Sundial: Harmonizing Concurrency Control and Caching in a Distributed OLTP Database Management System

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ABSTRACT

Distributed transactions suffer from poor performance due to two major limiting factors. First, distributed transactions suffer from high latency because each of their accesses to remote data incurs a long network delay. Second, this high latency increases the likelihood of contention among distributed transactions, leading to high abort rates and low performance.

We present **Sundial**, an in-memory distributed optimistic concurrency control protocol that addresses these two limitations. First, to reduce the transaction abort rate, Sundial dynamically determines the logical order among transactions at runtime, based on their data access patterns. Sundial achieves this by applying *logical leases* to each data element, which allows the database to dynamically calculate a transaction's logical commit timestamp. Second, to reduce the overhead of remote data accesses, Sundial allows the database to cache remote data in a server's local main memory and maintains cache coherence. With logical leases, Sundial integrates concurrency control and cache coherence into a simple unified protocol. We evaluate Sundial against state-of-the-art distributed concurrency control protocols. Sundial outperforms the next-best protocol by up to 57% under high contention. Sundial's caching scheme improves performance by up to 4.6× in workloads with high access skew.

PVLDB Reference Format:
Xiangyao Yu, Yu Xia, Andrew Pavlo, Daniel Sanchez, Larry Ruldoph, and Srinivas Devadas. Sundial: Harmonizing Concurrency Control and Caching in a Distributed OLTP Database Management System. *PVLDB*, 11 (10): 1289-1302, 2018.
DOI: https://doi.org/10.14778/3231751.3231763

1. INTRODUCTION

When the computational and storage demands of an on-line transactional processing (OLTP) application exceed the resources of a single server, organizations often turn to a distributed database management system (DBMS). Such systems split the database into disjoint subsets, called *partitions*, that are stored across multiple shared-nothing servers. If transactions only access data at a single server, then these systems achieve great performance [2, 3]. Performance degrades, however, when transactions access data distributed across multiple servers [38]. This happens for two reasons. First and foremost, long network delays lead to long execution time of distributed transactions, making them slower than single-partition transactions. Second, long execution time increases the likelihood of contention among transactions, leading to more aborts and performance degradation.

Proceedings of the VLDB Endowment, Vol. 11, No. 10

DOI: https://doi.org/10.14778/3231751.3231763

Recent work on improving distributed concurrency control has focused on protocol-level and hardware-level improvements. Improved protocols can reduce synchronization overhead among transactions [22, 35, 36, 46], but can still limit performance due to high coordination overhead (e.g., lock blocking). Hardware-level improvements include using special hardware like optimized networks that enable low-latency remote memory accesses [20, 48, 55], which can increase the overall cost of the system. Ideally, concurrency control protocols should achieve good performance on low-cost commodity hardware.

To avoid the long network latency, prior work has proposed to replicate frequently-accessed shared data across multiple database servers [16], so that some distributed transactions become local. Such replication requires profiling the database workload or manually identifying hot data, which adds complexity for users. It is desirable for the database to automatically replicate data through a caching mechanism without user intervention.

To address these issues, we introduce **Sundial**, an in-memory distributed concurrency control protocol that outperforms existing approaches. To address the long network latency problem, Sundial natively supports data caching in a server's local main memory without requiring an additional protocol or sacrificing serializability, and uses cached data only when beneficial. To address the high overhead of coordinating distributed transactions, Sundial employs a hybrid pessimistic/optimistic concurrency control protocol that reduces aborts by dynamically reordering transactions that experience read-write conflicts.

The enabling technique behind Sundial is a concept called *logical leases*, which allows the DBMS to dynamically determine the logical order among transactions while enforcing serializability. A logical lease comprises two logical timestamps indicating the range of logical time wherein the tuple is valid. The DBMS dynamically computes a transaction's commit timestamp, which must overlap with the leases of all tuples accessed by the transaction. Prior work has shown that logical leases are effective in improving performance and concurrency for both hardware cache coherence [52] and multicore concurrency control protocols [53]. To the best of our knowledge, this paper is the first to apply logical leases to a distributed system, and the first to seamlessly combine concurrency control and caching in a shared-nothing database.

To evaluate Sundial, we implemented it in a distributed DBMS testbed and compared it to three state-of-the-art protocols: MaaT [35], Google F1 [41], and two-phase locking with Wait-Die [9, 25]. We

used two OLTP workloads with different contention settings and cluster configurations. Sundial achieves up to 57% higher throughput and 41% lower latency than the best of the other protocols. We also show that Sundial's caching mechanism improves throughput by up to 4.6× for skewed read-intensive workloads.

2. BACKGROUND AND RELATED WORK

Concurrency control provides two critical properties for database transactions: *atomicity* and *isolation*. Atomicity guarantees that either all or none of a transaction's changes are applied to the database. Isolation specifies when a transaction can see other transactions' writes. We consider serializability in this paper: concurrent transactions produce the same results as if they are sequentially executed.

While serializability is a robust and easy-to-understand isolation level, concurrency control protocols that provide serializability incur large synchronization overhead in a DBMS. This has been shown in scalability studies of concurrency control in both multicore [51] and distributed [25] settings. The problem is worse in a distributed DBMS due to high network latencies between database servers.

Two classes of concurrency control protocols [9] are commonly used: two-phase locking (2PL) and timestamp ordering (T/O). 2PL [11, 21] protocols are pessimistic: a transaction accesses a tuple only after the transaction acquires a lock with the proper permission (e.g., read or write). In contrast, T/O protocols use logical timestamps to determine the *logical* commit order of transactions. Variants of T/O protocols include multi-version concurrency control (MVCC), which maintains multiple versions of each tuple to reduce conflicts, and optimistic concurrency control (OCC), where conflicts are checked only after transaction execution. OCC may incur more aborts than 2PL [51], but has the advantage of non-blocking execution. Sundial combines the benefits of 2PL and OCC by using them for write-write and read-write conflicts, respectively. Sundial further reduces aborts due to read-write conflicts through logical leases (cf. Section 3).

2.1 Distributed Concurrency Control

Recent research has proposed many distributed concurrency control protocols [15, 20, 35, 41, 48], which are all based on variants of 2PL (e.g., Spanner [15] and F1 [41]) or T/O (e.g., MaaT [35] and Lomet et al. [34]). Among these protocols, MaaT [35] is the closest to Sundial, as both use logical timestamps to *dynamically* adjust the commit order among transactions but using different techniques. MaaT requires all conflicting transactions to *explicitly* coordinate with each other to adjust their timestamp intervals, which hurts performance and incurs more aborts. By contrast, conflicting transactions do not coordinate in Sundial. Furthermore, Sundial uses caching to reduce network latency, whereas MaaT does not support caching.

Lomet et al. [34] proposed a multi-version concurrency control protocol that lazily determines a transaction's commit timestamp using timestamp ranges. The protocol works in both multicore and distributed settings. Upon a conflict, the protocol requires all involved transactions to shrink their timestamp ranges—an expensive operation that Sundial avoids through logical leases. Furthermore, their protocol requires a multi-version database while Sundial works in a single-version database. Section 6.8 compares the performance of Lomet et al.'s protocol and Sundial.

2.2 Multicore Concurrency Control

Fast transaction processing on single-server multicore systems has been intensively studied [28, 32, 37, 47, 49, 50, 53, 54]. Some of these techniques can be applied to a distributed setting as well; we incorporate some of them into our distributed concurrency control protocols. Other techniques developed for multicore processors can not be readily used in a distributed setting due to different system properties, such as high network latency.

In this paper, we focus on the performance of distributed concurrency control protocols and therefore do not compare to protocols that are designed for single-server multicore systems.

2.3 Data Replication and Cache Coherence

Data replication [16, 38] has been previously proposed to reduce the overhead of distributed transactions. Replication is particularly effective for hot (i.e., frequently accessed) read-only data. When replicated across servers, hot data can serve read requests locally, significantly reducing the number of remote requests.

Data replication has several drawbacks. First, the user of the database needs to either profile the workloads or manually specify what data to replicate—a daunting task in a rapidly evolving database. Second, when the DBMS updates data that is replicated, all servers holding replicas are notified to maintain consistency, which is complex and adds performance overhead. Third, full-table replication increases memory footprint, which is problematic if the replicated table is large.

Caching is a more flexible solution to leverage hot data. Specifically, the DBMS decides to cache remote data in a server's local memory without user intervention. A query that reads data from its local cache does not contact the remote server, thus reducing both network latency and traffic. The key challenge in a caching protocol is to maintain *cache coherence* (i.e., to avoid a machine reading stale cached data). Cache coherence is a classic problem in parallel computing and much prior work exists in different research fields including multicore and multi-socket processors [6, 42, 56], distributed shared memory systems [27, 31], distributed file systems [24], and databases [5, 23, 39]. In traditional DBMSs, caching and concurrency control are two separate layers; and both of them are notoriously hard to design and to verify [43]. In Section 4, we demonstrate how Sundial merges concurrency control and cache coherence into a single lightweight protocol with the help of logical leases.

