, powerful users called auditors that only gossip among themselves. The auditors check for the misbehavior of the database on behalf of the users.

The second threat model assumes that the database is replicated over a set of providers, the majority of which are trusted. Even though there are malicious providers, the system as a whole enforces the correct behavior. In particular, the providers participate in a distributed, Byzantine fault tolerant consensus protocol to ensure consistency of the database [7]. We note that such consensus-based systems provide stronger security guarantees than systems with single malicious providers, that is they can prevent misbehavior as opposed to only detecting it.

The final threat model assumes that the database server is malicious, but it is equipped with some trusted hardware that supports trusted execution environments (TEEs). The TEE protects the computation and data running inside the environment against malicious operating systems and hardware attacks. The entire database can run securely inside the TEE. However, this model assumes that both the computation and the TEE itself are free of vulnerabilities, which does not always hold in practice [6].

**Performance.** The performance of a verifiable ledger database is evaluated based on two metrics: the user’s verification cost, and the database throughput. The former depends on the complexity of the integrity proofs. An efficient proof is short and fast to verify. We further categorize integrity proofs into three types.

- **Inclusion proof:** given \( \text{digest}_{S,H} \) and a value \( v \) corresponding to a key \( k \), this proof ensures that this value is included at some point in \( H \).
- **Current-value proof:** given \( \text{digest}_{S,H} \) and a value \( v \) of a key \( k \), this proof ensures that \( v \) is the latest value of \( k \) in \( H \).
- **Append-only proof:** given \( \text{digest}_{S,H} \) and \( \text{digest}_{S,H'} \), the proof ensures that \( H \) is a prefix of \( H' \) (assuming that \( |H| \leq |H'| \)).

The database throughput is measured in terms of the number of user queries completed per second, and it depends on the cost of...
maintaining the security-related data structures for generating the proofs. Designs that exploit parallel execution and avoid contention will have high throughputs.

### 2.3 Transparency Log

Transparency log is an append-only log protected by a Merkle tree [10]. Each leaf represents an operation, for example updating a key-value tuple. This data structure supports all three types of integrity proofs. The *inclusion proof* consists of the Merkle path from the leaf to the root, which costs $O(\log(N))$ where $N$ is the size of the log. The *append-only proof* include intermediate nodes between two trees, and has the cost of $O(\log(N))$. The *current-value proof*, however, requires all the leaves of the tree, thus its cost is $O(N)$.

The security of transparency logs depends on auditing. In particular, users broadcast signed Merkle roots to a number of auditors which check that there is a single log with no forks. The check is done by requesting and verifying append-only proof from the database provider.

### 2.4 Review of Existing Systems

Table 1 compares existing verifiable ledger databases according to the design space above. These systems build on top of the transparency logs described above.

**Commercial verifiable ledger databases.** QLDB [2] and LedgerDB [31] are two recent services offered by major cloud providers. QLDB uses transparency logs for storing transactions, and executes the operations on indexed tables. However, its throughput is low due to the disk-based communication between the log and the indexed tables. LedgerDB [31] improves the performance of QLDB by batching multiple operations when updating the Merkle roots of the log. Since QLDB and LedgerDB build Merkle trees over transactions, the append-only proof costs $O(\log(N))$. However, both systems do not have protection over indexes, which require scanning to the latest transaction for current-value proof. The cost of this is $O(N)$.

**Forkbase.** Forkbase [28] is a state-of-the-art versioned, key-value storage system. It implements a variant of transparency logs called transparency maps. In particular, Forkbase builds a Merkle tree on top of immutable maps: each update operation results in a new map and a new Merkle root. Each Merkle root also includes a cryptographic pointer to the previous root. Unlike transparency logs, the current-value proof in Forkbase costs $O(\log(m))$ because the latest value is included in the map. However, the append-only proof is $O(N)$, since users have to follow the hash chain to ensure that there are no forks.

**Blockchain.** Existing blockchain systems assume the majority of trusted providers in a decentralized setting. The providers run a Byzantine fault tolerant consensus protocol to keep the ledger and global states consistent. As the system as a whole is trusted, signed statements from the blockchain can be used as integrity proofs. In particular, in a permissioned blockchain that tolerates $f$ Byzantine failures, the proof contains signatures from $f + 1$ providers. The proof complexity is therefore independent of the history, or $O(1)$. However, the performance of a blockchain is limited by the consensus protocol [12].

**CreDB** Instead of relying on consensus to protect against Byzantine database servers, CreDB assumes that the server can create trusted execution environments backed by trusted hardware. CreDB processes user transactions inside the TEE and produces signed witnesses that capture the history of the states. Both inclusion and current-value proofs in CreDB are efficient, because they are simple messages signed by the TEE. However, the hardware limitation, e.g. the limited memory available for Intel SGX, makes the TEE a performance bottleneck, and results in low throughputs.

**Public-key transparency logs.** Trillian [15] combines transparency logs and maps to implement new primitives called *verifiable log-based map*. It exposes a key-value interface, and is used for storing public key certificates. When a key is updated, the map is updated and a new Merkle root is computed on the map. It then appends the log with both the operation and the Merkle root. As the result, both the current-value and append-only proofs are efficient, i.e. $O(\log(m))$ complexity. On the other hand, Trillian relies on trusted auditors to regularly verify the consistency between the log and the corresponding map. More specifically, the auditors recompute the map from the log and ensure that the Merkle root included in the log is correct. This auditing process is expensive and should be performed by powerful, external entities rather than by the users. Other systems such as CONIKS[21], ECT [26], and Merkle2 [16] are similar to Trillian in our design space. They improve Trillian by adding support for privacy, revocation (non-inclusion proofs), and reducing the audit cost.

