Efficiently Supporting Multi-Level Serializability in Decentralized Database Systems

Zhanhao Zhao, Hongyao Zhao, Qiyu Zhuang, Wei Lu, Haixiang Li, Meihui Zhang, Anqun Pan, Xiaoyong Du

Abstract—In decentralized database systems, it is reported that serializability could still produce unexpected transaction orderings, leading to the stale read anomaly. To eliminate this anomaly, strict serializability imposes an additional ordering constraint, called the real-time order, which is required to be preserved among serializable transactions. Yet, preserving the real-time order in strict serializability often causes the performance to drop significantly. Because a weaker data consistency often yields better performance, in this paper, we model serializability from different consistency perspectives to properly leverage the performance and consistency. To do this, we first define a group of orderings, based on which we formulate multi-level serializability by preserving a certain set of ordering constraints among transactions. We then propose a bidirectional timestamp adjustment algorithm (abbreviated as BDTA) to support multi-level serializability with various optimizations. Our special design makes ordering constraints among transactions be preserved simply by adjusting timestamp intervals. Finally, we conduct extensive experiments to show the necessity of introducing multi-level serializability and confirm that BDTA achieves up to 1.19× better performance than the state-of-the-art concurrency control algorithms.

Index Terms—Database, Transactions, Serializability, Concurrency Control

1 Introduction

Decentralized database systems [37] like Google Spanner [14], CockroachDB [44], and TiDB [25] have become increasingly popular to support large-scale web applications. In these systems, each coordinator individually coordinates transactions, each of which reads/writes data from a snapshot using a given timestamp. Due to inconsistent local clocks across coordinators, recent studies [16], [40] show serializability still produces unexpected transaction orderings that make transactions read stale data.

Example 1. Consider a user who deposits money via ATM by submitting transaction T_1. To confirm the deposit, the user subsequently checks the account balance x via an online banking service by T_2. Because T_2 starts after T_1 is accomplished, the user expects to observe the balance x written by T_1. However, as shown in Fig. 1, T_1's write cannot be "seen" by T_2, leading to a stale read $R_2(x_0)$ of T_2. The reason is that different coordinators execute T_1 and T_2 with inconsistent local clocks, i.e., the snapshot (2:01 PM) of T_2 is earlier than the commit timestamp (2:02 PM) of T_1. □

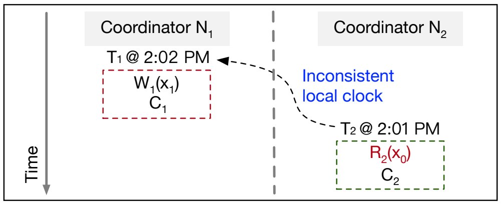

Fig. 1: The execution is serializable. However, due to two coordinators' inconsistent local clocks, a stale read anomaly $R_2(x_0)$ occurs in T_2: reading stale data x_0, highlighted in red. Symbol $W_i(x_i)$ represents a write by T_i on version x_i of data item x, $R_i(x_j)$ signifies a read by T_i on version x_j written by transaction T_j, and C_i denotes the commit of T_i.

The **real-time order** is first introduced in the linearizability consistency level [7], meaning that if one operation op_1 starts after another operation op_2 is accomplished, then op_1's read must observe op_2' write. Strict serializability [10], [24], [40] imposes the real-time order on serializability by extending the operation granularity to transaction granularity. Hence, it eliminates the stale read anomaly in serializable transactions, making T_2 observe T_1' write, i.e., read x_1, in Example 1. Thus far, preserving the real-time order can only be implemented by either (1) timestamp oracle [38] or (2) TrueTime [14]. When using timestamp oracle, each transaction is assigned with globally ordered timestamps, and hence every two transactions are comparable. For this method, however, obtaining the timestamps suffers from high network latency overhead and could become a bottleneck [8], [50]. TrueTime requires customized hardware like atomic clocks to avoid using the timestamp oracle but incurs expensive blocking overhead (i.e., commit-wait) to preserve the real-time order. For example, in the commit-wait scheme, transactions would wait for 4ms to commit, leading to significant performance degradation.

Often, weaker consistency yields better performance. Although strict serializability is taken as the strongest consistency level, it is not often supported in decentralized databases because of its poor performance. In practice, for better performance, a few newly-found consistency levels,

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with degrees weaker than strict serializability but stronger than serializability, are proposed. For example, strong session serializability [16] integrates session consistency with serializability, while Lynx [56] imposes read-your-writes consistency on serializability. However, these consistency levels are reported on a case-by-case basis, and hence, they cannot make the trade-off between consistency and performance to meet users' requirements. In this paper, we study the consistency over serializability and above, and achieve this trade-off by providing a systematic definition of consistency levels over serializability. We exclude weaker consistency levels, like snapshot isolation [33], [42], from our scope, because users often assume serializability is implicitly guaranteed [6], [20].

Inspired by different consistency models (popularized by linearizability, sequential consistency [28], causal consistency [27], etc.), we first define a group of orderings among transactions, including the write-read order, program order, causal-related order, real-time order, and write-legal order. We then model multi-level serializability to systematically formulate consistency: (1) serializability, (2) sequential serializability, and (3) strict serializability, by preserving these orders. For instance, sequential serializability is formulated by preserving the causal-related order and write-legal order. Besides providing systematic modeling, our ordering-based formulation of multi-level serializability is self-explanatory. Informally, given a transaction's write, serializability does not ensure it is always "seen" by late transactions; sequential serializability guarantees that it is always "seen" by some late transactions (e.g., subsequent transactions in the same session, ensured by the causal-related order), and strict serializability guarantees that it is always "seen" by all late transactions (ensured by the real-time order).

We then propose a novel concurrency control algorithm called **bidirectional timestamp adjustment** (abbreviated as BDTA). Inspired by dynamic timestamp adjustment (DTA) [31], [54], [55], BDTA introduces a timestamp interval $[LB, UB]$ for each transaction T. For every two transactions T_i, T_j with an ordering constraint (e.g., $T_i \rightarrow T_j$), we guarantee that their timestamp intervals are disjoint, i.e., $T_i.UB < T_j.LB$. Any transaction violating the required ordering constraint cannot produce a legal timestamp interval and aborts. We regulate the timestamp allocation scheme in BDTA to support multi-level serializability. In particular, we use the timestamp oracle to preserve the real-time order, and the hybrid logical clock [17] to preserve the causal-related order. Compared with existing DTA schemes, the differences of BDTA are two-fold: on one hand, BDTA adjusts timestamp intervals by preserving ordering constraints required in multi-level serializability; on the other hand, BDTA optimizes the size of the timestamp interval for each adjustment, leading to a lower transaction abort rate.

In summary, we make the following contributions:

- We systematically formulate multi-level serializability from different consistency perspectives. We define a group of orderings among transactions and use these orders to achieve a unified formulation.
- We design a concurrency control algorithm, called BDTA, to support multi-level serializability. We propose a heuristic method to adaptively determine the size of the timestamp interval for each adjustment, which helps reduce the abort rate. Our special design makes read-only transactions always commit.
- We conduct extensive experiments to show the necessity of multi-level serializability. Additionally, we integrate BDTA and state-of-the-art concurrency control algorithms into Deneva [22], and results show BDTA achieve up to 1.19× performance gain. We also integrate BDTA into Greenplum [21] and release our implementation publicly.

2 Background

In this section, we briefly introduce the system architecture of decentralized databases and discuss the state-of-the-art timestamp allocation schemes.

2.1 Decentralized Database Systems

Decentralized database systems are particularly designed to support scalable transaction processing. Typically, the system architecture of transaction processing can be decomposed into two layers: the coordination layer and the storage layer. The first layer contains multiple coordinators, in which each process coordinates incoming transactions and returns results to users. The second layer consists of participant servers, each responsible for storing and manipulating data items. Data items are spread across all participant servers and are partitioned by a specific strategy like hash partitioning. Each transaction is coordinated by a single process in the coordinator. The process decomposes a transaction into one or multiple local transactions, which are then distributed to the corresponding participant server(s) that is/are responsible for managing the data items to be read/written. These systems always maintain multiple versions of each data item and adopt multi-version concurrency control (MVCC) to enable a transaction to read appropriate versions based on its snapshot.

Most decentralized database systems achieve high availability and fault tolerance using data replication, implemented using consensus protocols like Paxos [29] or Raft [36]. In this case, each partition has multiple replicas, which construct a Paxos/Raft group with one replica chosen as the leader replica. Because data synchronization among the replicas based on Paxos/Raft is orthogonal to this paper, to simplify the discussion, we assume coordinators always send local transactions to the leader replica of the corresponding partition with the required data items.

2.2 Timestamp Allocation Schemes

In MVCC-based decentralized databases, each transaction should acquire a unique timestamp and use such a timestamp to determine the corresponding consistent snapshot. Some systems [38] use the timestamp oracle to allocate globally ordered timestamps. Under such a scheme, each transaction would communicate with the centralized timestamp oracle through the network, which is costly and potentially becomes a performance bottleneck. Recently proposed systems [44] rely on the hybrid logical clock (HLC) [17] scheme to achieve consistent snapshot reads. Unlike centralized timestamp oracle, HLC allows each process to allocate timestamps individually, i.e., acquire timestamps in a decentralized manner. Each timestamp allocated by HLC consists of two parts: (1) physical clock pts [32], which maintains the local timestamp of that process, and (2) Lamport clock lts [27], which traces orders among operations through different processes. These systems assign an HLC timestamp

TABLE 1: Symbols and their meanings

Symbol	Definition
P_i	i-th process in the coordinator
H_i	i-th transaction history
S_i	i-th transactionally sequential history
$T_i \to T_j$	a partial order between T_i and T_j
T_i	i-th transaction is a sequence of operations, which are either read $R_i(x_j)$, write $W_i(x_i)$, commit C_i or abort A_i
T_i^s	the local transaction of T_i in the participant s
$T_i.LB/UB$	the lower bound/upper bound of T_i's timestamp interval
$T_i^s.sl$	the spinlock of T_i
$T_i.rs/ws$	the read set/write set of T_i
$T_i.ss$	the snapshot of T_i
$T_i.c$	the commit timestamp of T_i
x	a data item, associated with four fields:
$x.pk$	the primary key of x
$x.RTS$	the maximum $T_i.c$ of the transactions that have read x
$x.WT$	the transaction that is currently modifying x
$x.RIDs$	a list recording non-committed transactions that read x
x_i	i-th version of the data item x
$x_i.cts$	$T_i.c$ of the transaction that writes x_i
$\mu_{i,j}$	the timestamp interval space for the adjustment between T_i and T_j

to each transaction and update HLC upon an operation, i.e., each operation in a transaction will trigger the update of HLC in that process. Consequently, for the applications where each transaction has a large number of reads/writes, frequently updating HLC may hurt the performance. To alleviate this problem, we propose a strategy to update HLC once per transaction instead of once per operation (with more details in Section 4.3).