2.4 Integrating Concurrency Control and Cache Coherence

The integration of concurrency control and cache coherence have also been studied in the context of *data sharing* systems [40]. Examples include IBM DB2 [26], Oracle RAC [13], Oracle Rdb [33], and the more recent Microsoft Hyder [10]. In these systems, servers in the cluster share the storage (i.e., shared disk architecture). Each server can access all the data in the database, and cache recently accessed data in a local buffer. A cache coherence protocol ensures the freshness of data in caches.

Sundial is different from data sharing systems in two aspects. First, Sundial is built on top of a shared-nothing architecture, and thus scales better than a data sharing system, which uses a shared disk. Second, existing data sharing systems typically use 2PL for concurrency control; the coherence protocol is also based on locking. By contrast, Sundial uses logical leases for both concurrency control and cache coherence, which reduces protocol complexity and increases concurrency (Section 4).

Another related system is G-Store [17], which supports transactional multi-key access over a key-value store. Before a transaction starts, the server initiates a *grouping protocol* to collect the exclusive ownership of keys that the transaction will access; after the transaction completes, the ownership is returned back. The grouping protocol has two downsides: (1) it requires the DBMS to know what keys a transaction will access before executing the transaction, and

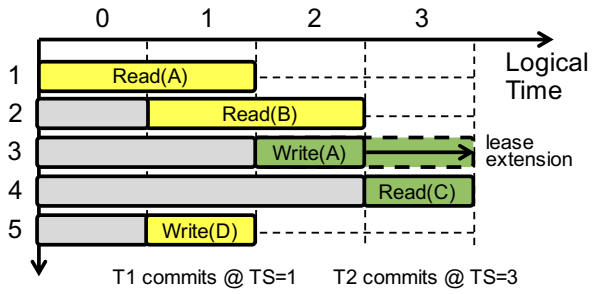


Figure 1: Logical Lease Example – Schedule of two transactions, *T1* and *T2*, accessing tuples **A**, **B**, **C**, and **D**. *T1*'s and *T2*'s operations are shadowed in light yellow and dark green, respectively. Since the logical timestamps are discrete, we represent each timestamp as an interval in the figure.

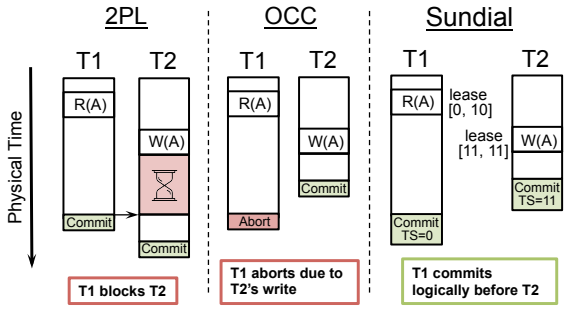


Figure 2: Read-Write Conflict Example – Example schedule of two transactions with a read-write conflict in 2PL, OCC, and Sundial.

(2) it does not allow multiple transactions to read the same key concurrently. These problems do not exist in Sundial, which supports dynamic working sets and concurrent reads.

3. SUNDIAL CONCURRENCY CONTROL

This section presents the Sundial distributed concurrency control protocol in detail. Our discussion assumes a homogeneous cluster of servers connected through a local area network (LAN). Data is partitioned across servers. Each tuple is mapped to a *home server* that can initiate a transaction on behalf of an external user, as well as process remote queries on behalf of peer servers. The server initiating the transaction is called the *coordinator* of the transaction; other servers involved in a transaction are called *participants*.

3.1 Logical Leases

Logical leases are based on logical time, and specifies a *partial logical order* among concurrent operations. A logical lease is attached to each data element, represented using two 64-bit timestamps, *wts* and *rts*. *wts* is the logical time when the tuple was last written; *rts* is the end of the lease, meaning that the tuple can be read at logical time *ts* such that $wts \leq ts \leq rts$. A transaction writes to a tuple only after the current lease expires, namely, at a timestamp no less than $rts + 1$. Since leases are logical in Sundial, the writing transaction does not 'wait' in physical time for a lease to expire—it simply jumps ahead in logical time.

To achieve serializability, the DBMS computes a single *commit timestamp* for a transaction T, which is a logical time that falls within the leases of all tuples the transaction accesses. Namely, for all tuples accessed by T, $tuple.wts \leq T.commit\_ts \leq tuple.rts$. From the perspective of logical time, T's operations are *atomically* performed at the commit timestamp. The DBMS calculates this commit timestamp using only the leases of tuples accessed by the transaction and thus no inter-transaction coordination is required.

Figure 1 shows an example illustrating the high-level idea of Sundial concurrency control. The DBMS executes two transactions, *T1* and *T2*. *T1* reads tuples **A** and **B** with logical leases [0, 1] and [1, 2], respectively; *T1* also writes to **D** and creates a new lease of [1, 1] for the new data. *T1* commits at timestamp 1 as it overlaps with all the leases that *T1* accesses.

T2 writes to **A**, and creates a new lease of [2, 2]. It also reads **C** at [3, 3]. These two leases, however, do not overlap. In this case, the DBMS extends the end of the lease on **A** from 2 to 3 such that both operations performed by *T2* are valid at timestamp 3. If the lease extension succeeds, namely, no other transaction in the system has written to **A** at timestamp 3, the DBMS commits *T2* at timestamp 3.

Note that in this example, when *T1* commits, *T2* has already modified **A**, which was read by *T1*. However, this does not cause *T1* to abort as in traditional OCC protocols, because Sundial serializes transactions in logical rather than physical time order. The physical and logical commit orders can differ, as shown in the example—although *T1* commits after *T2* in physical time order, *T1* commits with a smaller logical timestamp. This *time traveling* feature of Sundial allows the DBMS to dynamically determine a transaction's commit timestamp, which avoids some unnecessary aborts due to read-write conflicts and results in lower abort rate.

3.2 Conflict Handling

Sundial uses different methods to resolve different types of conflicts between transactions. Such hybrid schemes have also been proposed before in both databases [18, 44] and software transactional memory [19].

Sundial handles *write-write conflicts* using pessimistic 2PL. We made this choice because many writes are read-modify-writes, and two such updates to the same tuple always conflict (unless the DBMS exploits semantic information like commutativity); handling such conflicts using OCC causes all but one of the conflicting transactions to abort. In contrast, Sundial handles *read-write conflicts* using OCC instead of 2PL to achieve higher concurrency. This prevents transactions from waiting for locks during execution. More importantly, this allows the DBMS to dynamically adjust the commit order of transactions to reduce aborts, using the technique of logical leases discussed in Section 3.1.

Figure 2 shows an example to illustrate the difference between 2PL, traditional OCC, and Sundial in handling read-write conflicts. In 2PL, the DBMS locks a tuple before transaction *T1* reads it. This lock blocks transaction *T2* from writing to the same tuple, which increases the execution time of *T2*. In a traditional OCC protocol, a transaction does not hold locks during its normal execution. Therefore, *T2* commits before *T1* and updates tuple **A** in the database. When *T1* tries to commit, **A** has been changed since the last time *T1* reads it. The DBMS then aborts *T1* due to this data conflict.

In this example, aborting *T1* is unnecessary because there exists a logical commit order (i.e., *T1* commits before *T2*) between the two transactions that maintains serializability. Sundial is able to identify this order using logical leases. Specifically, *T1* reads a version of **A** with a lease [0, 10], and commits at a timestamp within that lease (e.g. timestamp 0). *T2* writes to **A** with a new lease of [11, 11], and therefore commits at timestamp 11. Although *T1* made the commit decision after *T2* in physical time order, both transactions are able to commit and *T1* commits before *T2* in logical time order.