### 3 GLASSDB

#### 3.1 Existing Designs

Figure 1 shows a design of verifiable ledger databases used in commercial systems such as QLDB [2]. The key idea is to replace the transaction log in conventional databases with a variant of transparency log called ledger. The ledger is a hash-chained sequence of

| System       | Abstraction | Threat model | Append-Only Proof | Current-Value Proof | Throughput |
|--------------|-------------|--------------|--------------------|---------------------|------------|
| QLDB [2]     | Transaction | Audit        | $O(\log(N))$       | $O(N)$              | Low        |
| LedgerDB [31]| Transaction | Audit        | $O(\log(N))$       | $O(N)$              | Medium     |
| Forkbase [28]| Key-value   | Audit        | $O(N)$             | $O(\log m)$        | Medium     |
| Blockchain [4]| Transaction | Consensus    | $O(1)$             | $O(1)$              | Low        |
| CreDB [20]   | Transaction | Trusted hardware | $O(1)$             | $O(1)$              | Low        |
| Trillian [15], ECT [26], Merkle2 [16] | Key-value | Audit        | $O(\log m)$       | $O(\log m)$        | Low        |
| **GLASSDB**  | Transaction | Audit        | $O(\log B)$       | $O(\log B + \log m)$ | High       |
blocks, each of which contains the operation type and parameters, and a Merkle tree is built on top of them to protect their integrity. Updating the ledger requires appending a new operation block and rebuilding the Merkle tree.

Transaction execution in this design is similar to that in a conventional database. The transaction is first committed to the ledger as a new block, under some concurrency control mechanisms. Then, the data and indices are updated. The transaction is considered committed once the ledger is updated and the data can be queried via the indices. The response to the client includes a block sequence number indicating where in the ledger the transaction is committed. During verification, the client requests a digest of the ledger, and then sends a GetProof request containing the sequence number and the digest. It receives a Merkle proof showing that the specified block is included in the ledger. After verifying the proof, it checks that the data is included in the block.

The main advantage of this design is that it is easy to extend an existing database system into a verifiable ledger database. In addition, the design is independent of the underlying data abstraction and layout. However, it has two major deficiencies. First, it incurs significant overhead in transaction processing, because updates of the Merkle tree are in the critical path. Second, the indices are not integrity protected, i.e., the server can respond with stale data. As a result, this design requires the client to scan the ledger to guarantee the returned value is current, which incurs $O(N)$ cost.

LedgerDB [31] improves the design above by updating the authenticated data structures asynchronously. Figure 2 shows the different indices and Merkle trees used in LedgerDB. In LedgerDB, each transaction is appended to a ledger in the form of a journal entry, and a Merkle tree built on top of the ledger is updated asynchronously in batch, which is called batch accumulated Merkle-tree (bAMT). LedgerDB maintains a skip-list index (called a clue index) for each individual data key, with each entry in the skip list pointing to the journal entry corresponding to the transaction that modifies the data key. The size of the index is stored as a leaf of a Merkle Patricia Trie, called clue-counter MPT(ccMPT). The root of ccMPT and bAMT are stored as a block in a hash chain. LedgerDB also supports data freshness by using another ledger that stores time entries from a timestamp authority.

There are three limitations of LedgerDB’s design that result in high verification cost. First, bAMT stores one transaction per leaf, therefore its size can be large when there are many transactions, which leads to larger proofs. Second, it is expensive to verify a value of a key, even in the presence of a trusted auditor. In particular, the ccMPT structure used to protect the clue index is not secure, because each leaf of the ccMPT stores only the size of each clue index, instead of capturing the content of the entire index. As a consequence, to verify the value of a key, the client needs to scan and verify the entire index to ensure that each entry in the clue index points to a correct journal entry. We note that even if a trusted auditor verifies the ccMPT and clue indexes, the client still needs to verify the clue index by itself, because a malicious server can modify the index without changing the ccMPT. Finally, the size of the proof for multiple keys, even when the keys belong to the same transaction, grows linearly with the number of keys because each key requires a separate proof from the ccMPT.

3.2 GlassDB Overview

GlassDB is a new, distributed verifiable ledger database that overcomes the limitations of the existing designs. It supports general transactions, which makes it easy to use by existing and future applications. It adopts the same threat model as QLDB and LedgerDB, which assumes that the database server is untrusted, and there exists a set of trusted auditors that gossip among each other. GlassDB achieves high throughputs and small verification costs. Table 1 shows how the system fits in the design space.

There are three novelties in the design of GlassDB that facilitate its high performance. First, GlassDB adopts hash-protected index structures. The key insight we identify from the limitation of existing ledger databases is the lack of comprehensive and efficient protection of the indexes, which leads to either security issues or high verification overhead. Such limitations can be eliminated by adopting hash-protected index structures. Second, GlassDB builds its ledger over the state of data instead of transactions. One advantage of this approach is that the system can retrieve the data and generate current-value proofs more efficiently. Another advantage is that it results in a smaller data structure. The Merkle trees of the existing systems are built over the transactions, which grow quickly and lead to higher storage and computation overhead. In contrast, GlassDB’s core data structure grows more slowly as it batches updates from multiple transactions. Third, GlassDB partitions the data over multiple nodes, which enables it to scale to achieve high
When ready to commit, the client invokes \( \text{Init}(pk, sk) \) which initializes the client’s session with the private key \( p_k \) and assigns \( sk \) to the verifier, and a ledger storage. A transaction request is forwarded to the transaction manager, which executes the transaction using a thread pool with optimistic concurrency control. A verification request is forwarded to the verifier, which returns the proof. The ledger storage maintains the core data structure that provides efficient data access and proof generation. Each shard maintains an individual ledger based on the records committed. The client keeps track of the key-to-shard mapping, and caches the digests of the shards’ ledgers. GlassDB uses write-ahead-log (WAL) to handle application failures. It can be extended to handle node failures by adding a replication layer on top of the ledger storage.