3 Multi-Level Serializability Modeling

In this section, we define ordering among transactions, and systematically formulate multi-level serializability from different consistency perspectives. Table 1 summarizes the notations used throughout the paper.

Each transaction, denoted by T, is a sequence of operations, that are either read $R_i(x_j)$, write $W_i(x_i)$, commit C_i or abort A_i. Without loss of generality, we assume each transaction is separately coordinated by a single process in the coordinator. Each operation, denoted by op, consists of an invocation event $Inv(op, P)$ and a response event $Res(op, P)$, where P represents a process in the coordinator. For simplicity, we omit process P or data item x_i when the context is clear, e.g., $Inv(R_2(x_0), P_2)$ can be simplified by $Inv(R_2(x_0))$.

Following widely adopted terminology defined in [1], [24], we denote an execution of a set of transactions as a history. A history, denoted by H, is a finite sequence of events in transactions. For example, we present history H_1 in Fig. 2 that corresponds to the execution of transactions in Fig. 1. We project a history to the data item level, transaction level, and process level:

- A *data item projection*, $H|x$, of a history H is the subsequence of all invocation and response events in H of operations executed on data item x.
- A *transaction projection*, $H|T$, of a history H is the subsequence of all events in H whose operations are from T.
- A *process projection*, $H|P$, of a history H is the subsequence of all events in H coordinating by P.

Definition 1. (Equivalent Histories) Two histories H and H' are **equivalent** if $\forall P$, $H|P = H'|P$. □

For example, history S_1 shown in Fig. 3 is equivalent to H_1 by swapping the order T_1 and T_2 located in P_1 and P_2 respectively, from the global clock perspective. A transaction T_i is said to be *well-formed* in H if its transaction projection $H|T_i$ satisfies the following conditions: (1) the first event is an invocation; (2) each invocation, except the last, is immediately followed by the response of the same operation; (3) each response, except the last, is immediately followed by an invocation; (4) no events follow the response of C_i or A_i. In this paper, we assume that in a history, transactions are well-formed and finally commit. Besides, we assume each process P coordinates transaction sequentially, i.e., P only starts the first event of one transaction after receiving the response of commit or abort of another transaction.

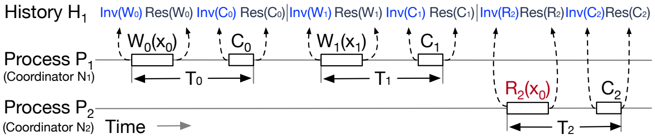

History H1
Inv(W0) Res(W0) Inv(C0) Res(C0) | Inv(W1) Res(W1) Inv(C1) Res(C1) | Inv(R2) Res(R2) Inv(C2) Res(C2)
W0(x0)
C0
W1(x1)
C1
R2(x0)
C2
Process P1
(Coordinator N1)
Process P2
(Coordinator N2)
Time
T0
T1
T2

Fig. 2: A history H_1 corresponds to Fig. 1.

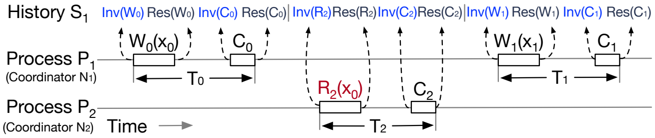

History S1
Inv(W0) Res(W0) Inv(C0) Res(C0) | Inv(R2) Res(R2) Inv(C2) Res(C2) | Inv(W1) Res(W1) Inv(C1) Res(C1)
W0(x0)
C0
R2(x0)
C2
W1(x1)
C1
Process P1
(Coordinator N1)
Process P2
(Coordinator N2)
Time
T0
T2
T1

Fig. 3: An equivalent history S_1 to H_1.

3.1 Ordering Definitions

Given a history H, and two operations op_1, op_2 of H, we define four partial orders between op_1 and op_2:

Definition 2 (Program Order, $\prec_H^{pr}$). $op_1 \prec_H^{pr} op_2$ if they are in the same P and $Res(op_1, P)$ precedes $Inv(op_2, P)$. □

Definition 3 (Write-Read Order, $\prec_H^{wr}$). $op_1 \prec_H^{wr} op_2$ if op_2 reads a version written by op_1. □

Definition 4 (Causal-related Order, $\prec_H^{cr}$). $op_1 \prec_H^{cr} op_2$ if (a) $op_1 \prec_H^{pr} op_2$ or (b) $op_1 \prec_H^{wr} op_2$, or they are related by a transitive closure leveraging (a) and/or (b). □

Definition 5 (Real-time Order, $\prec_H^{rt}$). $op_1 \prec_H^{rt} op_2$ if $Res(op_1, P_i)$ precedes $Inv(op_2, P_j)$, where op_1, op_2 are from P_i, P_j, respectively. □

Partial orders given in Definition 2–5 are defined in operation granularity. They are widely used in the concurrent system to model linearizability, sequential consistency, causal consistency, etc. In our case, we make an extension from operation granularity to transaction granularity.

Given two transactions T_i and T_j in H, we define four partial orders between T_i and T_j:

- $T_i \prec_H^{pr} T_j$, if T_i and T_j are in the same process P and the last event of T_i precedes the first event of T_j.
- $T_i \prec_H^{wr} T_j$, if there exists an operation op_1 in T_i and another operation op_2 in T_j such that $op_1 \prec_H^{wr} op_2$.
- $T_i \prec_H^{cr} T_j$, if (a) $T_i \prec_H^{pr} T_j$ or (b) $T_i \prec_H^{wr} T_j$, or they are related by a transitive closure leveraging (a) and/or (b).
- $T_i \prec_H^{rt} T_j$, if T_i's last event precedes the first event of T_j.

Definition 6 ((Transactionally) Sequential History). A history S is (transactionally) sequential if, for any two transactions T_i and T_j in S, either the last event of $S|T_i$ precedes the first event of $S|T_j$ or the last event of $S|T_j$ precedes the first event of $S|T_i$. We denote the order between T_i and T_j by $T_i \to T_j$ if T_i precedes T_j in S. □

For brevity, we refer to transactionally sequential history as sequential history unless otherwise specified.

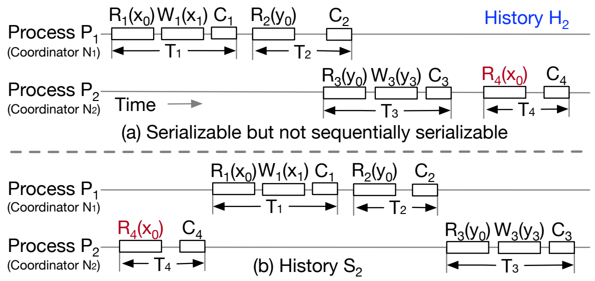


Fig. 4: A history H_2 and a sequential history S_2.

Definition 7 (**Write-legal Order**). A sequential history preserves the write-legal order if for $\forall x$, $Inv(R_j(x_i), P_k)$ in $S|x$ immediately comes after $Res(W_i(x_i), P_l)$ by removing events of other read operations in $S|x$, i.e., roughly, reads of x_i immediately come after the write of x_i in $S|x$. □

For example, S_1 shown in Fig. 3 is a sequential history, with $T_0 \prec^{pr}_H T_1, T_0 \prec^{wr}_H T_2$. Besides, S_1 preserves the write-legal order because $Inv(R_2(x_0))$ immediately comes after $Res(W_0(x_0))$ in $S_1|x$, indicating the order of S_1 is $T_0 \rightarrow T_2 \rightarrow T_1$. However, H_1 does not preserve the write-legal order since $Inv(R_2(x_0))$ does not immediately come after $Res(W_0(x_0))$ in $H_1|x$.

3.2 Multi-level Serializability

By selectively imposing orders on sequential history, we model multi-level serializability below. Given two histories H and S, $\prec^{cr}_H \subseteq \prec^{cr}_S$ means that $\forall T_i, T_j$, if $T_i \prec^{cr}_H T_j$, then $T_i \prec^{cr}_S T_j$ (this is also applicable to other orders).

Definition 8 (**Multi-level Serializability**).

- **Serializability.** A history H ensures serializability if there is a sequential history S_H, which preserves the write-legal order, with $\forall T$, $S_H|T = H|T$ and $\prec^{wr}_H \subseteq \prec^{wr}_{S_H}$.
- **Sequential Serializability.** H guarantees sequential serializability if H is equivalent to a sequential history S_H, which preserves the write-legal order, with $\prec^{cr}_H \subseteq \prec^{cr}_{S_H}$.
- **Strict Serializability.** H ensures strict serializability if H is equivalent to a sequential history S_H, which preserves the write-legal order, with $\prec^{cr}_H \subseteq \prec^{cr}_{S_H}$ and $\prec^{rt}_H \subseteq \prec^{rt}_{S_H}$. □

Informally, the execution of H is said to satisfy (1) serializability when there exists a sequential history S_H preserving the write-read order and write-legal order, (2) sequential serializability when an equivalent sequential history S_H to H preserves the causal-related order and write-legal order, (3) strict serializability when an equivalent sequential history S_H to H preserves the real-time order, causal-related order, and write-legal order. Take H_1, shown in Fig. 2, for example. H_1 satisfies sequential serializability because H_1 is equivalent to S_1 shown in Fig. 3, which is a sequential history preserving the write-legal order, with $\prec^{cr}_{H_1} \subseteq \prec^{cr}_{S_1}$. Assume T_2 reads x_1 instead of x_0 in H_1, i.e., $R_2(x_1)$, H_1 would satisfy strict serializability. On the contrary, consider history H_2 shown in Fig. 4(a). H_2 does not preserve the write-legal order. We can find a sequential history S_2 (shown in Fig. 4(b)) to H_2, which preserve the write legal order, with $\forall T \in H_2$, $H_2|T = S_2|T$ and $\prec^{wr}_{H_2} \subseteq \prec^{wr}_{S_2}$. Thus, H_2 is serializable but not sequentially serializable because $T_3 \prec^{pr}_{H_2} T_4$ is not preserved in S_2.