3.3 Protocol Phases

The lifecycle of a distributed transaction in Sundial is shown in Figure 3, which consists of three phases: (1) **execution**, (2) **prepare**,

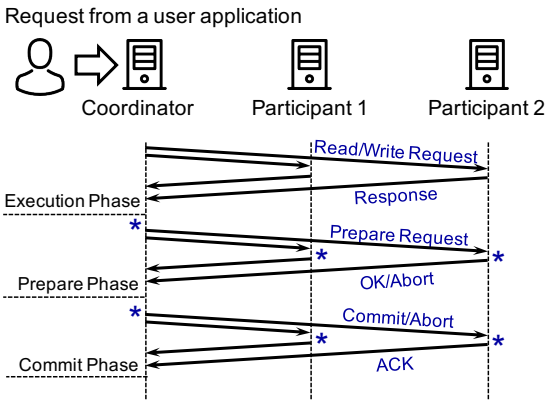


Figure 3: The lifecycle for a Distributed Transaction – A distributed transaction goes through the execution phase and two-phase commit (2PC) which contains the prepare and commit phases.

and (3) **commit**. The coordinator initiates a new transaction after receiving a request from a user application. In the first phase (execution), the coordinator executes the transaction's logic and sends requests to participants of the transaction. When the transaction completes the execution phase, the coordinator begins *two-phase commit* (2PC). In the prepare phase, the first phase in 2PC, the coordinator sends a prepare request to each participant involved in the transaction (i.e., the servers that were accessed during the execution phase). Each participant responds with either `OK` or `ABORT`. If all participants (including the coordinator) agree that the transaction can commit, then the transaction enters the final (commit) phase, where the coordinator sends a message to each participant to complete the transaction. Otherwise, the DBMS aborts the transaction and rolls back its modifications. To ensure that a transaction's modifications persist after a server/network failure, the DBMS performs logging at each server at different points during the 2PC protocol (shown as * in Figure 3).

In Sundial, the *wts* of a lease changes only when the tuple is updated during the commit phase of a transaction; the *rts* of a lease changes only in the prepare or commit phases. Both the *wts* and *rts* of a tuple can only increase but never decrease. During the three phases, the DBMS may coordinate the participants to calculate a transaction's commit timestamp or to extend logical leases. The DBMS piggybacks timestamp-related information in its normal runtime messages. We now describe the logic of each phase in more detail.

3.3.1 Execution Phase

During the execution phase, a transaction reads and writes tuples in the database and performs computation. Each tuple contains a logical lease (i.e., *wts* and *rts*). Sundial handles write-write conflicts using the 2PL Wait-Die algorithm [9]. Therefore, the DBMS also maintains the current *lock owner* and a *waiting list* of transactions waiting for the lock. Each tuple has the following format, where `DB` is the database and `DB[key]` represents the tuple that has `key` as its primary key:

```
DB[key] = {wts, rts, owner, waitlist, data}
```

Sundial handles read-write conflicts using OCC, and thereby the DBMS maintains the *read set* (RS) and the *write set* (WS) of each transaction. The data structure of the two sets are shown below. The `data` field contains a local copy of the database tuple that the transaction reads (in RS) or writes (in WS).

```
RS[key] = {wts, rts, data},  WS[key] = {data}
```

Algorithm 1: Execution Phase of Transaction T – *T.commit_ts* is initialized to 0 when T begins. Caching related code is highlighted in gray (cf. Section 4).

```
1  Function read(T, key)
2      if key ∈ T.WS:
3          return WS[key].data
4      elif key ∈ T.RS:
5          return RS[key].data
6      else:
7          if key ∈ Cache and Cache.decide_read():
8              T.RS[key].{wts, rts, data} = Cache[key].{wts, rts, data}
9          else:
10             n = get_home_node(key)
11             # read_data() atomically reads wts, rts, and data and
                 return them back
12             T.RS[key].{wts, rts, data} = RPC_n::read_data(key)
13             Cache[key].{wts, rts, data} = T.RS[key].{wts, rts, data}
14         T.commit_ts = Max(T.commit_ts, T.RS[key].wts)
15         return RS[key].data

16 Function write(T, key, data)
17     if key ∉ T.WS:
18         n = get_home_node(key)
19         # lock() tries to lock the tuple DB[key]; if locking is successful,
             it returns wts and rts of the locked tuple
20         {success, wts, rts} = RPC_n::lock(key)
21         if not success or (key ∈ T.RS and wts ≠ T.RS[key].wts):
22             Abort(T)
23         else:
24             T.commit_ts = Max(T.commit_ts, rts + 1)
25     T.WS[key].data = data
```

Algorithm 1 shows the logic for read and write requests. The code shadowed in gray is related to caching and will be explained in Section 4.

For a read request, if the requested tuple is already in transaction T's read or write set, the DBMS simply returns the data (lines 2–5). Otherwise, the DBMS sends a remote procedure call (RPC_n) to the home server n of the tuple, which *atomically* reads the *wts*, *rts*, and *data* of the tuple and returns them to the coordinator's read set (lines 10–12). The coordinator then updates *T.commit_ts* to be at least the *wts* of the tuple (line 14), reflecting that T's logical commit time must be no earlier than the logical time when the tuple was last written. Finally, the data is returned (line 15).

For a write operation, if the tuple is already in T's write set, the DBMS simply updates the local data in the write set (line 17, 25). Otherwise, the DBMS locks the tuple by issuing an RPC to its home server (lines 18–20). The RPC returns whether the lock acquisition succeeds, and if so, the *wts* and *rts* of the locked tuple. If locking fails, or if the locked key exists in the read set but the returned *wts* does not match the *wts* in the read set, then the transaction aborts (line 22). Otherwise, the DBMS advances the transaction's *commit_ts* to *rts* + 1 (line 24), and updates the data in the write set (line 25). Note that during the execution phase of T, other transactions cannot read tuples in T's write set—they become visible only after T commits (Section 3.3.3).

An important feature of Sundial is that a transaction reading a tuple does not block another transaction writing the same tuple (and vice versa). If a tuple is locked, a reading transaction still reads the data of the tuple, with its associated logical lease. The commit timestamp of the reading transaction will be smaller than the commit timestamp of the transaction holding the lock. But both transactions are able to commit as long as they both find commit timestamps satisfying their leases.

Algorithm 2: Prepare Phase of Transaction *T* – *validate_read_set()* is executed at the coordinator; *renew_lease()* is executed at the participants.

```
1  Function validate_read_set(T)
2      for key ∈ T.RS.keys() \ T.WS.keys():
3          if commit_ts > T.RS[key].rts:
4              n = get_home_node(key)
5              # Extend rts at the home server
6              resp = RPC_n::renew_lease(key, wts, commit_ts)
7              if resp == ABORT:
8                  Cache.remove(key)
9                  return ABORT
10     return COMMIT

11 # renew_lease() must be executed atomically
12 Function renew_lease(key, wts, commit_ts)
13     if wts ≠ DB[key].wts or (commit_ts > DB[key].rts and
         DB[key].is_locked()):
14         return ABORT
15     else:
16         DB[key].rts = Max(DB[key].rts, commit_ts)
17         return OK
```

3.3.2 Prepare Phase

The goal of the prepare phase is for the DBMS to determine whether all the reads and writes of a transaction are valid at the calculated *commit_ts*. Algorithm 2 shows the logic that the DBMS performs during the prepare phase; *validate_read_set()* is executed at the coordinator, which calls *renew_lease()* at the participants.

Since all tuples in the write set are already locked, the DBMS only validates tuples that are read but not written. For each key in transaction T's read set but not the write set (line 2), if T.*commit_ts* is within the lease of the tuple (i.e., tuple.*wts* $\leq$ T.*commit_ts* $\leq$ tuple.*rts*[1]), then the read is already valid and nothing needs to be done (line 3). Otherwise, an RPC is sent to the tuple's home server to renew its lease (lines 4–6). The transaction aborts if the lease renewal fails (line 9).

A participant executes *renew_lease()* to perform lease renewal. If the current *wts* of the tuple is different from the *wts* observed by the transaction during the execution phase, or if the extension is required but the tuple is locked by a different transaction, then the DBMS cannot extend the lease and ABORT is returned to the coordinator (lines 13–14). Otherwise, the DBMS extends the lease by updating the tuple's *rts* to at least *commit_ts* (line 16). In Sundial, lease extension is the only way to change a tuple's *rts*. Both *wts* and *rts* of each tuple can only increase but never decrease.

3.3.3 Commit Phase

During the commit phase, the DBMS either commits the transaction by copying all the writes from the write set to the database and releasing the locks, or aborts the transaction by simply releasing the locks. Algorithm 3 shows the functions that the coordinator executes. If a lock acquisition fails in the execution phase, or if the *validate_read_set()* returns ABORT, *abort()* is executed, otherwise, *commit()* is executed.

The DBMS does not perform any additional operations on a transaction's read set during the commit phase. Therefore, if a transaction does not write to any tuple at a participant, the DBMS skips the commit phase at that participant. Sundial applies this small optimization to reduce network traffic.