The life cycle of a transaction at the server can be divided into four phases: prepare, commit, persist, and get-proof. The prepare phase checks for conflicts between concurrent transactions before making commit or abort decisions. The commit phase stores the write set in memory and appends the transaction to a WAL for durability and recovery. The persist phase appends the committed in-memory data to the ledger storage and updates the authenticated data structures for future verification. The get-proof phase generates the requested proofs for the client. In GlassDB, the persist and get-proof phases are executed asynchronously and in parallel with the other two phases. The detail is illustrated in Figure 3.3.2.1 APIs. The user (or client) starts by calling \( \text{Init}(pk, sk) \), which initializes the client’s session with the private key \( sk \) for signing transactions, and sends the corresponding public key \( pk \) to the auditors for verification. The client invokes \( \text{BeginTxn}(t) \) to start a transaction, which returns a transaction ID \( tid \) based on client ID and timestamp. During the transaction, the client uses \( \text{Get}(tid, key, (timestamp, block_no)) \) and \( \text{Put}(tid, key, value) \). When ready to commit, the client invokes \( \text{Commit}(tid) \), which signs and sends the transaction, including the buffered writes, to the server. This method returns a promise, which can be passed to \( \text{Verify}(promise) \) to request a proof and verify it. The client frequently invokes \( \text{Audit}(digest, block_no) \) to send a digest of a given block to the auditors.

An auditor uses \( \text{VerifyBlock}(digest, block_no) \) to request the server for the block at \( block_no \), proof of the block, and the signed block transactions. It verifies that all the keys in the transactions are included in the ledger. It also uses \( \text{VerifyDigest}(digest, block_no) \) to verify that the given digest and the current digest correspond to a linear history, by asking the server to generate append-only proofs. If the given block number is larger than the current block number, it uses \( \text{VerifyBlock} \) to verify all the blocks in between. Finally, the auditor calls \( \text{Gossip}(digest, block_no) \) to broadcast the current digest and block number to other auditors.

### 3.3 GlassDB Design

#### 3.3.1 Ledger storage

The design goal of GlassDB is to build a storage system that not only offers efficient access to the data, but also supports efficient inclusion, latest, and append-only proofs. To this end, we use a Merkle variant called two-level pattern-oriented split tree (or two-level POS-tree).

A POS-tree is an instance of Structurally Invariant and Reusable Index (SIRI) [28, 32], which combines the Merkle tree and balanced search tree. A parent node in the POS-tree stores the cryptographic hash of its child nodes, such that the root node contains the digest of the entire tree. The user can perform efficient data lookup by traversing the tree. The POS-tree is built from the globally sorted sequence of data. The data is split into leaf nodes using content-defined chunking, in which a new node is created when a pattern is matched. The cryptographic hash values of the nodes in one level form the byte sequence for the layer above. The byte sequence is split into index nodes using similar content-defined chunking approach. POS-tree is optimized for high deduplication rates because of its content-defined chunking. Finally, it is immutable, that is, a new tree is created, using copy-on-write, when a node is updated.

The core data structure of GlassDB is shown in the right part of Figure 3. It consists of an upper level POS-tree and a lower level POS-tree. The lower level POS-tree is built on the database states, and its root node, called the data block, contains the root hash and other block meta info such as block number. The data blocks are stored as the leaves of the upper level POS-tree. This POS-tree serves as an index over the data blocks, and its root is the digest of the entire ledger. Retriving a key from a given block number entails getting the data block with the corresponding block number from the upper level POS-tree, then traversing the lower level POS-tree to locate the data. Metadata such as the block number where the previous version of data resides are stored together with the data in the leaf nodes, making it efficient to trace the history of data. When updating a key, new nodes are created at both levels using copy-on-write. One advantage of this authenticated data structure is that it provides efficient current-value proofs, in addition to the inclusion and append-only proofs. Since each data block represents a snapshot of the database states, the latest values always appear in the last block, thus current-value proof can be verified with only one block.

#### Comparison with QLDB and LedgerDB’s storage

Both QLDB and LedgerDB use Merkle trees to ensure the integrity of the data. However, they offer weak security and incur significant verification overhead, as we discussed in Section 3.1. The fundamental difference between their design and ours is that our ledger storage protects the integrity of the indices. Specifically, both the database indices and the clue indices in QLDB and LedgerDB are not protected. As the result, the server can return stale data, or tamper with the indices without being detected. For example, in LedgerDB, because only the sizes of the clue indices are protected by a Merkle tree, the server can change the pointers inside the skip lists to point to stale journal entries. To detect against such tampering, the client needs to verify all entries in the skip lists, therefore incurring significant costs. In contrast, the two-level POS-tree protects both the data, the indices, and the history. In particular, the upper level protects the lineage of the states, while the lower level protects the data and serves as the index. A proof in GlassDB includes relevant nodes from the leaf of lower level POS-tree to the root of upper level POS-tree. Since both levels are tamper-evident, it is not possible for the server to modify the data or skip some versions without....
3.3.2 Transaction. GLASSDB partitions the keys into shards based on their hash values. When a transaction involves multiple shards, GLASSDB achieves atomicity using 2PC. Each client is a coordinator. It generates the read set and write set of the transaction, then sends prepare message to the shards. The transaction manager at each shard logs the transaction and responds with a commit or abort based on the concurrency control algorithm. GLASSDB uses optimistic concurrency control to achieve serializability. In particular, the read set and write set of concurrent transactions are validated to check for the read-write and write-write conflicts. The shard returns “commit” if there are no conflicts, and returns “abort” otherwise. The client waits for the responses from all shards involved in the transactions, and it resend the messages after a timeout period. If all shards return commits, the client sends the commit messages to the shards, otherwise it sends abort. Each shard then commits or aborts the transaction accordingly, and returns an acknowledgment to the client.