In essence, we model multi-level serializability by combining serializability with the consistency model, including linearizability and sequential consistency. In the following, we theoretically show that the combination of serializability with causal consistency and consistency below it can be reduced to sequential serializability.

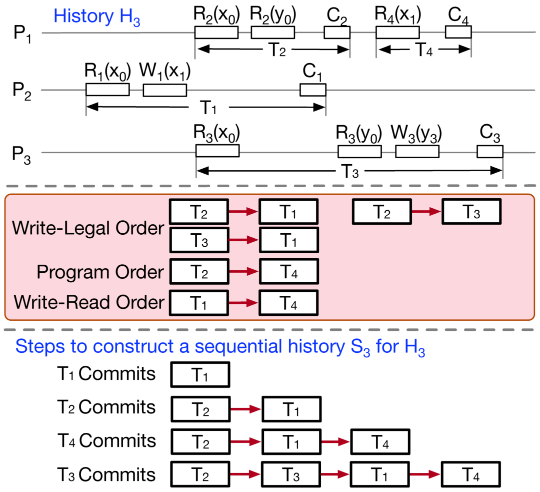


Fig. 5: An example of dynamic ordering using BDTA.

Theorem 1. *Imposing causal consistency and consistency below it on serializability can be reduced to sequential serializability.*

Proof. As mentioned in [34], causal consistency and weaker consistency levels, like read-your-write consistency, cannot preserve a total order of operations, leading to different processes observing conflict orders, e.g., $T_i \rightarrow T_j$ observed from the process P_1 and $T_j \rightarrow T_i$ observed from P_2. Since serializability imposes a total order of transactions, imposing causal consistency or weaker consistency levels on serializability is reduced to sequential serializability. □

4 Concurrency Control Algorithm

In this section, we give an overview of BDTA to support multi-level serializability and elaborate on how BDTA works correctly in decentralized MVCC-based databases.

4.1 An Overview of BDTA

The basic idea of BDTA is to preserve required orders defined in multi-level serializability during the transaction execution. To start, we give an example to show how BDTA preserves required orders under serializability.

Example 2. Consider history H_3 shown on the top part of Fig. 5. For reference, we list all orders required in serializability. We present how to construct S_3 during the execution, where S_3 is a sequential history that preserves the write-legal order of H_3, with $\forall T$, $S_3|T = H_3|T$ and $\prec^{wr}_{H_3} \subseteq \prec^{wr}_{S_3}$. From the global clock perspective, T_1 first commits, and we set T_1 as the first transaction in S_3. T_2 then commits. Theoretically, T_2 can be ordered before T_1 or after T_1 in S_3. BDTA orders T_2 before T_1 by detecting the write-legal order $T_2 \rightarrow T_1$. Next, T_4 commits and is ordered after T_1 in S_3 because of the write-read order $T_1 \rightarrow T_4$. Finally, T_3 commits. Due to the write-legal orders $T_3 \rightarrow T_1$ and $T_2 \rightarrow T_3$, T_3 can only be ordered between T_2 and T_1 in S_3. In conclusion, S_3 is shown at the bottom part of Fig. 5, with the order as $T_2 \rightarrow T_3 \rightarrow T_1 \rightarrow T_4$. □

Different from other concurrency control algorithms, like T/O, or 2PL, that order transactions statically (e.g., T/O orders transactions based on their start timestamps), BDTA orders transactions dynamically, and hence possibly leads to

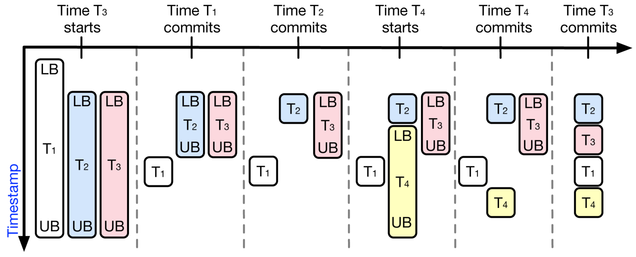


Fig. 6: An example of bidirectional timestamp adjustment.

a lower transaction abort rate. As we can see from Example 2, by using BDTA, T_2 is ordered before T_1 and can commit successfully, while by using T/O, T_2 is ordered after T_1 and should abort. BDTA relies on timestamp intervals to order transactions dynamically. Inspired by the DTA scheme [9], [30], we introduce a timestamp interval $[LB, UB]$ for each transaction T, For every two transactions T_i, T_j, during the entire execution, we guarantee that:

$$T_i.UB < T_j.LB \qquad \text{if } T_i \rightarrow T_j \tag{1}$$

Eq. 1 ensures that, for any two transactions T_i and T_j, if there exists a partial order $T_i \rightarrow T_j$, we have $T_i.UB < T_j.LB$, i.e., ordering T_i before T_j in the sequential history. Any transaction violating the required ordering constraint cannot produce a legal timestamp interval and aborts. We then give an example to show how BDTA preserves required orders by adjusting the timestamp intervals of transactions.

Example 3. Reconsider H_3 in Example 2. We present how the timestamp intervals are adjusted in Fig. 6. From the global clock perspective, T_1 first starts, followed by T_2, T_3, and T_4. First, when T_3 starts, the timestamp intervals of T_1, T_2, and T_3 are shown in the first column. Next, when T_1 commits, we can detect the write-legal orders ($T_2 \rightarrow T_1$ and $T_3 \rightarrow T_1$) and bidirectionally adjust the timestamp intervals of T_2 and T_3 with T_1, making $T_2.UB < T_1.LB$ and $T_3.UB < T_1.LB$ (second column). Then, when T_2 commits, because we cannot detect the write-legal order $T_2 \rightarrow T_3$ and the program order $T_2 \rightarrow T_4$, we do not perform the adjustment of T_2 with other transactions but simply set $T_2.UB$ to $T_2.LB$ (third column). Afterward, when T_4 starts, by detecting program order $T_2 \rightarrow T_4$, we adjust $T_4.LB$ to guarantee $T_4.LB > T_2.UB$ (fourth column). When T_4 commits, we adjust $T_4.LB$ to guarantee $T_4.LB > T_1.UB$ because of the write-read order $T_1 \rightarrow T_4$ (fifth column). Finally, when T_3 commits, we detect write-legal order $T_2 \rightarrow T_3$ and adjust $T_3.LB$ to guarantee $T_3.LB > T_2.UB$ (sixth column). □

As illustrated in Example 3, we preserve the partial orders required in sequential history S_3 by adjusting timestamp intervals of transactions. We must emphasize that BDTA is different from existing DTA algorithms, like Sundial [55], MaaT [31], TCM [30]. First and foremost, BDTA adjusts timestamp intervals to preserve required orders in multi-level serializability. Second, BDTA optimizes the size of the timestamp interval for each adjustment, leading to a lower transaction abort rate. Take history H_3 as an example. As discussed, the order $T_2 \rightarrow T_3 \rightarrow T_1$ needs to be preserved. However, existing DTA algorithms cannot preserve such an order, causing T_2 or T_3 to abort. Specifically, Sundial and MaaT do not have the capability to adjust timestamp intervals bidirectionally, meaning that if there exists an order $T_i \rightarrow T_j$, when T_i or T_j commits, the timestamp interval of T_i or T_j is adjusted individually. For this reason, when T_1 commits, they set $T_1.UB = T_1.LB$ without adjusting $T_2.LB$ and $T_2.UB$. In Fig. 6, T_2 starts after T_1, indicating $T_2.UB \geq T_2.LB > T_1.LB$. When T_2 attempts to commit, due to the write-legal order $T_2 \rightarrow T_1$, there does not exist a legal timestamp interval of T_2 to guarantee $T_2.UB < T_1.LB$, causing T_2 to abort. For TCM, although it performs the bidirectional adjustment, its adjustment cannot leave enough legal interval space for transactions to commit. For example, to preserve $T_2 \rightarrow T_1$, TCM sets $T_1.LB = T_2.LB + 1$ and $T_2.UB = T_2.LB$ to make $T_2.UB < T_1.LB$. However, by doing this, there does not exist any interval space between $T_2.UB$ and $T_1.LB$, and any transaction ordered between T_2 and T_1, like T_3 will abort. BDTA solves the interval space problem of TCM by introducing an adaptive timestamp interval selection method, which is discussed in Section 5.1.

According to Definition 8, if a transaction violates the ordering constraints, the corresponding history must contain a cycle of partial orders. BDTA ensures such a transaction cannot produce a legal timestamp interval:

Theorem 2. *Given a set of transactions in the history that form a cycle of partial orders, there must exist at least one transaction T with $T.LB > T.UB$.* □

Proof. If a history H contains a cycle of partial orders, there must exist the order $T_i \rightarrow T_j \rightarrow ... \rightarrow T_i$. Suppose each transaction T in the history H satisfies $T.LB \leq T.UB$, According to Eq. 1, we ensure $T_i.UB < T_j.LB \leq T_j.UB < T_i.LB$, which indicates $T_i.UB < T_i.LB$. Therefore, T_i cannot obtain a legal timestamp interval, and the history H containing a cycle of partial orders must include a transaction like T_i with $T_i.LB > T_i.UB$. □

Theorem 2 guarantees that, during the entire execution, if a given set of transactions forms a cycle of partial orders, we can abort the transactions with illegal timestamp intervals to destroy the cycle and ensure correctness.

4.2 BDTA in Action

We elaborate on how BDTA works in decentralized MVCC-based databases, especially when and how timestamp intervals of transactions are initialized and adjusted. BDTA follows the optimistic way to do concurrency control. For this purpose, the process P_k coordinates the entire lifecycle of a transaction T_i from the initialization, through the local execution, to the validation and commit.