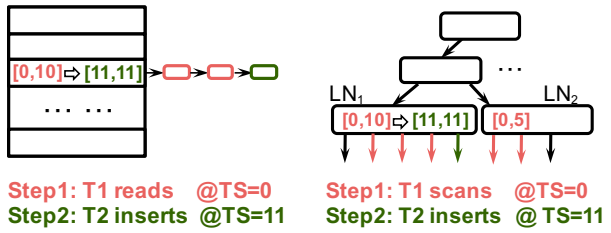
[1]Note that *tuple.wts* $\leq$ T.*commit_ts* must be true due to the way T.*commit_ts* was updated during the execution phase (see Algorithm 1, lines 14 and 24).

Algorithm 3: Commit Phase of transaction *T* – The DBMS either commits or aborts the transaction.

```
1  Function commit(T)
2      for key ∈ T.WS.keys():
3          n = get_home_node(key)
4          RPC_n::update_and_unlock(key, T.WS[key].data, T.commit_ts)
5          Cache[key].wts = Cache[key].rts = T.commit_ts
6          Cache[key].data = T.WS[key].data

7  Function abort(T)
8      for key ∈ T.WS.keys():
9          n = get_home_node(key)
10         # unlock() releases the lock on DB[key]
11         RPC_n::unlock(key)

12 Function update_and_unlock(key, data, commit_ts)
13     DB[key].data = data
14     DB[key].wts = DB[key].rts = commit_ts
15     unlock(DB[key])
```



(a) Hash Index **(b)** B+tree Index

Figure 4: Concurrent Index Read/Scan and Insertion in Sundial – Logical leases are embedded into the leaf nodes of a B+tree index to enable high concurrency in index accesses.

3.4 Indexes and Phantom Reads

Beyond regular reads and writes, indexes must support inserts and deletes. As a result, an index requires extra concurrency control mechanisms for correctness. Specifically, a *phantom read* occurs if a transaction reads a set of tuples twice using an index but gets different sets of results due to another transaction's inserts or deletes to the set. Serializability does not permit phantom reads. This section discusses how Sundial avoids phantom reads.

By treating inserts and deletes as writes to index nodes, and lookups or scans as reads to index nodes, the basic Sundial protocol can be extended to handle index accesses. This way, each index node (e.g., a leaf node in a B+tree index or a bucket in a hash index) can be treated as a regular tuple and the protocol discussed in Section 3.3 can be applied to indexes. The logical leases can also be maintained at a finer granularity (e.g., each pointer in the leaf node or each block in a bucket) to avoid unnecessary aborts due to false sharing; in Sundial, we attach a logical lease to each index node. In order to ensure that multiple index lookups/scans to the same index node return consistent results, later accesses must verify that the index node's version has not changed.

Figure 4 shows two examples of transactions concurrently accessing a hash index (Figure 4a) and a B+tree index (Figure 4b). In the hash index example, *T1* reads all the tuples mapped to a given bucket with a lease of [0, 10]. *T2* then inserts a tuple into the same bucket, and updates the lease on the bucket to [11, 11]. *T1* and *T2* have a read-write conflict but do not block each other; both transactions can commit if each finds a commit timestamp satisfying all the accessed leases.

In the B+tree index example, *T1* performs a scan that touches two leaf nodes, LN_1 and LN_2, and records their logical leases ([0,

10] and [0, 5]). After the scan completes, *T2* inserts a new key into LN_1. When *T2* commits, it updates the contents of LN_1, as well as its logical lease to [11, 11]. Similar to the hash index example, both *T1* and *T2* may commit and *T1* commits before *T2* in logical time order. Thus, concurrent scans and inserts need not cause aborts.

3.5 Fault Tolerance

Sundial tolerates single- and multi-server failures through the two-phase commit (2PC) protocol, where the coordinator and participants log to persistent storage before sending out certain messages (Figure 3). The logical leases in Sundial require special treatment during 2PC: failing to properly log logical leases can lead to non-serializable schedules, as shown by the example in Listing 1.

The example contains two transactions (*T1* and *T2*) accessing two tuples, **A** and **B**, that are stored in servers 1 and 2, respectively. When server 2 recovers after crashing, the logical leases of tuples mapped to server 2 (i.e., tuple **B**) are reset to [0, 0]. As a result, the DBMS commits *T1* at timestamp 0, since the leases of tuples accessed by *T1* (i.e., **A** of [0, 9] and **B** of [0, 0]) overlap at 0. This execution, however, violates serializability since *T1* observes *T2*'s write to **B** but not its write to **A**. This violation occurs because the logical lease on **B** is lost and reset to [0, 0] after server 2 recovers from crash. If server 2 had not crashed, *T1*'s read of **B** would return a lease starting at timestamp 10, causing *T1* to abort due to non-overlapping leases and a failed lease extension.

Listing 1: Serializability violation when logical leases are not logged – Tuples A and B are stored in servers 1 and 2, respectively

```
T1 R(A)                  lease [0, 9]
T2 W(A), W(B), commit    @ TS=10
Server 2 crashes
Server 2 recovers
T1 R(B)                  lease [0, 0]
```

One simple solution to solve the problem above is to log logical leases whenever they change, and restore them after recovery. This, however, incurs too much writing to persistent storage since even a read operation may extend a lease, causing a write to the log.

We observe that instead of logging every lease change, the DBMS can log only an *upper-bound timestamp* (UT) that is greater than the end time of all the leases on the server. After recovery, all the leases on the server are set to [UT, UT]. This guarantees that a future read to a recovered tuple occurs at a timestamp after the *wts* of the tuple, which is no greater than UT. In the example shown in Listing 1, *T1*'s read of **B** returns a lease of [UT, UT] where UT is greater than or equal to 10. This causes *T1* to abort due to non-overlapping leases. Note that UT can be a loose upper bound of leases. This reduces the storage and logging overhead of UT since it is logged only when the maximum lease exceeds the last logged UT.

4. SUNDIAL DATA CACHING

Caching a remote partition's data in a server's local main memory can reduce the latency and network traffic of distributed transactions, because reads that hit the local cache do not contact the remote server. Caching, however, causes data replication across servers; it is a challenging task to keep all the replicas up to date when some data is updated, a problem known as cache coherence [7]. Due to the complexity of maintaining coherence, existing distributed DBMSs rarely allow data to be cached across multiple servers. As we now present, Sundial's logical leases enable such data caching by integrating concurrency control and caching into a single protocol.

Figure 5 shows an overview of Sundial's caching architecture in a DBMS. The system only caches tuples for reads and a write request updates both the tuple at the home server and the locally cached copy. For a read query, the DBMS always checks the coordinator's local cache. For a hit, the DBMS decides to either read the cached tuple or ignore it and send a query to the tuple's home server. Later in Section 4.2, we will show that this decision depends on the workloads.

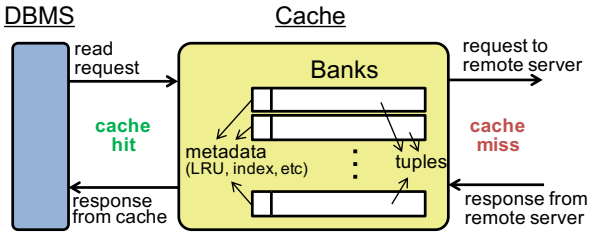


Figure 5: Caching Architecture – The cache is at the network side, containing multiple banks with LRU replacement.

To avoid centralized bottlenecks, Sundial organizes the cache into multiple banks. A tuple's bank is determined by hashing its primary key. Each bank maintains the metadata for the tuples it contains using a small index. When the bank is full, tuples are replaced following a *least-recently-used* (LRU) policy.

4.1 Cache Coherence with Logical Leases

In a system where data can be cached at multiple locations, a cache coherence protocol enforces that the value at each location is always up-to-date; namely, when one copy is updated, the change must propagate to all the copies. Existing coherence protocols either (1) require an invalidation mechanism to update or delete all the shared copies, or (2) check the data freshness by contacting the home server for each read request.

The downside of the invalidation-based approach is the complexity and the performance overhead of broadcasting each tuple update. The downside of the checking approach is that each read request incurs the round-trip latency (although data is not transferred if the cached copy is up-to-date), reducing some of the benefits of caching.

The caching mechanism in Sundial is a variant of the checking approach mentioned above. However, instead of checking freshness for each read request, the use of logical leases reduces the number of checks. Specifically, a transaction can read a cached tuple as long as its *commit_ts* falls within the lease of the tuple, even if the tuple has been changed at the home server—the transaction reading the "stale" cached copy can still be serializable with respect to other transactions in logical time order. In this sense, Sundial relaxes the requirement of cache coherence: there is no need to enforce that all cached copies are up-to-date, only that serializability is enforced. Logical leases provide a simple way to check serializability given the read and write sets of a transaction, regardless of whether the reads come from the cache or not.