At each shard, the transaction is processed by the transaction manager as follows. All incoming requests are buffered in the transaction queue, waiting to be assigned to available transaction threads. If the queue is full, the transaction is aborted. The transaction threads store the prepared transactions and committed data in the shared memory. The persisting thread persists the committed data asynchronously to the ledger storage.

**Asynchronous persistence.** Committing transactions to the ledger incurs large overheads due to high contention and long execution time. To address this, GLASSDB updates the ledger asynchronously. In particular, when receiving the commit message, the transaction manager stores the transaction data in a multi-version “committed data map” (key, ver, val) in memory, and writes to the WAL for durability and recovery. After a timeout, a background thread persists the data in the map to the ledger storage. The persisted data is then removed from the committed data map to keep the memory consumption low. This approach moves the updating of the ledger out of the critical path, thus reducing transaction latency. The trade-off here is that the users cannot retrieve the proofs for data that has not been persisted to the ledger. We explain the verification process in Section 3.3.3.

**Transaction batching.** The cost of updating and persisting the authenticate data structures is large, even though they are now out of the critical path of transaction execution. It is because both levels of the POS-tree need to be updated and written to disk. To reduce this cost, GLASSDB batches multiple committed transactions before updating the ledger. In particular, it uses an aggressive batching strategy that collects independent data from recently committed transactions into a data block. All the blocks created within a time window are appended to the ledger storage. To form a block, the server selects data from the “committed data map” version by version. For a given data version, it can compute the sequence number of the block at which the data will be committed, by adding the current block sequence with the version sequence in the data map. This estimation is used for deferred verification (explained later in Section 3.3.3).

**Comparison with QLDB and LedgerDB.** In LedgerDB and QLDB, the ledgers are built from transactions, thus the size of the Merkle tree grows with the number of transactions, which can be large. The bigger the Merkle tree, the longer the proofs, and the more expensive it is to update and generate proofs. By batch- ing multiple transactions, GLASSDB affords a smaller Merkle tree, therefore it is more efficient.

3.3.3 Verification. Verifying a transaction requires checking both the read set and the write set. To verify the read set, the client checks that the data is correct and is the latest (for example, for the default Get() operation). In other words, the server needs to produce current-value proof. To verify the write set, the client checks that the new ledger is append-only, and that the data written to the ledger is correct. In other words, the server needs to produce an append-only proof and an inclusion proof. The inclusion and current-value proofs in GLASSDB contain the hashes of the nodes in the two-level POS-tree along the path from the leaf to the root, through the specific block and the latest block, respectively. The append-only proof contains the hashes of nodes along the path where the old root resides. If the old root node does not exist in the new Merkle tree (i.e., because the old Merkle tree is not a complete tree), a proof for its left child node is generated. To verify the proof, the client computes the digest and compares it with the digest
saved locally. In GlassDB, the verification requires getting proofs from all participating shards. There is no coordination overhead, because the ledger is immutable with copy-on-write which means read operations can run concurrently with other transactions. **Deferred verification.** GlassDB supports deferred verification, meaning that transaction verification occurs within a time window, as opposed to immediately. This strategy is suitable for applications that cannot afford even a temporary violation of data integrity. For these applications, the client gets a promise from the server containing the future block sequence number where the data will be committed, transaction ID, current digest, the key and the value. The client can verify the transaction after the block is available by sending a verification request taking the promise as parameter. The server, on receiving the verification request, will check if the block has been persisted. It generates the inclusion proof and append-only proof if the check passes, and returns the proofs and new digest to the client. The client can then verify the integrity of the data as mentioned above. The two-level POS-tree allows the server to batch proofs for multiple keys (especially when they are packed in the same data block). Furthermore, getting the data and the proof can be done at the same time by traversing the tree, which means proof generation can be done with little cost when fetching the data during transaction processing. This is as opposed to LedgerDB requiring the server to traverse one data structure to retrieve the data, and then another data structure to retrieve the proof. To alleviate the burden of deferred verification, in GlassDB, the proof of persisted data is returned immediately during transaction processing, and proof for data to be persisted in future blocks will be generated in deferred verification requests in batch.

This approach leaves a window of vulnerability during which a malicious database can tamper with the data, but any misbehavior will be detected once the promised block number appears in the ledger. GlassDB allows clients to specify customized delay time for verification to find suitable trade-offs between security guarantee and performance according to their needs. Particularly, zero delay time means immediate verification. In this case, the transactions are persisted to the ledger synchronously during the commit phase. This strategy is suitable for applications that cannot afford even a temporary violation of data integrity.

### 3.3.4 Auditing

While the user verification ensures that the user’s own transactions are executed correctly, GlassDB ensures the correct execution of the database server across multiple users. In particular, it relies on a set of auditors, some of which are honest, to ensure that different users see consistent views of the database.

Each auditor performs two important tasks. First, it checks that the server does not fork the history log, by checking that the users receive digests that correspond to a linear history. It maintains a current digest \(d\) and block number \(b\) corresponding to the longest history that it has seen so far. When it receives a digest \(d’\) from a user, it asks the server for an append-only proof showing that \(d\) and \(d’\) belong to a linear history.