- **Initialization.** The process P_k creates an execution context for T_i, including transaction snapshot $T_i.ss$, timestamp interval $[LB, UB]$, and commit timestamp $T_i.c$, etc. Because we target MVCC-based databases, we process read requests based on snapshot isolation, i.e., T_i does reads and writes based on the snapshot $T_i.ss$. For this reason, $T_i.ss$ is initialized below:

$$T_i.ss = \begin{cases} \texttt{GET\_LC()} & \text{serializability,} \\ \texttt{GET\_HLC()} & \text{sequential serializability,} \\ \texttt{TS\_ORACLE()} & \text{strict serializability} \end{cases} \tag{2}$$

  Function GET_LC() returns the local timestamp of the process P_k and is used for serializability. Function GET_HLC(), shown in Alg. 1, returns an HLC timestamp, which is used for sequential serializability. Note that HLC timestamps of two transactions with the causal-related order are pairwise comparable. Function

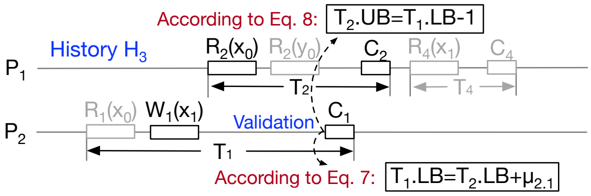


Fig. 7: Timestamp interval adjustment for Example 3.

TIME_ORACLE() returns the current global timestamp allocated from a centralized timestamp oracle [38] and is used for strict serializability. $[LB, UB]$ of T_i is initialized:

$$T_i.LB = T_i.ss, T_i.UB = +\infty \tag{3}$$

$[LB, UB]$ of T_i will be dynamically adjusted during the local execution and validation. Given a distributed transaction T_i, we denote the set of participant servers that are involved in the execution of T_i as $S(T_i)$, and denote the local transaction executed in the participant server $s \in S(T_i)$ as T_i^s. We do the initialization for T_i^s below.

$$T_i^s.ss = T_i.ss, T_i^s.LB = T_i.LB, T_i^s.UB = T_i.UB \tag{4}$$

- **Local execution.** Local transaction T_i^s of T_i is executed in participant server s respectively. We now present how to adjust $[LB, UB]$ of T_i^s to preserve the write-legal order during the local execution. Upon a read $R_i(x_m)$ by T_i^s, if BDTA detects that a new version x_{m+1} is generated by another committed transaction T_{m+1}, the timestamp interval of T_i^s is adjusted below:

$$T_i^s.UB = x_{m+1}.cts - 1 \tag{5}$$

where $x_{m+1}.cts$ is the commit timestamp of T_{m+1}, denoted as $T_{m+1}.c$ (version x_{m+1} is written by T_{m+1} that takes the same subscripts). Note that if the write $W_{m+1}(x_{m+1})$ happens after $R_i(x_m)$ from the global clock perspective, the write-legal order is guaranteed during the local validation of T_{m+1}^s. Besides, we preserve the write-read order based on snapshot isolation. Because for each data item x_m, only T_i^s with $T_i^s.ss \geq x_m.cts$ can "see" x_m, which guarantees the write-read order $T_m \rightarrow T_i$. We will elaborate on the local execution in Section 4.4.
- **Validation.** After completing local execution, the process P_k coordinates all local transactions T_i^s following two-phase commit (2PC). To begin with, in the first phase of 2PC, called the prepare phase, each local transaction does the local validation and determines a proper $[LB, UB]$ of T_i^s. To preserve the write-legal order, we examine the write set $T_i^s.ws$ of T_i^s and adjust $T_i^s.LB$:

$$\begin{aligned} T_i^s.LB = &\max\{T_i^s.LB, \\ &\max\{x.RTS + 1 | x \in T_i^s.ws\}\} \end{aligned} \tag{6}$$

where $x.RTS$ is the maximum commit timestamp of all committed transactions that ever read data item x. We then adjust the timestamp intervals of T_i^s and T_j^s bidirectionally, i.e., we identify every concurrent transaction T_j^s that reads data item $x \in T_i^s.ws$, and adjust $T_i^s.LB$:

$$\begin{aligned} T_i^s.LB = &\max\{T_i^s.LB, \\ &\max\{T_j^s.LB + \mu_{j,i} | T_i^s.ws \cap T_j^s.rs \neq \emptyset\}\} \end{aligned} \tag{7}$$

where $\mu_{j,i}$ represents the interval space for the bidirectional adjustment. Finally, we adjust $T_j^s.UB$ of every T_j^s:

$$T_j^s.UB = \min\{T_j^s.UB, T_i^s.LB - 1\} \tag{8}$$

Reconsider Example 3. As shown in Fig. 7, during the validation of T_1^s, by examining the write set of T_1^s, BDTA identifies transactions T_2^s and T_3^s that read the data item x, and hence bidirectionally adjusts $T_1^s.LB$ and $T_2^s.UB$ ($T_1^s.LB$ and $T_3^s.UB$) to preserve the write-legal order $T_2 \rightarrow T_1$ ($T_3 \rightarrow T_1$). To achieve this, we first set $T_1^s.LB$ to $\max\{T_2^s.LB + \mu_{2,1}, T_3^s.LB + \mu_{3,1}\}$ based on Eq. 7 and then set $T_2^s.UB$ and $T_3^s.UB$ to $T_1^s.LB - 1$ based on Eq. 8.
- **Commit.** After all local transactions finish the validation phase, T_i comes to the second phase of 2PC named as commit phase. In the commit phase, the process P_k collects $[LB, UB]$ of T_i^s from each participant server $s \in S(T_i)$ and updates $[LB, UB]$ of T_i based on Eq. 9. If $T_i.LB > T_i.UB$, P_k notifies each participant to abort the local transaction; otherwise, P_k notifies each participant server to commit the local transaction.

$$\begin{aligned} T_i.LB = \max\{T_i^s.LB | s \in S(T_i)\} \\ T_i.UB = \min\{T_i^s.UB | s \in S(T_i)\} \end{aligned} \tag{9}$$

Finally, the commit timestamp of T_i is set below.

$$T_i.c = T_i.LB \tag{10}$$

Using Eq. 10, we guarantee the order of transactions' commit timestamps follows that determined by BDTA. We will elaborate on the validation and commit in Section 4.5.

4.3 Multi-level Serializability Guarantee

BDTA preserves orders among serializable transactions by maintaining disjoint timestamp intervals.

Theorem 3. *Given a history H, BDTA guarantees the execution of H satisfies serializability.* □

Proof. Given any transaction T_i in H, for local transaction T_i^s in each participant server $s \in S(T_i)$, BDTA guarantees there exists a sequential history $\overline{H}$ preserving the write-legal order (Eq. 5–8), with $\overline{H}|T_i^s = H|T_i^s$. Besides, due to snapshot isolation, we ensure the write-read order in $\overline{H}$. Thus, according to Definition 8, BDTA achieves serializability in each participant server. Further, by imposing 2PC on $\forall s \in S(T_i)$ to make an agreement on $[LB, UB]$ of T_i (Eq. 9), plus Eq. 10, we guarantee that H satisfies serializability. □

Theorem 3 guarantees a serializable execution using BDTA. We now discuss how BDTA guarantees strict serializability and sequential serializability, respectively.

- **Strict serializability guarantee.** We additionally preserve the real-time order based on TIME_ORACLE(). In fact, when T_i commits, if $T_i.LB \leq$ TIME_ORACLE(), the real-time order is preserved by Eq. 10, ensuring $T_i.c \leq$ TIME_ORACLE(). By so doing, a new transaction T_j starting after T_i's commit will have $T_j.ss \geq$ TIME_ORACLE(), and hence, T_j can always "see" T_i's writes. Otherwise, if $T_i.LB >$TIME_ORACLE(), to preserve the real-time order, T_i waits until $T_i.LB \leq$TIME_ORACLE() to commit. Thus, under strict serializability, we introduce an additional constraint for T_i to commit, as shown below.

$$T_i.LB \leq \text{TIME\_ORACLE}() \tag{11}$$

- **Sequential serializability guarantee.** We preserve the causal-related order based on HLC [17]. We implement HLC by allowing each process to allocate timestamps individually. We must emphasize that for each transaction, BDTA updates HLC only once. Alg. 1 describes the HLC timestamp allocation, while Alg. 2 presents the HLC update

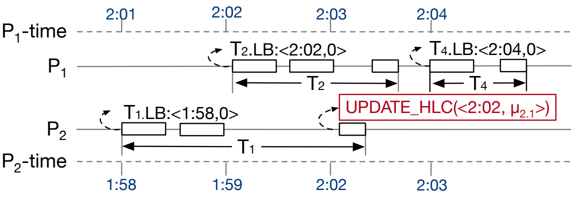


Fig. 8: An example of allocating HLC timestamps.

upon T_i commit using $T_i.c.pts$ and $T_i.c.lts$. Note that pts_k and lts_k denote the physical clock pts and Lamport clock lts of the process P_k, respectively. Reconsider Example 3. As shown in Fig. 8, upon the commit of T_1, $T_1.c$ is set to $\langle 2{:}02, \mu_{2.1}\rangle$, larger than $T_2.LB$, $\langle 2{:}02, 0\rangle$. The process P_2 updates its HLC timestamp using $T_1.c$. T_2 then commits with $T_2.LB$. All subsequent transactions in the processP_2, e.g., T_4, take larger HLC timestamps than $T_2.c$. Our transaction-level HLC scheme preserves the causal-related order. For example, since $T_4.ss$ is larger than $T_2.c$ and $T_1.c$, all writes seen by T_2 and T_1 can also be seen by T_4, preserving the causal-related orders $T_2 \rightarrow T_4$ and $T_1 \rightarrow T_4$.