Supporting caching requires a few changes to the protocol presented so far (Section 3.3); they are shadowed in gray in Algorithms 1–3. During the execution phase, a remote read request checks the cache (Algorithm 1, lines 7–8) and either reads from the cache (Section 4.2) or requests the home server home server (line 13). In the validation phase, if a lease extension fails, the tuple is removed from the cache to prevent repeated failures in the future (Algorithm 2, line 8). Finally, if a transaction commits, it updates the data copies in both the home server and the local cache (Algorithm 3, lines 5–6). These are relatively small protocol changes.

The caching mechanism discussed so far works for primary key lookups using an equality predicate. But the same technique can also be applied to range scans or secondary index lookups. Since the index nodes also contain leases, the DBMS caches the index nodes in the same way it caches tuples.

4.2 Caching Policies

We now discuss different ways to manage the cache at each server and their corresponding tradeoffs.

Always Reuse: This is the simplest approach, where the DBMS always returns the cached tuple to the transaction for each cache hit. This works well for read-intensive tuples, but can hurt performance for tuples that are frequently modified. If a cached tuple has an old lease, it is possible that the tuple has already been modified by another transaction at the home server. In this case, a transaction reading the scale cached tuple may fail to extend the lease of that tuple, which causes the transaction to abort. These kinds of aborts can be avoided if the locally cached stale data is not used in the first place.

Always Request: An alternative policy is where the DBMS always sends a request to the remote server to retrieve the tuple, even for a cache hit. In this case, caching does not reduce latency but may reduce network traffic. For a cache hit, the DBMS sends a request to a remote server. The request contains the key and the *wts* of the tuple that is being requested. At the home server, if the tuple's *wts* equals the *wts* in the request, the tuple cached in the requesting server is the latest version. In this case, the DBMS does not return the data in the response, but just an acknowledgment that the cached version is up-to-date. Since data comprises the main part of a message, this reduces the total amount of network traffic.

Hybrid: `Always Reuse` works best for read-intensive workloads, while `Always Request` works best for write-intensive workloads. Sundial uses a hybrid caching policy that achieves the best of both. At each server, the DBMS maintains two counters to decide when it is beneficial to read from the cache. The counter *vote_cache* is incremented when a tuple appears up-to-date after a remote check, or when a cached tuple experiences a successful lease extension. The counter *vote_remote* is incremented when a remote check returns a different version or when a cached tuple fails a lease extension. The DBMS uses `Always Reuse` when the ratio between *vote_cache* and *vote_remote* is high (we found 0.8 to be a good threshold), and `Always Request` otherwise.

4.3 Read-Only Table Optimizations

Care is required when the logical lease of a cached tuple is smaller than a transaction's *commit_ts*. In this case, the DBMS has to extend the tuple's lease at its home server. Frequent lease extensions may be unnecessary, but hurt performance. The problem is particularly prominent for read-only tables, which in theory do not require lease extension. We now describe two techniques to reduce the number of lease extensions for read-only tables. The DBMS can enable both optimizations at the same time. We evaluate their efficacy in Section 6.4.1.

The first optimization tracks and extends leases at table granularity to amortize the cost of lease extensions. The DBMS can tell that a table is read-only or read-intensive because it has a large ratio between reads and writes. For each table, the DBMS maintains a *tab_wts* that represents the largest *wts* of all its tuples. The DBMS updates a table's *tab_wts* when a tuple has greater *wts*. A read-only table also maintains *tab_rts*, which means all tuples in the table are extended to *tab_rts* automatically. If any tuple is modified, its new *wts* becomes `Max`(*rts* +1, *tab_rts* +1, *wts*). When the DBMS requests a lease extension for a tuple in a read-only table, the DBMS extends all the leases in the table by advancing *tab_rts*. The *tab_rts* is returned to the requesting server's cache. A cache hit of a tuple in that table considers the lease to be [`wts`, `Max(tab_rts, rts)`].

Another technique to amortize lease extension costs is to speculatively extend the lease to a larger timestamp than what a transaction requires. Instead of extending the *rts* (or *tab_rts*) to the *commit_ts* of the requesting transaction, Sundial extends *rts* to *commit_ts* + δ for presumed read-only tables. Initially being 0, δ is incrementally increased over time as the DBMS gains more information that the table is indeed read-only. This reduces the frequency of lease extensions since it takes longer time for an extended lease to expire.

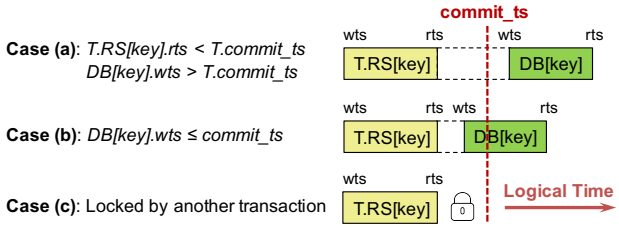


Figure 6: Transaction Aborts due to Read-Write Conflicts – Three cases where the DBMS aborts a transaction in Sundial due to read-write conflicts.

5. DISCUSSION

We now discuss the types of transaction aborts in Sundial (Section 5.1), quantitatively compare Sundial with MaaT (Section 5.2), and describe some limitations of Sundial (Section 5.3).

5.1 Transaction Aborts

As described in Section 3.2, it is difficult for a DBMS to avoid transaction aborts due to write-write conflicts. Therefore, we focus our discussion on aborts caused by read-write conflicts.

In Sundial, a transaction T must satisfy the following two conditions in order to commit:

$$T.commit\_ts \geq tuple.wts, \qquad \forall tuple \in T.RS \cup T.WS \quad (1)$$

$$T.commit\_ts \leq tuple.rts, \qquad \forall tuple \in T.RS \quad (2)$$

Condition (1) is always satisfied since *commit_ts* is no less than the *wts* of a tuple when it is read by a transaction (Algorithm 1) and that each write locks the tuple to prevent it from being changed by another transaction. Therefore, during the prepare phase, the DBMS can abort a transaction only if it fails Condition (2), i.e., the transaction fails to extend a lease since the tuple was locked or modified by another transaction (Algorithm 2). There are three scenarios where a transaction T fails Condition (2), which Figure 6 illustrates:

Case (a): The tuple's *wts* in the database is greater than or equal to T's *commit_ts*. The DBMS must abort T because it is unknown whether or not the version read by T is still valid at T's *commit_ts*. It is possible that another transaction modified the tuple after $T.RS[key].rts$ but before *commit_ts*, in which case the DBMS has to abort T. But it is also possible that no such transaction exists such that the version in T's read set is still valid at *commit_ts* and thus T can commit. This uncertainty could be resolved by maintaining a history of recent *wts*'s in each tuple [53].

Case (b): Another transaction already wrote the latest version of the tuple to the database before T's *commit_ts*. The DBMS is therefore unable to extend the lease of the transaction's local version to *commit_ts*. As such, the DBMS has to abort T.

Case (c): Lastly, the DBMS is unable to extend the tuple's *rts* because another transaction holds the lock for it. Again, this will cause the DBMS to abort T.

For the second and third conditions, Sundial can potentially avoid the aborts if the DBMS extends the tuple's lease during the execution phase. This reduces the number of renewals during the prepare phase, thereby leading to fewer aborts. But speculatively extending the leases also causes the transactions that update the tuple to

jump further ahead in logical time, leading to more extensions and potential aborts. We defer the exploration of these optimizations in Sundial to future work.

5.2 Sundial vs. MaaT

Similar to Sundial, previous concurrency control protocols have also used timestamp ranges to dynamically determine the transactions' logical commit timestamps. The technique, first proposed as *dynamic timestamp allocation* (DTA), was applied to both 2PL protocols for deadlock detection [8] and OCC protocols [12, 29, 30]. More recently, similar techniques have been applied to multi-version concurrency control protocols [34], as well as to MaaT, a single-version distributed concurrency control protocol [35].

In all these protocols, the DBMS assigns each transaction a timestamp range (e.g., 0 to ∞) when the transaction starts. After detecting a conflict, the DBMS shrinks the timestamp ranges of transactions in conflict such that their ranges do not overlap. If a transaction's timestamp range is not empty when it commits, the DBMS can pick any timestamp (in practice, the smallest timestamp) within its range as the commit timestamp; otherwise the transaction aborts.

Timestamp-range-based protocols have one fundamental drawback: they require the DBMS to *explicitly coordinate* transactions to shrink their timestamp ranges when a conflict occurs. In a distributed setting, they incur higher overhead than Sundial.