Second, the auditor re-executes the transactions to ensure that the current database states are correct. This is necessary to prevent the server from arbitrarily adding unauthorized transactions that tamper with the states. It also defends against undetected tampering when some users do not perform verification (because they are offline, or due to resource constraints). The auditor starts with the same initial states as the initial states at the server. For each digest \(d\) and corresponding block number \(b\), the auditor requests the signed transactions that are included in the block, and the proof of the block and of the transactions. It then verifies the signatures on the transactions, executes them on its local states, computes the new digest, and verifies it against \(d\).

When the auditor receives a digest corresponding to a block number \(b’\) which is larger than the current block number \(b\), it first requests and verifies the append-only proof from the server. Next, for each block between \(b\) and \(b’\), it requests the transactions and verifies that the states are updated correctly. After that, it updates the current digest and block number to \(d’\) and \(b’\) respectively. Finally, after a pre-defined interval, the auditor broadcasts its current digest and block number to other auditors.

#### 3.3.5 Failure Recovery

GlassDB supports transaction recovery after a node crashes and reboots. In particular, if a node fails before the commit phase, the client aborts the transaction after a timeout. Otherwise, the client proceeds to commit the transaction. When the failed node recovers, it queries the client for the status of transactions, then decides to whether abort or commit. It then checks the WAL for updates that have not been persisted to the ledger storage, and updates the latter accordingly. If the client fails, the nodes have to wait for it to recover, because the 2PC protocol is blocking. We note that this can be mitigated by replacing 2PC with a non-blocking atomic commitment protocol, such as three-phase commit (3PC).

GlassDB tolerates permanent node failures by replicating the nodes using a crash-fault tolerant protocol, namely Raft. To ensure consistent ledgers across the replicas, GlassDB uses a fixed batch size when creating the blocks during the persistence phase. A timeout is set in case the number of upcoming transactions are insufficient to build a block. When it is expired, a dummy transaction is replicated to all replicas to enforce the block creation. We evaluate the performance impact of node crashes on both schemes in section 5.

### 3.4 Analysis

#### 3.4.1 Cost analysis

Similar to other verifiable databases, GlassDB incurs additional costs to maintain the authenticated data structure and to generate verification proofs compared to conventional databases. We now analyze the asymptotic computational costs of the main operations in GlassDB.

**Persistence.** The persistence phase updates the committed data to the two-level POS-tree. The cost of this phase is bounded by the height of the tree, which is the height of upper level plus that of the lower level, i.e., \(O(\log B + \log m)\), where \(B\) is the number of blocks and \(m\) is the number of distinct keys. In contrast, LedgerDB needs to update both the bAMT and ccMPT, which is \(O(\log N + \log m)\), where \(N\) is the total number of transactions. We note that due to batching, \(B\) is much smaller than \(N\). QLDB also updates the Merkle tree over the transactions, thus its cost is \(O(\log N)\).

**Inclusion proof.** To generate an inclusion proof, GlassDB traverses the two-level POS-tree to get the nodes on the path from the leaf to the root. Hence, the cost is \(O(\log B + \log m)\). For LedgerDB
and QLDB, the proof includes the Merkle proof for a transaction, and the transaction content. The cost is \(O(\log N)\), since the transaction content is small compared to the number of transactions.

**Current-value proof.** In GlassDB, the lower-level POS-tree captures the entire states, therefore the latest value always appears in the right-most block. The current-value proof is a special case of inclusion proof that includes the right-most block. In other words, the cost is \(O(\log B + \log m)\). In contrast, LedgerDB and QLDB do not have protection over indexes. Therefore, their current-value proofs require scanning from one transaction to the latest transaction to check for any new updates on the key. The cost of this is \(O(N)\).

**Append-only proof.** The append-only proof checks if the two digests belong to a linear history. Such a proof contains the nodes created between one digest and another (see Figure ??). The cost is \(O(\log B)\) for GlassDB, and \(O(\log N)\) for LedgerDB and QLDB.

### 3.4.2 Security analysis

GlassDB is a verifiable ledger database since it supports the four operations described in Section 2. We now sketch the proof that GlassDB is secure, which involves showing that it satisfies both integrity and append-only property.

For integrity, we first consider Get operation that returns the latest value of a given key (the other Get variants are similar) at a given digest. The user checks that the returned proof \(\pi\) is a valid inclusion proof corresponding to the latest value of the key in the POS-tree whose root is digest. Since POS-tree is a Merkle tree, integrity holds because a proof to a different value will not correspond to the Merkle path to the latest value, which causes the verification to fail. Next, consider the Put operation that updates a key. The user verifies that the new value is included as the latest value of the key in the updated digest. By the property of the POS-tree, it is not possible to change the result (e.g., by updating a different key or updating the given key with a different value) without causing the verification to fail.

For append-only, the auditor keeps track of the latest digest \(\text{digest}_{S,H_i}\) corresponding to the history \(H\). When it receives a digest \(\text{digest}_{S,H'}\) from a user, it asks the server to generate an append-only proof \(\pi \leftarrow \text{ProveAppend} (\text{digest}_{S,H'}, \text{digest}_{S,H}).\) Since our POS-tree is a Merkle tree whose upper level grows in the append-only fashion, the server cannot generate a valid \(\pi\) if \(H'\) is not a prefix of \(H\) (assuming \(|H'| < |H|\)). Therefore, the append-only property is achieved.

In GlassDB, each individual user has a local view of the latest digest \(\text{digest}_{S,H_i}\) from the server. Because of deferred verification, the user sends \(\text{digest}_{S,H_i}\) together with the server’s promise during verification. When the latest digest at the server \(\text{digest}_{S,H_a}\) corresponds to a history log \(H_g\) such that \(|H_g| > |H_i|\), the server also generates and includes the proof \(\pi \leftarrow \text{ProveAppend} (\text{digest}_{S,H_a}, \text{digest}_{S,H_i})\) in the response to the user. This way, the user can detect any local forks in its view of the database. After an interval, the user sends its latest digest to the auditor, which uses it to detect global forks.