Algorithm 1: GET_HLC() [17]

```
if $pts_k \geq$ current process timestamp then $lts_k$++;
else $pts_k \leftarrow$ current process timestamp, $lts_k \leftarrow 0$;
return $\langle pts_k, lts_k \rangle$;
```

Algorithm 2: UPDATE_HLC(pts, lts) [17]

```
$temp \leftarrow pts_k$;
$pts_k \leftarrow \max\{pts_k, pts,$ current process timestamp$\}$;
if $pts_k = temp$ and $pts_k = pts$ then
    $lts_k \leftarrow \max\{lts_k, lts\} + 1$ ;
else if $pts_k = temp$ then $lts_k++$ ;
else if $pts_k = pts$ then $lts_k \leftarrow lts++$ ;
else $lts_k \leftarrow 0$ ;
```

• **Summarization.** To summarize BDTA, the adjustment is triggered by a transaction T_i upon either (1) Condition 1: T_i reads a version x_m, and a new version x_{m+1} is generated by a committed T_{m+1} before T_i's read, or (2) Condition 2: T_i enters the validation phase. Condition 1, 2 are used to preserve the write-legal order, and Condition 1 plus snapshot isolation preserves the write-read order.

4.4 Local Execution

We present how local execution in BDTA works. In our design, a data item x is associated with metadata that has four fields (shown in Fig. 9): (1) $x.pk$ is the primary key of x; (2) $x.RTS$ is the maximum commit timestamp of all committed transactions that ever read x; (3) $x.WT$ is the transaction that is currently modifying x. It is set during the validation, and acts like a “soft-lock” to prevent write-write conflicts, i.e., two transactions are disallowed to modify x simultaneously; (4) $x.RIDs$ is a lock-free list, recording every non-committed transaction that reads x. Like many optimistic algorithms, we maintain the read set $T_i^s.rs$ and write set $T_i^s.ws$ of T_i^s. To enable exclusive access to $[LB, UB]$ of T_i^s, we provide a spinlock $T_i^s.sl$, and any access to $[LB, UB]$ of T_i^s must hold the lock.

Alg. 3 shows the pseudo-code of `Read()` and `Write()` functions. `Read()` takes a local transaction T_i^s and a search key key as the input (line 1). We directly return x_i if it is already in $T_i^s.ws$ (line 2). Otherwise, we add key to $T_i^s.rs$ (line 3), find x, and update $x.RIDs$ by adding T_i^s (lines 4–5). We next invoke `SnapshotRead()` to read a proper version x_m and its next version x_{m+1} (if any) (line 6). In `SnapshotRead()`, if we detect (1) some T_j^s in the validation phase is writing x (i.e., $x.WT = T_j^s$), and (2) x_m is the latest version while x_j is not visible yet (the order between T_i^s and T_j^s remains undetermined), we do not read x until T_j^s commits to guarantee correctness. If x_{m+1} exists, we then adjust $T_i^s.UB$ based on Eq. 5 by holding the lock $T_i^s.sl$ (lines 7–10). Finally, x_m is returned (line 11). Function `Write()` takes a local transaction T_i^s, x's primary key $x.pk$, and a new version x_i to be written as the input. If a version x_i' with the same $x.pk$ is in $T_i^s.ws$, x_i' is updated by x_i; otherwise, a pair $\langle x.pk, x_i\rangle$ is added into $T_i^s.ws$.

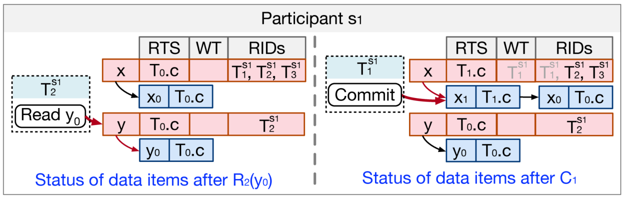


Fig. 9: Status of data items using BDTA.

Algorithm 3: Execution of local transaction T_i^s

```
1  Function Read($T_i^s$, $key$):
2      if $\langle key, x_i \rangle \in T_i^s.ws$ then return $x_i$;
3      $T_i^s.rs \leftarrow T_i^s.rs \cup \{key\}$;
4      $x \leftarrow$ location the data item according to $key$;
5      $x.RIDs \leftarrow x.RIDs \cup \{T_i^s\}$;
6      $x_m, x_{m+1} \leftarrow$ SnapshotRead($key$, $T_i^s.ss$);
7      if $x_{m+1}$ then
8          # lock() acquires the spinlock $T_i^s.sl$
9          $T_i^s.UB \leftarrow \min\{T_i^s.UB, x_{m+1}.cts - 1\}$;
10         # unlock() releases the spinlock $T_i^s.sl$
11     return $x_m$;
12 Function Write($T_i^s$,$x.pk$, $x_i$):
13     if $\langle x.pk, x_i' \rangle \notin T_i^s.ws$ then
           $T_i^s.ws \leftarrow T_i^s.ws \cup \{\langle x.pk, x_i \rangle\}$;
14     else replace $\langle x.pk, x_i' \rangle$ with $\langle x.pk, x_i \rangle$ in $T_i^s.ws$;
```

Example 4. In reference to Fig. 5 and Fig. 6, let us reconsider the history H_3. T_1 first starts and executes $R_1(x_0)$, during which we store $x.pk$ into $T_1.rs$, insert T_1^s into $x.RIDs$, and read the proper version x_0. T_1 then executes $W_1(x_1)$ to store $\langle x.pk, x_1'\rangle$ into $T_1.ws$. After that, T_2 and T_3 perform $R_2(x_0)$, $R_3(x_0)$ and $R_2(y_0)$ using the same logic as $R_1(x_0)$, described in Alg. 3. Now we have $x.RIDs = \{T_1^s, T_2^s, T_3^s\}$ and $y.RIDs = T_2^s$, as shown in the left part of Fig. 9.

4.5 Validation and Commit

We introduce the validation of a local transaction T_i^s in Alg. 4. $\forall x_i \in T_i^s.ws$, we set a soft-lock on x by T_i^s using compare-and-swap (lines 2–4). If a write-write conflict on x is detected, we abort T_i^s. Next, by invoking the function `BiAdjust()`, we bidirectionally adjust the timestamp intervals of T_i^s with transactions in $x.RIDs$ based on Eq. 6–8 (line 5). We then adjust $T_i^s.LB$ to preserve the write-read order (line 7). We abort T_i^s if its timestamp interval is illegal (line 9); otherwise, the validation of T_i^s is passed (line 10).

We present the commit of a local transaction T_i^s in Alg. 5. We encapsulate the local validation in the prepare phase of 2PC, and once the validation phase of T_i completes successfully, the process P_k coordinates T_i^s to commit by writing data items to the database, updating $x.RTS$, and releasing the "soft lock" (setting $x.WT$ to 0, lines 2–5). Besides, for each $key \in T_i^s.rs$, we update $x.RTS$ by the commit timestamp of T_i using atomic read-modify-write (RMW), and remove T_i^s from the read list $x.RIDs$ (lines 6–8). If T_i's validation fails, the process P_k coordinates T_i^s to abort by resetting $x.WT$ and removing T_i^s from $x.RIDs$.

Handling contentions on list $x.RIDs$. We use a lock-free list [23] to implement $x.RIDs$ (line 12, Alg. 4) for better performance. It is unnecessary to acquire locks on $x.RIDs$, and the reasons are two-fold. First, setting $x.WT$ to T_i^s during the validation phase of the transaction T_i (line 3, Alg. 4) blocks other transactions to read the current version of x (line 6, Alg. 3). Second, for transactions that read previous versions of x but are not in $x.RIDs$, their timestamp intervals are adjusted in line 9, Alg. 3.

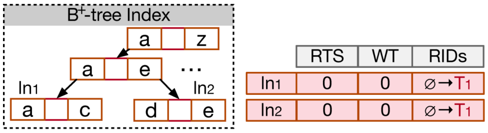
Algorithm 4: Validation of local transaction T_i^s

```
1  Function Validation ($T_i^s$):
2      for $\langle x.pk, x_i \rangle \in T_i^s.ws$ do
3          if $x.WT \neq T_i^s$ and $\neg$ CAS ($x.WT, 0, T_i^s$) then
4              return false;
5          BiAdjust ($T_i^s, x$);
6          # lock() acquires the spinlock $T_i^s.sl$
7          $T_i^s.LB \leftarrow \max\{T_i^s.LB, x.RTS + 1\}$;
8          # unlock() releases the spinlock $T_i^s.sl$
9          if $T_i^s.LB > T_i^s.UB$ then return false ;
10     return true;
11 Function BiAdjust ($T_i^s, x$):
12     for $T_j^s \in x.RIDs$ do
13         # lock() acquires the spinlocks $T_i^s.sl$,$T_j^s.sl$ by the
             order $T_i \rightarrow T_j$
14         if $T_j^s$ has been local validated then
15             wait until Commit($T_j^s$,$T_j.c$) finishes or
                 timeouts;
16             continue;
17         if $T_i^s.LB \leq T_j^s.LB$ then
18             $T_i^s.LB \leftarrow T_j^s.LB + \mu_{j,i}$;
19         $T_j^s.UB \leftarrow \min\{T_j^s.UB, T_i^s.LB - 1\}$;
20         # unlock() releases the spinlocks $T_i^s.sl$,$T_j^s.sl$ by
             the order $T_i \rightarrow T_j$
```

Algorithm 5: Commit of local transaction T_i^s

```
1  Function Commit ($T_i^s, T_i.c$):
2      for $\langle x.pk, x_i \rangle \in T_i^s.ws$ do
3          make $x_i$ visible in the database;
4          $x.RTS \leftarrow \max\{x.RTS, T_i.c\}$ ;
5          # atomic RMW $x.WT \leftarrow 0$;
6      for $key \in T_i^s.rs$ do
7          $x.RTS \leftarrow \max\{x.RTS, T_i.c\}$ ;
8          # atomic RMW $x.RIDs \leftarrow x.RIDs \setminus \{T_i^s\}$;
9  Function Abort ($T_i^s$):
10     for $\langle x.pk, x_i \rangle \in T_i^s.ws$ do CAS ($x.WT, T_i^s, 0$) ;
11     for $key \in T_i^s.rs$ do $x.RIDs \leftarrow x.RIDs \setminus \{T_i^s\}$ ;
```