We use MaaT [35], a distributed DTA-based concurrency control protocol, as an example to illustrate the problem. In MaaT, the DBMS assigns a transaction with the initial timestamp range of [0, $+\infty$]. The DBMS maintains the range at each server accessed by the transaction. When a transaction begins the validation phase, the DBMS determines whether the *intersection* of a transaction's timestamp ranges across servers is empty or not. To prevent other transactions from changing the validating transaction's timestamp range, the DBMS *freezes* the timestamp range at each participating server. Many transactions, however, have ranges with an upper bound of $+\infty$. Therefore, after the DBMS freezes these ranges in the prepare phase, it must abort any transaction that tries to change the frozen timestamp ranges, namely, transactions that conflict with the validating transaction. This problem also exists in other timestamp-range-based protocols. Section 6 shows that these aborts degrade the performance of MaaT.

5.3 Limitations of Sundial

As discussed above, the two advantages of Sundial are (1) improving concurrency in distributed transaction processing, and (2) lightweight caching to reduce the overhead of remote reads. Sundial also has some limitations, which we now discuss, along with potential solutions to mitigate them.

First, Sundial requires extra storage to maintain the logical leases for each tuple. Although this storage overhead is negligible for large tuples, which is the case for workloads evaluated in this paper, it can be significant for small tuples. One way to reduce this overhead is for the DBMS to maintain the tuples' logical leases in a separate *lease table*. The DBMS maintains leases in this table only for tuples that are actively accessed. The leases of all 'cold' tuples are represented using a single (*cold_wts*, *cold_rts*). When a transaction accesses a cold tuple, the DBMS inserts an entry for it to the lease table with its lease assigned as (*cold_wts*, *cold_rts*). When a tuple with (*wts*, *rts*) is deleted from the lease table (e.g., due to insufficient space), the DBMS updates *cold_wts* and *cold_rts* to `Max`(*cold_wts*, *wts*) and `Max`(*cold_rts*, *rts*), respectively.

The second issue is that Sundial may not deliver the best performance for partitionable workloads. Sundial does not assume that the workload can be partitioned and thus does not have special optimizations for partitioning. Systems like H-Store [2] perform better in this setting. Our experiments show that if each transaction only accesses its local partition, Sundial performs 3.8× worse than a protocol optimized for partitioning. But our protocol handles distributed (i.e., multi-partition) transactions better than the H-Store approaches.

Finally, the caching mechanism in Sundial is not as effective if the remote data read by transactions is frequently updated. This means the cached data is often stale and transactions that read cached data may incur extra aborts. A more detailed discussion can be found in Section 6.4.

6. EXPERIMENTAL EVALUATION

We now evaluate the performance of Sundial. We implemented Sundial in a distributed DBMS testbed based on the DBx1000 in-memory DBMS [51]. We have open-sourced Sundial and made it available at `https://github.com/yxymit/Sundial.git`.

Each server in the system has one input and one output thread for inter-server communication. The DBMS designates all other threads as workers that communicate with the input/output threads through asynchronous buffers. Workload drivers submit transaction requests in a blocking manner, with one open transaction per worker thread.

At runtime, the DBMS puts transactions that abort due to contention (e.g., lock acquisition failure, validation failure) into an abort buffer. It then restarts these transactions after a small back-off time randomly selected between 0–1 ms. The DBMS does not restart transactions caused by user-initiated aborts.

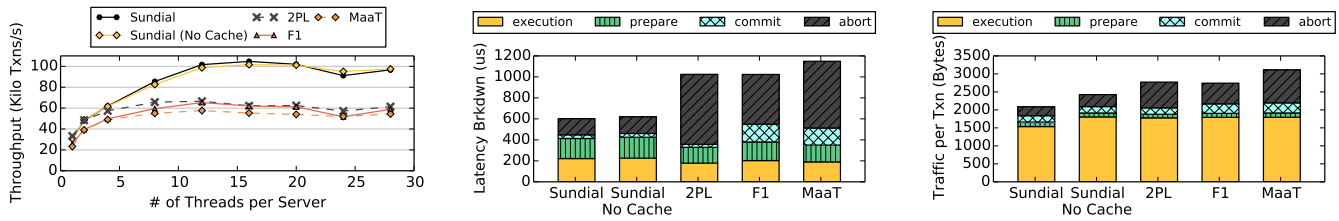
Most of the experiments are performed on a cluster of four servers running Ubuntu 14.04. Each server contains two Intel Xeon E5-2670 CPUs (8 cores × 2 HT) and 64 GB DRAM. The servers are connected together with a 10 Gigabit Ethernet. For the datacenter experiments in Section 6.7, we use the Amazon EC2 platform. For each experiment, the DBMS runs for a warm-up period of 30s, and then results are collected for the next 30s of the run. We also ran the experiments for longer time but the performance numbers are not different from the 1 minute runs. We assume the DBMS logs to battery-backed DRAM.

6.1 Workloads

We use two different OLTP workloads to evaluate the performance of concurrency control protocols. All transactions are executed as stored procedures that contain program logic intermixed with queries. We implement hash indexes since our workloads do not require table scans.

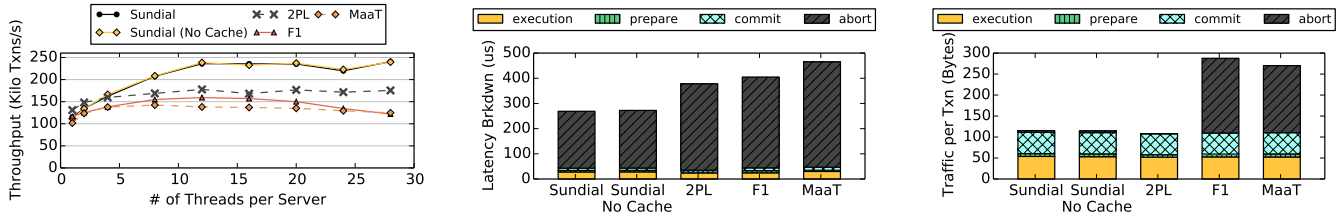
YCSB: The Yahoo! Cloud Serving Benchmark [14] is a synthetic benchmark modeled after cloud services. It contains a single table that is partitioned across servers in a round-robin fashion. Each partition contains 10 GB data with 1 KB tuples. Each transaction accesses 16 tuples as a mixture of reads (90%) and writes (10%) with on average 10% of the accesses being remote (selected uniformly at random). The queries access tuples following a power law distribution controlled by a parameter (θ). By default, we use θ=0.9, which means that 75% of all accesses go to 10% of hot data.

TPC-C: This is the standard benchmark for evaluating the performance of OLTP DBMSs [45]. It models a warehouse-centric order processing application that contains five transaction types. All the tables except `ITEM` are partitioned based on the warehouse ID. By default, the `ITEM` table is replicated at each server. We use a single warehouse per server to model high contention. Each warehouse contains 100 MB of data. For all the five transactions, 10% of `NEW-ORDER` and 15% of `PAYMENT` transactions access data across multiple servers; other transactions access data on a single server.



(a) Throughput **(b)** Latency Breakdown **(c)** Traffic Breakdown

Figure 7: Performance Comparison (YCSB) – Runtime measurements when running the concurrency control algorithms for the YCSB workload. The latency and traffic breakdown are measured on a single server in the cluster with 16 threads.



(a) Throughput **(b)** Latency Breakdown **(c)** Traffic Breakdown

Figure 8: Performance Comparison (TPC-C) – Runtime measurements when running the concurrency control algorithms for the TPC-C workload. The latency and traffic breakdown are measured on a single server in the cluster with 16 threads.

6.2 Concurrency Control Algorithms

We implemented the following concurrency control algorithms in our testbed. All the codes are available online.

2PL: We used a deadlock prevention variant of 2PL called *Wait-Die* [9]. A transaction waits for a lock only if its priority is higher than the current lock owner; otherwise the DBMS will abort it. We used the current wall clock time attached with the thread id as the metric of priority. This algorithm is similar to the approach that Google Spanner [15] used for read-write transactions.

Google F1: This is an OCC-based algorithm used in Google's F1 DBMS [41]. During the read-only execution phase, the DBMS tracks a transaction's read and write set. When the transaction begins the commit process, the DBMS locks all of the tuples accessed by the transaction. The DBMS aborts the transaction if it fails to acquire any of these locks or if the latest version of any tuple is different from the version that the transaction saw during its execution.

MaaT: This is a state-of-the-art distributed concurrency control protocol discussed in Section 5.2 [35]. We integrated the original MaaT source code into our testbed. We also improved the MaaT implementation by (1) reducing unnecessary network messages, (2) adding multi-threading support to the original single-thread-per-partition design of MaaT, and (3) improving its garbage collection.

Sundial: This is our proposed protocol as described in Sections 3 and 4. We enabled all of Sundial's caching optimizations from Section 4 unless otherwise stated. Each server maintains a local cache of 1 GB. Sundial by default uses the hybrid caching policy.