### 4 BENCHMARK

Even though the verifiable databases expose database-like interface to applications, the existing database benchmarks do not contain verification workloads. To fairly compare GlassDB with other systems, we extend YCSB and TPC-C by including verification workloads.

#### 4.1 YCSB

The existing YCSB workloads include simple put and get operations. We add three more operations, called VerifiedPut, VerifiedGetLatest, and VerifiedGetHistory, and a new parameter delay. These operations return integrity proofs that can be verified by the user. The delay parameter allows for deferred verification, that is, the database generates the proofs only after the specified duration. When set to 0, the operations return the proof immediately. When greater than 0, the database can improve its performance by batching multiple operations in the same proof.

- VerifiedPut\((k, v, \text{delay})\): returns a promise. The user then invokes GetProof\((\text{promise})\) after delay seconds to retrieve the proof.
- VerifiedGetLatest\((k, \text{fromDigest}, \text{delay})\): returns the latest value of \(k\). The user only sees the history up to headDigest, which may be far behind the latest history. For example, the user last interacts with the database, the latter’s history digest is fromDigest. After a while, the history is updated to another digest latestDigest. This query allows the user to specify the last seen history. The integrity proof of this includes an append-only proof showing a linear history from fromDigest to latestDigest.
- VerifiedGetAt\((k, \text{atDigest}, \text{fromDigest})\): returns the value when the database history is at atDigest. fromDigest is the last history that user sees. The integrity proof for this query includes an append-only proof from fromDigest to atDigest.

Based on these operations, we add two new workflows to YCSB. First, Workload-X consists of 50% VerifiedPut, 50% VerifiedGetLatest, with 100ms delay. Second, Workload-Y consists of 20% VerifiedPut, 40% VerifiedGetLatest, 40% VerifiedGetAt, with 100ms delay.

#### 4.2 TPC-C

We extend all five types of transactions in TPC-C to the verified versions. Similar to YCSB, each new transaction has a delay parameter for specifying deferred verification. When delay > 0, each transaction returns a promise which is later used to request the integrity proof. In addition to the five new transactions, we add a new one called VerifiedWarehouseBalance, which retrieves the last 10 versions of \(w_{ytd}\). This transaction is possible with verifiable ledger databases because they maintain all historical versions of the data.

### 5 EVALUATION

#### 5.1 Baselines

We compare GlassDB against three state-of-the-art verifiable ledgers, namely QLDB, LedgerDB, and Trillian. We do not compare against blockchains due to the different threat models. QLDB and LedgerDB are not open-sourced, thus we implement them based on the documentation available online, or based on the details in the papers. We denote them by QLDB∗ and LedgerDB∗ respectively.

To facilitate fair performance comparison, we implement QLDB∗, LedgerDB∗ and GlassDB on top of the same distributed layer, which
When committing a new transaction, the system appends a new log with it, and returns the status to the client. A background thread executes the transaction and updates the TSA, which is used for security in LedgerDB, as its complexity ensures sufficient details regarding the experiments, for example it does not say how it is compared against QLDB (whether the authors used the QLDB service from Amazon, or implemented an emulated one). Third, since the technique details of QLDB are not public, it is not clear from [31] how much the performance gap is due to the differences in hardware, low-level communication protocol, or serialization. Finally, it is not possible to reproduce the results in [31] due to the experiment artifacts being unavailable.

5.3 Micro-Benchmarks

In this section, we evaluate the cost at the server in terms of execution time and storage consumption. We extend the vanilla YCSB benchmark to support transactions, by batching every 10 operations as a transaction. We characterize the workloads as read-heavy (8 reads and 2 writes), balanced (5 reads and 5 writes), and write-heavy (2 reads and 8 writes).

5.3.1 Cost breakdown of GlassDB. We break down the server cost into four phases as described in Section 3.3.2: prepare, commit, persist, and get-proof. For the last two phases, we report the average latency per key, because the these phases’ costs depend on the number of records in the batch.

Figure 4(a) shows the latency of different phases with varying numbers of operations per transaction (or transaction sizes). We observe that the latency of prepare and commit phase increases as the transactions become larger, which is due to more expensive conflict checking and data operation. Figure 4(b) shows the latency under different workloads. The latency of the prepare phase increases slightly as the workload move from read-heavy to write-heavy because a larger write set leads to more write-write and write-read conflict checking. In contrast, the commit latency of read-heavy workload is much higher than that of write-heavy workload, since read operations are more expensive than the write operations in GlassDB as explained in Section 3.2. Figure 4(c) shows the latency breakdown for varying number of nodes. The latency of the prepare and commit phase decrease as the number of nodes increases, because having more shards means fewer keys to process per node. Figure 4(d) shows the impact of increasing the persist interval. It can be seen that with a longer interval, the persist phase is invoked less frequently, which reduces contention with other phases. As a result, the latency of prepare and commit phases decrease. The persist batch size increases with longer persist intervals, larger transaction sizes, higher write ratio, or with fewer nodes because
they lead to more data committed per node. A large persist batch size results in larger data blocks created in the ledger, which in turn increase the batch size of get-proof phases. The results in Figure 4 show that persist and get-proof costs decrease as the persist batch size increases, demonstrating the effectiveness of batching.