Example 5. Let us continue Example 4 to validate whether T_1 can commit. We set $x.WT$ to T_1^s, adjust $T_1^s.LB$ to ensure $T_1^s.LB > x.RTS$, and bidirectionally adjust the timestamp intervals of T_1^s and transactions in $x.RIDs$ (T_2^s and T_3^s). Because of the order $T_2 \rightarrow T_1$ and $T_3 \rightarrow T_1$, we adjust $T_1^s.LB$ to $\max(T_2^s.LB + \mu_{2,1}, T_3^s.LB + \mu_{3,1}, T_1^s.LB)$. We also set $T_2^s.UB$ and $T_3^s.UB$ to $T_1^s.LB - 1$. We calculate $T_1.LB$ based on $T_1^s.LB$ as discussed in Eq. 9, and then commit T_1 with $T_1.c = T_1.LB$. Besides, we update $x.RTS$ to $T_1.c$, reset $x.WT$ to 0, remove T_1^s from $x.RIDs$, and write version x_1 to the data item x, according to Alg. 5. The status of data items is shown in the right part of Fig. 9. Next, T_2 commits with $T_2.c = T_2.LB$, removes T_2^s from $x.RIDs$ and $y.RIDs$, and updates $y.RTS$ to $T_2.c$. After that, T_4 then reads x_1 and commits, and hence, $T_4.c$ is larger than $T_1.c$. Finally, T_3 executes $R_3(y_0)$ and $W_3(y_3)$, and start to commit. During the validation, T_3 acquires $y.WT$, adjusts $T_3.LB$ to $y.RTS + 1$ ($T_2.c + 1$), and examines whether $T_3.UB > T_3.LB$. Because we introduce the adaptive timestamp interval selection method, $\mu_{2,1}$ and $\mu_{3,1}$ are larger enough to obtain a legal timestamp interval for T_3, and therefore, T_3 can commit successfully. We follow Alg. 5 to commit T_3 and write version y_3 into y.



	RTS	WT	RIDs
ln1	0	0	∅→T1
ln2	0	0	∅→T1

Fig. 10: Status of a B^+-tree in BDTA.

4.6 Preventing Phantom Reads

We present how BDTA handles the phantom read, which occurs when one transaction issues a predicate-based read twice but obtains two different read sets. Given two concurrent transactions T_1, T_2, T_1's snapshot $T_1.ss$ might be larger than T_2's commit timestamp due to inconsistent local clocks. When T_1 triggers a predicate-based read through the index, it may observe T_2's write after T_2 commits, leading to the phantom read. We handle the phantom read by encapsulating BDTA into the index scheme. Without loss of generality, we assume predicate-based reads can be regarded as traversing the B^+-tree index. We treat each leaf node of the index as a data item, and we associate each leaf node (denoted as ln) of the index with metadata $ln.RTS$, $ln.WT$, and $ln.RIDs$ similar to the data item (Fig. 9). Because a predicate-based read needs to access leaf nodes of the index, and a write needs to update a leaf node, we then preserve the write-read order and write-legal order over the leaf nodes. Consider two concurrent transactions T_1 and T_2. T_1 has a predicate-based read to search keys in the range $[a, d]$. As shown in Fig. 10, T_1 needs to access leaf nodes ln_1 and ln_2, and T_1 is added to $ln_1.RIDs$ and $ln_2.RIDs$. Afterward, suppose that T_2 writes the index key b to the leaf node ln_1 and commits. BDTA preserves the write-legal order $T_1 \rightarrow T_2$ by ensuring $T_1.UB < T_2.LB$. Since $T_1.ss < T_2.c$ is preserved, T_1 cannot observe the index key b. In this way, the phantom read is eliminated by BDTA.

5 Optimizations

In this section, we introduce a heuristic method to adaptively determine the size of the timestamp interval for each adjustment and explain how BDTA makes read-only transactions always commit.

5.1 Adaptive Timestamp Interval Selection

As discussed in Section 4.1, selecting a good timestamp interval size is essential to reduce the transaction abort rate. Reconsider Example 3. If no interval space exists between $T_2.LB$ and $T_1.LB$, transactions ordered between T_2 and T_1 (e.g., T_3) would abort. Given any two transactions T_i and T_j with order constraint $T_i \rightarrow T_j$, we use $\mu_{i,j}$ to denote the interval space $[T_i.LB, T_j.LB]$ between T_i and T_j, i.e., $\mu_{i,j} = T_j.LB - T_i.LB$. Theoretically, a proper $\mu_{i,j}$ should meet the following two requirements. First, we require $\mu_{i,j} > \mathcal{N}_{i,j}$, where $\mathcal{N}_{i,j}$ is the number of transactions ordered between T_i and T_j. By so doing, transactions ordered between T_i and T_j are more likely to find a legal timestamp interval and commit. Second, we need $\mu_{i,j} \leq T_k.UB - T_i.UB$, where T_k is the transaction with the smallest UB among transactions ordered after T_j. This property ensures transactions ordered after T_j will not be influenced by $\mu_{i,j}$. Otherwise, if $\mu_{i,j} > T_k.UB - T_i.UB$, $T_j.LB = T_i.UB + \mu_{i,j}$ can be larger than $T_k.UB$, causing transactions ordered after T_j (e.g., T_k) to abort.

Yet, computation of the best $\mu_{i,j}$ for any two transactions T_i and T_j with constraint $T_i \rightarrow T_j$ is infeasible because we cannot obtain the precise value of $\mathcal{N}_{i,j}$ and detect T_k in advance. For this reason, we instead propose a heuristic method to adaptively estimate $\mu_{i,j}$ based on the contention level of the data items T_i and T_j accessed. For each data item x, we collect the number of calls in bidirectional adjustment ($x.cno$) to represent the contention level on x, denoted as $\mathcal{L}(x)$. Recall that during the validation phase of T_j, for each $x \in T_j^s.ws$, we use $\mu_{i,j}$ to bidirectionally adjust the timestamp intervals of T_j^s and any other T_i^s in $x.RIDs$ (line 18, Alg. 4). Consequently, a higher contention level $\mathcal{L}(x)$ indicates more transactions are likely to be ordered between T_i and T_j, which requires $\mu_{i,j}$ to be positively correlated with $\mathcal{L}(x)$, i.e., the higher $\mathcal{L}(x)$ is, the larger $\mu_{i,j}$ should be assigned. We classify $\mathcal{L}(x)$ into three contention levels: low, medium, and high contention, by simply comparing $x.cno$ with two pre-defined thresholds τ_1 and τ_2. Besides, we assign μ_l, μ_m, and μ_h for each contention level to represent the optimal timestamp interval space of that contention level, as shown in Eq. 12.

$$\mu_{i,j} = \begin{cases} \mu_l & x.cno \leq \tau_1 \quad \text{low contention,} \\ \mu_m & \tau_1 < x.cno \leq \tau_2 \quad \text{medium contention,} \\ \mu_h & \tau_2 \leq x.cno \quad \text{high contention} \end{cases} \tag{12}$$

We adaptively refine these interval spaces during the execution based on Alg. 6. Initially, μ_l, μ_m, μ_h are set to 1. Then, we create an individual thread and periodically refine them using Alg. 6, which is constructed based on the well-known simulated annealing (SA) algorithm. We take the timestamp interval to be adjusted μ_k, $\mu_k \in \{\mu_l, \mu_m, \mu_h\}$, and the temperature threshold $\mathcal{T}_{min}$ as the input. We denote $\mathcal{F}(\mu_k)$ as the abort rate after applying μ_k. After initialization (line 2), we iteratively select a random $\hat{\mu}$ (line 4) and examine whether adopting $\hat{\mu}$ can reduce the abort rate. If the abort rate drops, we update $\mu_k = \hat{\mu}$; otherwise, we accept $\hat{\mu}$ with a certain probability (lines 6–8). The probability follows the Boltzmann distribution by examining $e^{-\Delta t/c\mathcal{T}}$ and a random value $seed \in (0, 1)$, where c is Boltzmann constant (line 6). For each iteration, temperature $\mathcal{T}$ is decreased to $\lambda \cdot \mathcal{T}$, where λ is a hyper-parameter and set to 0.6 by default (line 9). We terminate the iteration and output μ_k if $\mathcal{T}$ is decreased to the temperature threshold $\mathcal{T}_{min}$ (line 10).

5.2 Non-validation for Read-only Transactions

We observe in BDTA, the timestamp interval of every read-only transaction T_i is always legal, i.e., $T_i.LB \leq T_i.UB$ is guaranteed. The reason is that according to Eq. 5–8, $T_i.LB = T_i.ss$ and $T_i.ss < T_i.UB$ are always true. Thus, we skip the validation in this case and replace the costly 2PC with one phase commit for read-only transactions.

Algorithm 6: Adjust timestamp interval μ_k

```
1  Function AdaptiveAdjust($\mu_k, \mathcal{T}_{min}$):
2      Initialize $\mathcal{F}^* \leftarrow \mathcal{F}(\mu_k)$, $\mathcal{T}$;
3      while $\mathcal{T} > \mathcal{T}_{min}$ do
4          Generate a random timestamp interval $\hat{\mu}$;
5          $\Delta t \leftarrow \mathcal{F}(\hat{\mu}) - \mathcal{F}^*$ ;
6          if $\Delta t < 0$ or ($\Delta t \geq 0$ and $e^{-\Delta t/c\mathcal{T}} > seed$) then
7              $\mathcal{F}^* \leftarrow \mathcal{F}(\hat{\mu})$;
8              $\mu_k \leftarrow \hat{\mu}$ ;
9          $\mathcal{T} \leftarrow \lambda \cdot \mathcal{T}$;
10     return $\mu_k$;
```

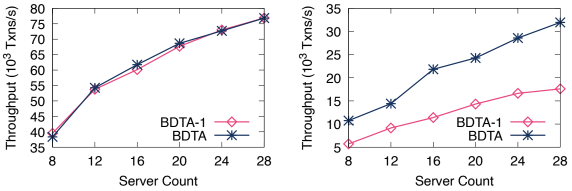
6 Implementation

In this section, we present our prototype system by integrating BDTA into Greenplum. Greenplum [21] is a distributed database system technically built on top of PostgreSQL. It has a single coordinator (master) and several participant servers (segments). Each master/participant server runs a PostgreSQL instance. To integrate BDTA into Greenplum, we make the following extensions, and our implementation is publicly available via **https://github.com/dbiir/BDTA**.