6.3 Performance Comparison

We perform our experiments using four servers. For each workload, we report throughput as we sweep the number of worker threads from 1 to 28. After 28 threads, the DBMS's performance drops due to increased context switching. To measure the benefit of Sundial's caching scheme, We run Sundial with and without caching enabled. In addition to throughput measurements, we also provide a breakdown of transactions' latency measurements and network traffic. These metrics are divided into Sundial's three phases (i.e., execution, prepare, and commit), and when the DBMS aborts a transaction.

The results in Figures 7a and 8a show that Sundial outperforms the best evaluated baseline algorithm (i.e., 2PL) by 57% in YCSB and 34% in TPC-C. Caching does not improve performance in these workloads in the current configuration. For YCSB, this is because the fraction of write queries per transaction is high, which means that the DBMS always sends a remote query message to the remote server even for a cache hit. As such, a transaction has the same latency regardless of whether caching is enabled. In TPC-C, all remote requests are updates instead of reads, therefore Sundial's caching does not help.

Figures 7b and 7c show the latency and network traffic breakdown of different concurrency control protocols on YCSB at 16 threads. The `Abort` portions represent the latency and network traffic for transaction executions that later abort; this metric measures the overhead of aborts. It is clear from these results that Sundial performs the best because of fewer aborts due to its dynamic timestamp assignment for read-write conflicts. Enabling Sundial's caching scheme further reduces traffic in the execution phase because the DBMS does not need to send back data for a cache hit. Section 6.4 provides a more detailed analysis of Sundial's caching mechanism.

Another interesting observation in Figure 7b is that F1 and MaaT both incur higher latency in the commit phase than 2PL and Sundial. This is because in both 2PL and Sundial, the DBMS skips the commit phase if a transaction did not modify any data on a remote server. In F1 and MaaT, however, the DBMS cannot apply this optimization because they have to either release locks (F1) or clear timestamp ranges (MaaT) in the commit phase, which requires a network round trip.

The latency and traffic breakdown of TPC-C (Figures 8b and 8c) show trends similar to YCSB in that Sundial achieves significant gains from reducing the cost of aborts. Since only one warehouse is modeled per server in this experiment, there is high contention on the single row in the `WAREHOUSE` table. As a result, all algorithms waste significant time on execution that eventually aborted. Both 2PL and Sundial incur little network traffic for aborted transactions because contention on the `WAREHOUSE` table happens at the beginning of each transaction. In 2PL, the DBMS resolves conflicts immediately (by letting transactions wait or abort) before sending out any remote queries. Sundial also resolves write-write conflicts early; for read-

write conflicts, Sundial's logical leases allow it resolve most conflicts without having to abort transactions.

Although not shown due to limited space, we also evaluated these protocols with YCSB at low contention (90% read, all accesses are uniformly random), and found that Sundial and 2PL have the same performance, which is 30% better than that of F1 and MaaT. The performance gain comes from the optimized commit protocol as discussed above.

6.4 Caching Performance

We describe the experimental results of different aspects of Sundial's caching in this subsection.

6.4.1 Caching with Read-Only Tables

We first measure the effectiveness of Sundial's caching scheme on databases with read-only tables. For this experiment, we use the TPC-C benchmark which contains a read-only table (i.e., `ITEM`) shared by all the database partitions. To avoid remote queries on `ITEM`, the DBMS replicates the table across all of the partitions. Table replication is a workload-specific optimization that requires extra effort from the users [38, 16]. In contrast, caching is more general and transparent, thereby easier to use. We use two configurations for the `ITEM` table:

- **Replication (Rep):** The DBMS replicates the table across all the partitions, thereby all accesses to the table are local.
- **No Replication (NoRep):** The DBMS hash partitions `ITEM` on its primary key. A significant portion of queries on this table have to access a remote server.

For the configuration without table replication, we test two different caching configurations:

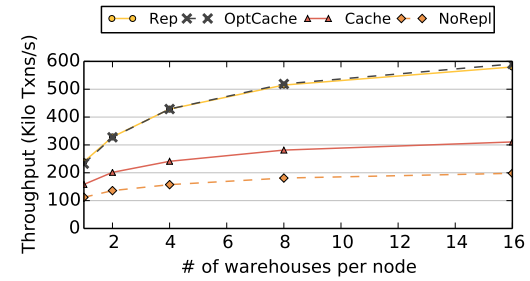
- **Default Caching (Cache):** The caching scheme described in Section 4.1.
- **Caching with Optimizations (OptCache):** Sundial's caching scheme with the read-only optimizations from Section 4.3.

According to Figure 9, the DBMS incurs a performance penalty when it does not replicate the `ITEM` table. This is because the table is accessed by a large fraction of transactions (i.e., all `NewOrder` transactions which comprise 45% of the workload) that become distributed if `ITEM` is not replicated. The performance gap can be closed with caching, which achieves the same performance benefit as manual table replication but hides the complexity from the users.

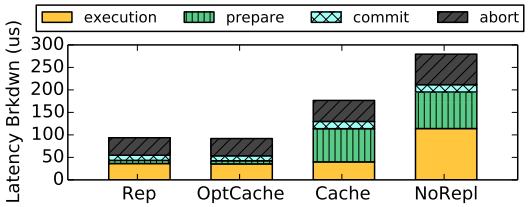
From Figure 9, we observe that the read-only table optimizations from Section 4.3 are important for performance. Without them, a cached tuple in the `ITEM` table may require extra lease extensions during the prepare phase. This is because contentious tuples have rapidly increasing *wts*; transactions accessing these tuples have large *commit_ts*, leading to lease extensions on tuples in `ITEM`. These lease extensions increase both network delays and network traffic, which hurt performance. With the read-only table optimizations, the DBMS extends all leases in the `ITEM` table together which amortizes the extension cost.

6.4.2 Caching with Read-Write Tables

In this section, we measure the effectiveness of caching for read-write tables. We use a variant of the YCSB workload to model a social network application scenario. A transaction writes tuples following a uniformly random distribution and reads tuples following a power law distribution. This is similar to the social network application where the data of popular users are read much more often than data of less popular users. We sweep the skew factor (i.e., θ) for the read distribution from 0.6 to 1.7. The percentage of read queries per transaction is 90% for all trials.



(a) Throughput



(b) Latency Breakdown (16 warehouses per server)

Figure 9: Caching with Read-Only Tables – Performance of different TPC-C configurations in Sundial with caching support.

Figure 10 shows the performance of Sundial with and without caching, in terms of throughput, network traffic, and latency breakdown. When the read distribution is less skewed (θ=0.6), caching does not provide much improvement because hot tuples are not read intensive enough. As the reads become more skewed, performance of Sundial with caching improves significantly because the hot tuples are read intensive and can be locally cached. With a high skew factor (θ=1.7), the performance improvement derived from caching is 4.6×; caching also reduces the amount of network traffic by 5.24× and transaction latency by 3.8×.

6.4.3 Cache Size

Table 1: Throughput (in Kilo Txns/s) with Different Cache Sizes in Sundial.

Cache Size	0 MB	16 MB	64 MB	256 MB	1 GB	4 GB
Throughput	129	429	455	467	462	462

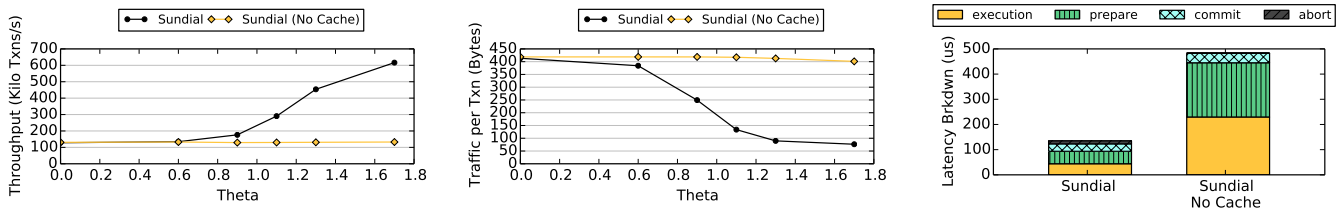
We now evaluate how sensitive the performance is to different cache sizes. Table 2 shows the throughput of Sundial on the same social-network-like workload as used in Section 6.4.2 with a skew factor $\theta = 1.3$.

At this level of skew, performance is significantly improved even with a small cache size of 16 MB. Performance further increases as the cache gets bigger, until it plateaus with 256 MB caches.