We quantify the cost at the client in terms of verification latency and the proof size (which is proportional to the network cost) as shown in Figure 5. We vary the verification delay to show the impact on the costs. The client batches more keys for verification when the delay time is higher, which results in larger proofs as shown in Figure 5(b), and therefore increases the verification latency 5(a). We note that the cost per key decreases with higher delay, demonstrating that batching is effective.

We evaluate the impact of the persistence interval on the overall performance by fixing the client verification delay to 1280ms, while varying the persistence interval from 10ms to 1280ms. Figure 6(a) shows the performance for read-heavy, balanced, and write-heavy workloads. It can be seen that longer intervals lead to higher throughputs for all workloads except for write-heavy workloads. This is because less frequent updates of the core data structure helps reduce contention and increase the effect of batching. For write-heavy workload, however, a long interval causes the update of the core data structure to block transaction execution for longer, which increases the abort rate. In particular, we observe that the abort rate increases to 21.6% at interval of 1280ms for write-heavy workloads, while it remains 1.5% and 3.5% for read-heavy and balanced workloads. Next, we evaluate the impact of verification delay by fixing the persistence interval to 10 ms and varying the delay from 10 ms to 1280 ms. The results are shown in Figure 6(b), in which the throughput increases with larger delays due to proof batching. However, the throughput drops after the peak at 800ms. This is because the batched proof becomes too large that the network cost becomes significant.

5.3.2 Cost breakdown versus other baselines. We compare the latency breakdown of GlassDB with that of two other baselines. We do not compare against Trillian because it does not support transactions.

Figure 7(a) shows that GlassDB and LedgerDB* have lower latency than QLDB* in most phases. The commit latency of QLDB* is especially high because it includes the cost of persisting the authenticated data structure, which explains why Figure 7(a) does not show the cost of the persist phase for QLDB*. In contrast, GlassDB and LedgerDB* persist the authenticated data structures asynchronously, therefore they have lower latency. GlassDB has the lowest commit latency because it only persists the write-ahead logs when the transaction commits. Furthermore, it has lower latency in the persist and get-proof phases because the size of the data structure is smaller.

Figure 7(b) and Figure 7(c) compare the verification latency and per-key proof size of different systems. We measure the proof size per key because each proof is for the entire block containing multiple keys. QLDB* has the smallest proof size, and therefore lowest verification time, due to its small Merkle tree. However, we note that it locks the entire tree during proof generation, thus its latency for the get-proof phase is high. The per-key proof size of GlassDB is smaller than that of LedgerDB* for two reasons. First, the authenticated data structure in GlassDB is smaller, resulting in a smaller proof for a block. This leads to smaller verification time in Figure 7(b). Second, GlassDB has more keys per block, therefore the per-key proof is even smaller.

5.3.3 Storage consumption. We measure the storage cost of GlassDB with varying batch sizes, and compare them against the other two baselines. Figure 7(d) shows that GlassDB consumes less storage as the batch size increases, because there are fewer saved snapshots. It is most space-efficient when the batch size exceeds 1,000 keys per batch, which can be achieved with 16 nodes and...
with 100ms delay. LedgerDB∗ consumes more storage because its authenticated data structure is larger than that of GlassDB.

5.3.4 Impact of design choices. To quantify the impacts of our three novel design choices, we remove these features from GlassDB and compare the resulting system with the baselines. The result is shown in Figure 8. With only the two-level POS-tree, the system (GlassDB-no-DV-no-BA) outperforms QLDB∗ by 1.2x. By adding deferred verification, the system (GlassDB-no-BA) improves the performance by 2.4x, outperforming LedgerDB∗, a system with deferred verification, by 1.3x. By further adding batching, the throughput of the final system (GlassDB) increases by another 1.3x.

5.4 YCSB Workloads
In the experiments, we run read-heavy, balanced, and write-heavy workloads with number of nodes ranging from 1 to 16, number of clients ranging from 8 to 80, and delay time ranging from 10ms to 1280ms. We first measure peak throughput by fixing the number of nodes to 16, while increasing the number of clients until the systems are saturated. Figure 9(a) compares the systems under the balanced uniform workload, i.e. Zipf factor is 0. GlassDB outperforms QLDB∗ and LedgerDB∗ by up to 3.7x and 1.7x respectively. Both GlassDB and LedgerDB∗ are better than QLDB∗ because they persist the authenticated data structure asynchronously, that is, they avoid updating the Merkle tree in the critical path. Furthermore, they both use batching that helps improve the throughput. In particular, GlassDB collects non-overlapping keys from multiple transactions when creating a new block, whereas LedgerDB∗ batches newly committed transactions when constructing the Merkle tree. The latter constructs Merkle trees on top of all transactions, which results in larger Merkle trees, and hence, higher overheads during the persist and get-proof phases.

Figure 9(b) shows that all systems scale linearly, and GlassDB achieves the highest throughput. The linear scalability demonstrates that the two-phase commit’s overhead is small.

Figure 9(c) displays the throughput comparison under different workloads. It can be seen that GlassDB consistently outperforms the baselines across all workloads. In particular, its throughput increases with higher write ratio, because write operations are more efficient as data is kept in memory. We note that higher write ratio leads to more aborts and larger search space for conflicts. For QLDB∗, the time to update the Merkle tree is dominant, therefore the abort rate is a key factor that affects the throughput. For LedgerDB∗, since the update of Merkle tree is asynchronous, its reduction of throughput is due to higher disk I/Os and larger conflict search space.

5.5 TPC-C Workloads
We run a mixed workload containing all six types of TPC-C transactions mentioned in Section 4.2, with new order and payment transactions accounted for 42%, and other types accounted for 4% each. We implement the tables in TPC-C on top of the key-value stores in all the systems. In particular, each field in a row is a data unit, and the key-value pair becomes <ColumnName_PrimaryKey, FieldValue>. We make a further optimization to combine fields that are not frequently updated. For example, we combine c_first, c_middle, and c_last to c_name.