- **Storage Engine.** We re-construct the storage layer from the traditional heap store to the key-value store using RocksDB. We then implement data partitioning based on the hash strategy.
- **Multi-coordinator architecture.** We extend Greenplum to support multi-coordinator architecture. In this extension, each coordinator runs a PostgreSQL instance, in which each process coordinates transactions individually.
- **Timestamp Allocation.** We implement timestamp oracle and HLC as discussed to assign timestamps. To ensure high available timestamp allocation, timestamp oracle is implemented as a raft-based service. In our implementation, timestamp oracle serves around ten million timestamps per second. The performance may be influenced by high network latency over a WAN network.
- **Concurrency Control.** We integrate BDTA into Greenplum to support multi-level serializability. First, we replace the globally shared snapshot to avoid costly deadlock detection by our timestamp allocation schemes. We then encapsulate the validation phase and commit phase into 2PC. To accommodate BDTA in Greenplum, we maintain read/write sets of transactions in segments to reduce the communication overhead. Besides, for simplicity, we store data items and their metadata for concurrency control separately. The metadata is stored in memory and indexed with a red-black tree. We further use a separate thread to execute Alg. 6 to periodically update the optimal interval space for different contention levels.

7 Evaluation

Our experimental evaluation is conducted from two perspectives. First, we integrate BDTA and the state-of-the-art



(a) Low contention (b) High contention

Fig. 11: Effect of adaptive timestamp interval selection.

concurrency control algorithms into a distributed transaction testbed, called Deneva [22]. We compare them in the same context and report our findings. Second, we conduct experiments on Greenplum integrated with BDTA to verify the necessity of introducing multi-level serializability.

7.1 Workloads and Experiment Setup

We use the following workloads to conduct the experiments:

YCSB [13] is a synthetic benchmark modeling large-scale Internet applications. It uses a relation with 10 attributes, in which one is taken as the primary key. Each record in this relation occupies 1KB. The dataset is horizontally partitioned, and each partition is assigned to a participant server. Following Deneva [22], we set each partition to have 16 million records, indicating the data size of each participant server is 16GB. By aiming to simulate different contention levels, we follow Zipfian distribution to control the access on the same records using a skew factor, denoted as *theta*. When *theta*=0, we access each record in equal probability. Besides, we vary the *write ratio* to control the ratio of reads and writes by taking operations from transactions as a whole, i.e., *write ratio*=50% means there are totally 50% writes and 50% reads in transactions. By default, we set *write ratio*=50% and *theta*=0.6.

TPC-C [46] is a popular OLTP benchmark simulating a warehouse order processing application. It contains 9 relations. Each warehouse contains 100MB data size, and by default, we set 32 warehouses per participant server. TPC-C simulates 5 types of transactions, in which NewOrder, Payment, and Delivery are read-write transactions, and Stock-Level and Order-Status are read-only transactions (a transaction with both reads and writes is referred to as a read-write transaction). Following Deneva [22], we do not include “think time” and user data errors that cause 1% of NewOrder transactions to abort, aiming to test the peak performance. Unless otherwise specified, we use the default transaction mix of standard TPC-C in our experiments.

We conduct experiments except Section 7.5 using an in-house cluster with 28 virtual nodes, each of which has 4 cores/8 threads and 32GB memory. Unless otherwise specified, we run the protocols on 16 nodes, each containing 1 coordinator and 1 participant server. The RTT of the network is around 0.3ms. For each experiment, we first run 30s for warm-up and then collect results of the following 60s. We evaluate the performance in terms of: (1) throughput, which is the number of committed transactions; and (2) abort rate, which is the percentage of aborted transactions against all finished transactions.

7.2 Effect of Adaptive Timestamp Interval Selection

We first study the effectiveness of the adaptive timestamp interval selection method by comparing BDTA and BDTA without adaptive timestamp interval (denoted as BDTA-1) under sequential serializability. We set μ adaptively in BDTA, and fix μ=1 in BDTA-1. We run them under the low contention workload (*theta*=0.25) and high contention workload (*theta*=0.75), respectively. We vary the cluster from 8 to 28 nodes, and plot the results in Fig. 11. Fig. 11a shows that under the low contention workload, BDTA achieves comparable performance with BDTA-1, showing the additional cost for running the auto-tuning algorithm is negligible. We further study the benefit of adaptive timestamp interval selection over the high contention workload, and plot the results in Fig. 11b. We can observe that BDTA achieves higher throughput and better scalability than BDTA-1 by up to 91.42%. The performance of BDTA gains from the adaptive timestamp interval selection, which helps most transactions get a proper timestamp interval, thereby reducing the abort rate. As shown in Table 2, although more transactions need to abort under the high contention workload, the abort rate of BDTA is lower than that of BDTA-1 by a factor of 21.96%.

TABLE 2: Comparison of the abort rate between BDTA and BDTA-1

	Low Contention	High Contention
BDTA	0.80%	55.37%
BDTA-1	0.88%	77.33%

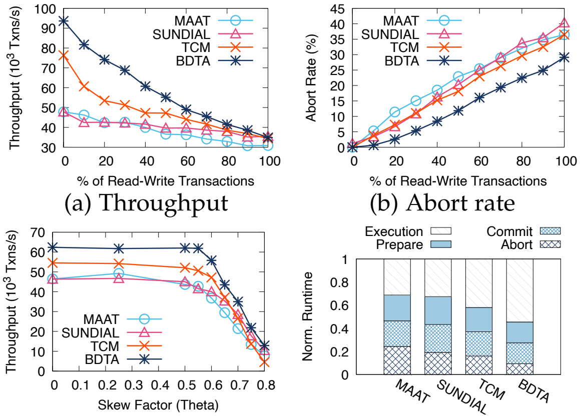
In the following experiments, we adopt the adaptive timestamp interval selection in BDTA by default.

7.3 Comparisons with Dynamic Ordering Algorithms

We compare BDTA with three recently proposed concurrency control algorithms using the DTA scheme, i.e., **MaaT** [31], **Sundial** [55], and **TCM** [30]. Because MaaT and Sundial only support serializability, we conduct our experiments under serializability for fair comparisons.

We make the comparison under different contentions by varying *write ratio*, and plot the results in Fig. 12a. As we can see, for the read-only transactions (0% of read-write transactions), BDTA outperforms the others by a factor of 38.66%. This is because, for read-only transactions, BDTA eliminates the expensive 2PC cost, and hence reduces the coordination overhead. Besides, when the percentage of read-write transactions increases, all algorithms suffer higher abort rates (shown in Fig. 12b), causing the performance to drop. Due to the adaptive timestamp interval selection, transactions are more likely to obtain proper timestamp intervals and commit, and therefore, BDTA performs the best with the lowest abort rate.

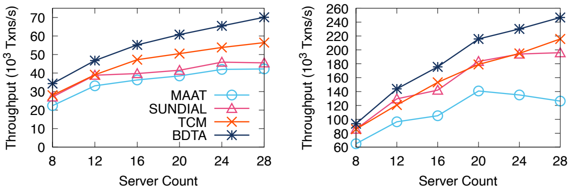
We evaluate the effect of *theta*, and plot the results in Fig. 12c. BDTA outperforms MaaT, Sundial, and TCM by up to 22.32% due to three reasons: First, MaaT and Sundial are single-version based, while BDTA is multi-version based, which allows reads do not block by the writes to increase concurrency. Second, MaaT and Sundial have to issue expensive 2PC for read-only transactions to commit while BDTA does not. Third, MaaT, Sundial, and TCM use a fixed space for timestamp adjustment, while BDTA leverages the adaptive timestamp interval selection, which further reduces abort rates and improves performance. The time breakdown in Fig. 12d with *theta*=0.6 indicates that the time spent on aborting transactions in MaaT, Sundial, and TCM is much higher than that in BDTA.



(a) Throughput (b) Abort rate

(c) Throughput (d) Time breakdown

Fig. 12: Serializability with varying *theta* and *write ratio*.



(a) Medium contention (b) TPC-C

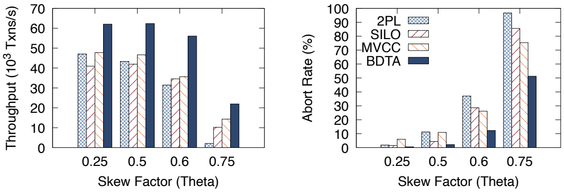
Fig. 13: Scalability under serializability.

We next investigate the scalability by varying the cluster from 8 to 28 nodes, and plot the results in Fig. 13. *(1) Scalability over YCSB.* We study the scalability over the medium contention workload (*theta*=0.6), and plot the results in Fig. 13a. We can observe that BDTA achieves up to 24.23% performance gain and the best scalability when the number of nodes varies. *(2) Scalability over TPC-C.* We further evaluate the performance under the TPC-C workload, and report the results in Fig. 13b. In this experiment, we customize the TPC-C workload with 50% NewOrder transactions and 50% Payment transactions. BDTA still achieves up to 20.51% higher throughput over the next-best algorithm. Again, the scalability benefit of BDTA mainly comes from our special design that adjusts timestamp bidirectionally, which reduces the overhead of coordinators. As discussed in Section 4.5, each transaction in BDTA locally adjusts timestamp intervals in involved participant servers, and coordinators are just responsible for collecting all local timestamp intervals.

7.4 Comparisons with Static Ordering Algorithms

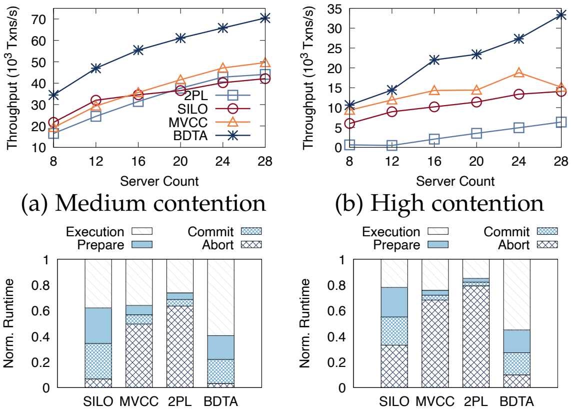
We compare BDTA with three static ordering concurrency control algorithms under sequential serializability: **2PL** [4], **MVCC** [5], and **Silo** [47]. For 2PL, we implement the No-Wait variant to prevent deadlock. We implement MVCC by ordering transactions based on their start timestamps. Silo is an OCC-based algorithm and uses the serialization point to order transactions, and we extend it into distributed setting according to Google F1 [41]. We make local timestamps of each process monotonically increase using HLC, which is capable of preserving the program order.