Figure 10(a) shows the throughput with an increasing number of clients. GlassDB outperforms LedgerDB∗ by 1.3x and outperforms QLDB∗ by 2.3x. We note that the TPC-C workload has larger and more complex transactions than YCSB workloads, therefore we observe 2.1x lower throughput. In particular, GlassDB achieves peak throughput at 48 clients, as opposed to 64 clients for YCSB. This is because large transaction size involves more nodes and increases the overhead of coordination. Figure 10(b) shows the latency breakdown at the peak throughput for each transaction type; GlassDB consistently has the lowest latency among all types of transactions.

5.6 Verification Workloads
We use workload-X as described in Section 4 to compare GlassDB with QLDB∗, LedgerDB∗, and Trillian. We omit the results for workload-Y since it displays a similar trend. We run key-value workloads, as Trillian does not support concurrent transactions. For each verified operation, the client performs verification of the proof.

In the distributed settings with 16 nodes, Figure 12(a) shows the throughput for workload-X with an increasing number of clients. GlassDB achieves the highest throughput: 2.5x higher than QLDB∗ and 1.6x higher than LedgerDB∗. We evaluate the impact of deferred verification by measuring the throughput with 0ms delay, that is, every operation is verified synchronously. Without deferred verification, the throughput is lower than LedgerDB∗, and higher than QLDB∗. Figure 12(b) shows the latency for each operation. For GlassDB and LedgerDB∗, which use deferred verification, we separate out the cost of verifying one key. GlassDB outperforms the other systems in the read and write latency due to its efficient proofs (smaller proof sizes) and efficient persist phase. Even when
combining the cost of transaction execution with that of verification, the total cost of GlassDB and LedgerDB* are still lower than that of QLDB*. This is because the verification request contains multiple keys, and the two former systems can batch multiple keys in the same proof, whereas QLDB* has one proof per key.

To fairly compare with Trillian, which is a single node system that only supports key-value abstraction, we use the single-node version of GlassDB, LedgerDB*, and QLDB*. The results are shown in Figure 13. GlassDB outperforms LedgerDB*, QLDB*, and Trillian by up to 2.0×, 5.7× and two orders of magnitude, respectively. The performance gap is due to the cost of the put and get operations in Trillian being orders of magnitude more expensive. In particular, Trillian stores all data in a separate, local MySQL database instance, thus each operation incurs cross-process overheads.

Finally, we evaluate the cost of the auditing process. We use 16 servers with 64 clients, running the balanced transaction workload. After an interval, an auditor sends VerifyBlock(·) requests to the servers and verifies all the new blocks created during the interval. Figure 14 shows the auditing costs with varying intervals from 20ms to 100ms. Both the latency for verifying the new blocks, and the number of new blocks grows almost linearly with the audit interval. This is because more blocks are created during a longer interval, and it takes a roughly constant time to verify each block. We remark that the auditing process is expensive, especially when the rate of block creation is high. However, it can be done off the critical path, and is amenable to distributed processing.

5.7 Failure Recovery
In this section, we test the impact of crash failures and the recovery process of GlassDB. We compare the two implementation, i.e., the failure recovery with respect to 2PC and fault tolerance with replication, as described in Section 3.3.5. We set the replica group size to be 3 to tolerate one node failure for the replication setting. The experiment is conducted with 16 nodes and 160 clients. After the performance of the system becomes stable, we let the system continues running for 40 seconds. Next, we kill one node and reboot it after 20 seconds. After that, we let the system run for another 40 seconds. We take measurement of the throughput for every second. The results are shown in Figure 11. In normal scenario where no crash failure occurs, replication contributes to around 22% overhead. When one node crashes, GlassDB without replication has to abort all transactions accessing keys in the partition hosted by the failed node, therefore, has low throughput until the crashed
node is brought back at 60 seconds. For GlassDB with replication, in the case of a leader failure, the system encounters a temporary low throughput because of leader election, synching of the states, and transaction aborts due to timeouts. It takes around 7 seconds to recover to peak throughput and continues to work as normal. In the case of a replica failure, the system will continue to process the transactions at the peak throughput.

6 RELATED WORK

Verifiable OLAP databases. Zhang et al. [33] propose interactive protocols for verifiable SQL queries. However, their techniques rely on expensive cryptographic primitives. Systems that use trusted hardware include EnclaveDB [25], Opaque [35], and ObidiB [13], and they support full-fledged SQL query execution inside trusted enclaves. VeritasDB [27] and Concerto [5] leverage trusted hardware to ensure the integrity of key-value operations. VeriDB [36] extends Concerto to support general SQL queries. All of these systems make a strong security assumption on the availability and security of the trusted hardware.

Authenticated data structure. Li et al. [18] propose multiple index structures based on Merkle tree and B*-tree. IntegriDB [34] proposes efficient authenticated data structures that support a wide range of queries such as join and aggregates. We note that these data structures do not guarantee the integrity of the data history.

Blockchain databases. Veritas [1] proposes a verifiable table abstraction, by storing transaction logs on a blockchain. vChain [30] and FalconDB [23] combine authenticated data structures with blockchain, by storing digests of the authenticated index structures in the blockchain. The disadvantage of blockchain-based systems is that they have poor performance.

7 CONCLUSIONS

In this paper, we described the design space of verifiable ledger databases. We designed and implemented GlassDB that addresses the limitations of existing systems. GlassDB supports transactions, has efficient proofs, and high performance. We evaluated our system against three baselines, using new benchmarks supporting verification workloads. The results show GlassDB significantly outperforms the baselines.

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