We first study the effect of contentions by varying the skew factor *theta*, and plot the results in Fig. 14. As we can see, BDTA performs up to 56.58% better than the next-best algorithm. As shown in Fig. 14a, when *theta*$<$ 0.6, Silo performs the worst because Silo introduces additional overhead in the validation phase, where a transaction reads data items in its read set again to examine whether they remain unchanged. When *theta* reaches 0.6, the cost of aborting transactions increases and becomes the bottleneck for 2PL, MVCC, and Silo, which can be verified in Fig. 14b. Because BDTA orders transactions dynamically, BDTA shows a better tolerance on contentions, leading to a higher throughput.



(a) Throughput (b) Abort rate

Fig. 14: Sequential serializability with varying *theta*.



(a) Medium contention (b) High contention

(c) Medium contention (d) High contention

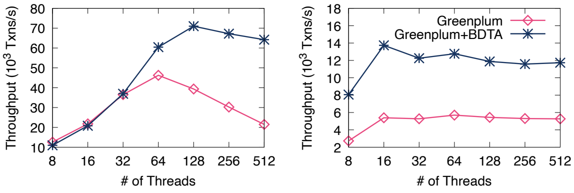
Fig. 15: Scalability under sequential serializability.

We then perform the scalability evaluation under sequential serializability. As observed in Fig. 15, BDTA achieves up to 1.19× higher throughput than the second-best algorithm under the medium contention workload (*theta*=0.6) and high contention workload (*theta*=0.75). The performance of BDTA is mainly due to the bidirectional timestamp adjustment mechanism, ensuring the lowest abort rate, as verified in Fig. 15c and 15d.

7.5 Comparisons of Multi-level Serializability

In this section, we conduct experiments on an in-house cluster with 3 high-performance nodes running CentOS 7.4. Each node has two Intel(R) Xeon(R) Platinum 8276 CPUs (28 cores × 2 HT), 8 × 128GB DRAM, and 3TB NVMe SSDs. We deploy Greenplum with 2 coordinators and 3 participant servers in this cluster. Each node hosts at most 1 coordinator and 1 participant server. By default, the Round-Trip Time (RTT), an indicator to measure the network latency, in the cluster is 0.03 ms. To better evaluate the performance of different serializability levels, we set RTT=1.5ms to simulate the deployment over a WAN network (e.g., a cross datacenter cluster). Note that setting RTT=1.5ms to simulate a cross datacenter deployment is reasonable. For example, the RTT from New York to Dallas is 40ms [35]. Thus, we use RTT = 0.03ms, and RTT=1.5ms to simulate the network latency over a LAN network, and WAN network, respectively.

We first study the effectiveness of integrating BDTA into Greenplum (denoted as Greenplum+BDTA), and report the comparison between Greenplum+BDTA and Greenplum in Fig. 16. Note that Greenplum+BDTA is set under the sequential serializability level. Since Greenplum only supports



(a) YCSB (b) TPC-C

Fig. 16: Effect of integrating BDTA into Greenplum.

the read committed and repeatable read isolation level, we set Greenplum under the read committed level to obtain the peak performance. As we can see, even if Greenplum is set under the read committed level, Greenplum+BDTA still outperforms Greenplum by a factor of up to 2.01× and 1.95× on YCSB and TPC-C workload, respectively. The reason is twofold. On the one hand, Greenplum+BDTA can tolerate more transaction concurrency, which leads to better performance. As mentioned, BDTA is employed in Greenplum+BDTA which reduces the abort rate and improves performance. On the other hand, Greenplum coordinates transactions with a costly distributed deadlock detection component, which is eliminated in Greenplum+BDTA.

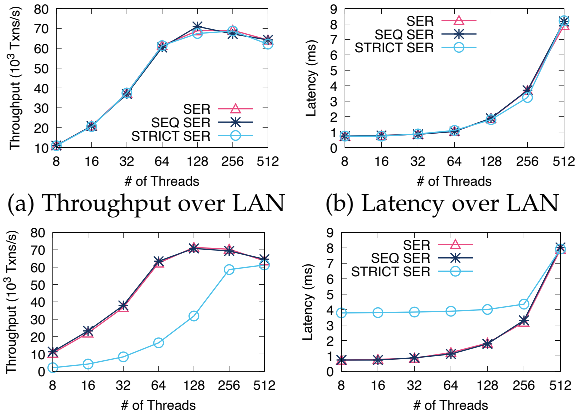
We then report the experimental results of executing Greenplum+BDTA under different serializability levels over LAN in Fig. 17a, 17b. We observe that the performance under strict serializability (labeled as `STRICT SER`), sequential serializability (labeled as `SEQ SER`), and serializability (labeled as `SER`) almost coincide. This is because, in a low latency network environment, like LAN, the effect of requesting timestamps from timestamp oracle service on the overall performance is negligible. The main cost comes from doing concurrency control, which is roughly the same under strict serializability and sequential serializability.

We finally report the experimental results over a simulated WAN network in Fig. 17c, 17d. We find that sequential serializability and serializability almost perform the same, and their throughput is up to 4.53× higher than that of strict serializability. The reason is that, in a high latency network environment, like WAN, the cost of requesting timestamps is comparable to that of doing concurrency control, and probably becomes a dominant factor to the overall performance (could be verified in Fig. 17d). Besides, by varying the number of client connections from 8 to 128, sequential serializability and serializability take an increasingly significant benefit against strict serializability. Yet, by adding more client connections, the contentions among transactions become the bottleneck and cause the performance to drop.

7.6 Summary

We summarize the major experimental findings below:

- We show the efficiency and effectiveness of the adaptive timestamp interval selection method, which reduces the abort rate by up to 21.96% and improves the throughput by up to 91.42% (Section 7.2).
- We confirm that BDTA outperforms the state-of-the-art concurrency control algorithms, including dynamic ordering and static ordering algorithms (Section 7.3 and Section 7.4).
- We recommend using strict serializability in the low latency network, e.g., LAN, and sequential serializability in the high latency network, e.g., WAN (Section 7.5).



(a) Throughput over LAN (b) Latency over LAN

(c) Throughput over WAN (d) Latency over WAN

Fig. 17: Multi-level serializability on Greenplum+BDTA.

8 Related Work

Our study relates to formalizing consistency and isolation levels, as well as distributed concurrency control algorithms.

In ACID databases, isolation levels are typically defined by disallowing certain kinds of data anomalies. The ANSI/ISO SQL-92 specifies four data anomalies (e.g., dirty write/read) and defines four isolation levels accordingly [51]. By arguing that the definitions in SQL-92 lack mathematical formalization and could incur ambiguous interpretations, a few works make formal re-definitions of data anomalies [1], [3], [15], [19], [43]. Much effort has been devoted to the identification of new data anomalies, including skewed read/write [3], aborted read [53], intermediate read [53], etc. There are quite a few works to model data consistency from different perspectives, e.g., result visibility [43], state matrix [15], dependency graph [1], [2], and abstract execution [11]. Recently, there is an increasing interest in imposing consistency models [11], [24], [27], [28], [49] on isolation levels. Quite a few works [12], [18], [48] impose additional constraints like the causal-related order on snapshot isolation [3]. Salt [52] imposes the eventual consistency [11] on ACID transactions to provide BASE transactions. To be more related, strict serializability [40] imposes the real-time order on serializability. Strong session serializability [16] imposes the program order on serializability. Lynx [56] studies serializability with the read-your-writes order. These works impose partial orders on serializability in a case-by-case manner. We model multi-level serializability to provide a systematic analysis of consistency levels over serializability. It is worth mentioning that strong session serializability [16] and Lynx [56] can be reduced to sequential serializability.

Distributed concurrency control algorithms are typically divided into two categories: (1) static ordering algorithms and (2) dynamic ordering algorithms. The first category determines the order of transactions statically. T/O [4] orders transactions based on their start timestamps. OCC [26] and its variants like Silo [47] determine the order based on either the validation point or the serialization point. 2PL [4], [19] orders transactions by the first granted lock on conflict data items. Calvin [45] uses a deterministic method to order transactions before execution. Imposing T/O over MVCC [39] can potentially support sequential serializability by the monotonic increasing local timestamp and strict serializability by the timestamp oracle [38]. Yet, the static ordering could cause a high abort rate due to their strict order requirements, which is verified in our experiments. On the contrary, the second category determines the order of transactions dynamically. Similar to BDTA, they determine the order by adjusting the timestamp intervals of transactions. Boksenbaum et al. are the first to use DTA in distributed concurrency control [9]. MaaT [31] and Sundial [55] are single-version based, and employ logical timestamps to do the adjustment. TCM [30] integrates DTA into the multi-version 2PL protocol, which is mainly designed for centralized databases. TCM requires all concurrent transactions to shrink their timestamp intervals upon a conflict, which could incur unnecessary adjustment overhead for aborted transactions. BDTA eliminates this overhead by only adjusting other transactions' timestamp intervals during the validation. BDTA is different from the other algorithms. First, BDTA adjusts timestamp intervals to preserve required orders in multi-level serializability. Second, BDTA adopts the adaptive timestamp interval selection, leading to a lower transaction abort rate.

9 Conclusions

In this paper, we study serializability from different consistency perspectives and formalize multi-level serializability. To support multi-level serializability, we propose a novel concurrency control algorithm called BDTA. BDTA can dynamically order serializable transactions and preserve partial orders among transactions required in the consistency models. We integrate BDTA into Greenplum, and release the implementation as open source. We conduct extensive experiments to show the necessity of introducing multi-level serializability and the performance gain of BDTA compared with state-of-the-art concurrency control algorithms.

Acknowledgments

We would like to thank the anonymous reviewers for their constructive comments. This work was partially supported by National Natural Science Foundation of China under Grant 61972403, 61732014, and Tencent Rhino-Bird Joint Research Program. Wei Lu and Xiaoyong Du are the corresponding authors.

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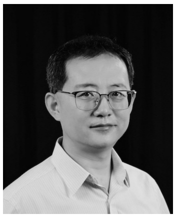

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