6.4.4 Caching Policies

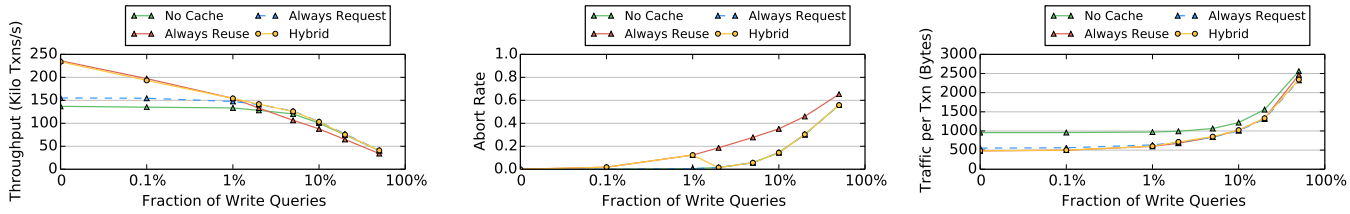
This section studies different caching policies in Sundial (see Section 4.2). We control the percentage of write queries in transactions. This changes whether or not the DBMS designates reading from cache as beneficial or not. For these experiments, both reads and writes follow a power law distribution with θ=0.9. We use the following caching configurations:

- **No Cache:** The Sundial's caching scheme is disabled.
- **Always Reuse:** The DBMS always reuses a cached tuple if it exists in its local cache.



(a) Throughput **(b)** Network Traffic **(c)** Latency Breakdown ($\theta = 1.3$)

Figure 10: Caching with Read-Write Tables – Performance of Sundial with and without caching on YCSB as the skew factor of read distribution changes.



(a) Throughput **(b)** Abort Rate **(c)** Network Traffic

Figure 11: Caching Policies – Performance measurements for Sundial with the caching policies from Section 4.2 when varying the percentage of write queries per transaction in the YCSB workload.

- **Always Request:** The DBMS always sends a request to retrieve the tuple even if it exists in local cache.
- **Hybrid:** The DBMS reuses cached tuples for read-intensive tables only when caching is beneficial (cf. Section 4.2).

The results in Figure 11 show that `Always Reuse` improves the DBMS's performance when the data is read-intensive. In this workload, the cached tuples are unlikely to be stale, thus there will be fewer unnecessary aborts. As the number of writes increases, however, many transactions abort due to reading stale cached tuples. The performance of `Always Reuse` is even worse than `No Cache` when more than 1% of queries are writes.

In contrast, `Always Request` never performs worse than `No Cache`. It has the same abort rate as no caching since a transaction always reads the latest tuples. The DBMS incurs lower network traffic than `No Cache` since cache hits on up-to-date tuples do not incur data transfer. For a read intensive table, `Always Request` performs better than `No Cache` but worse than `Always Reuse`.

Lastly, the `Hybrid` policy combines the best of both worlds by adaptively choosing between `Always Reuse` and `Always Request`. This allows the DBMS to achieve the best throughput with any ratio between reads and writes.

6.5 Measuring Aborts

We designed this next experiment to better understand how transaction aborts occur in the Sundial and MaaT protocols. For this, we executed YCSB with the default configuration. We instrumented the database to record the reason why the DBMS decides to abort a transaction, i.e., due to what type of conflict. A transaction is counted multiple times in our measurements if it is aborted and restarted multiple times. To ensure that each protocol has the same amount of contention in the system, we keep the number of active transactions running during the experiment constant.

The tables in Figure 12 show the percentage of transactions that the DBMS aborts out of all of the transactions executed. We see that the transaction abort rate under Sundial is 3.3× lower than that of MaaT. The main cause of aborts in MaaT is due to conflicts with the frozen range of $[x, \infty)$ where x is some constant. As discussed in Section 5.2, this happens when a transaction reads a tuple and

Abort Cases	Abort Rate
Case (a): $commit\_ts < DB[key].wts$	1.79%
Case (b): $commit\_ts \geq DB[key].wts$	1.56%
Case (c): tuple locked	6.60%
Aborts by W/W Conflicts	4.05%
Total	**14.00%**

(a) Sundial

Abort Cases	Abort Rate
Conflict with $[x, \infty)$	42.21%
Empty range due to other conflicts	4.45%
Total	**46.66%**

(b) MaaT

Figure 12: Measuring Aborts – Different types of aborts that occur in Sundial and MaaT for the YCSB workload. For Sundial, we classify the aborts due to read-write conflicts into the three categories from Section 5.1.

enters the prepare phase with a timestamp range of $[x, \infty)$. While the transaction is in this prepare phase, the DBMS has to abort any transaction that writes to the same tuple as it cannot change a frozen timestamp range. In Sundial, most of the aborts are caused by Case (c) in read-write conflicts, where a transaction tries to extend a lease that is locked by another writing transaction. There are also many aborts due to write-write conflicts. The number of aborts due to Cases (a) and (b) are about the same and lower than the other two cases.

6.6 Dynamic vs. Static Timestamps

One salient feature of Sundial is its ability to dynamically determine the commit timestamp of a transaction to minimize aborts. Some concurrency control protocols, in contrast, assign a static timestamp to each transaction when it starts and use multi-versioning to avoid aborting read queries that arrive later [1, 18, 32]. The inability to flexibly adjust transactions' commit order, however, leads to unnecessary aborts due to write conflicts from these late arriving transactions (i.e., writes arriving after a read has happened with a larger timestamp).

In this experiment, we compare Sundial without caching against a multi-version concurrency control (MVCC) protocol with varying amounts of clock skew between servers. Our MVCC implementa-

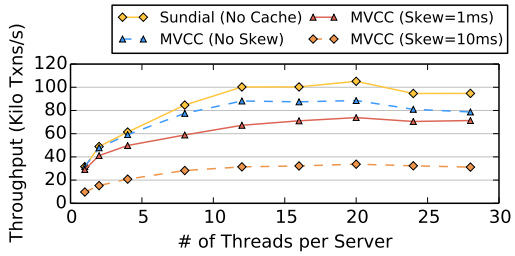


Figure 13: Dynamic vs. Static Timestamp Assignment – Performance comparison between Sundial and a baseline MVCC protocol that statically assigns timestamps to transactions.

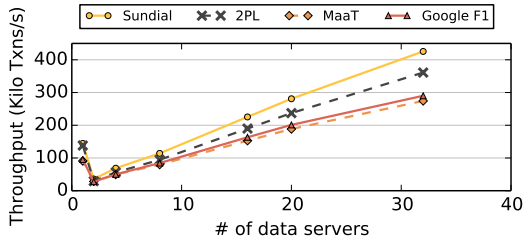


Figure 14: Scalability – Throughput of concurrency control algorithms for the YCSB workload on Amazon EC2.

tion is idealized as it does not store or maintain the data versions, and therefore does not have associated memory and computation overhead (e.g., garbage collection) [49]. This allows us to compare the amount of concurrency enabled by Sundial and MVCC. We use `ptp` [4] to synchronize the servers' clocks and then adjust the drift from 1 to 10 ms.

In Figure 13, we observe even with no clock skew (less than 10 μs) that the DBMS performs worse with MVCC than with Sundial. This degradation is mostly caused by the extra aborts due to writes that arrive late. Sundial's dynamic timestamp assignment allows the DBMS to move these writes to a later timestamp and thus reduce these aborts. Increasing the clock skew further degrades the throughput of the MVCC protocol. This is because writes from servers that fall behind in time will always fail due to reads to the same tuples from other servers. The DBMS's performance with Sundial does not suffer with higher amounts of clock skew since its timestamps are logical.

6.7 Scalability

For this experiment, we deployed DBx1000 on Amazon EC2 to study its scalability as we increase the number of servers in the cluster. Each server has an instance type of `m4.2xlarge` with eight virtual threads and 32 GB main memory. We assign two threads to handle the input and output communications, and the remaining six threads as worker threads. We run the YCSB workload using the workload mixture described in Section 6.1.

The first notable result in Figure 14 is that the performance of all the protocols drop to the same level when the server count increases from one to two. This is due to the overhead of the DBMS having to coordinate transactions over the network [25]. Beyond two servers, however, the performance of all of the algorithms increases as the number of servers increases. We see that the performance advantage of Sundial over the other protocols remains as the server count increases.

6.8 Comparison to Dynamic Timestamp Range

In Section 2, we qualitatively discussed the difference between Sundial and Lomet et al [34]. We now quantitatively compare their performance and discuss why Sundial performs better. Our implementation of [34] strictly follows procedures 1 to 3 in Appendix A in the paper. To simplify our implementation, we made two changes of their protocol.

First, instead of implementing it in a multiversion database, we only maintained a single latest version for each tuple. For the YCSB workload that we used for the evaluation, this offers a performance upper bound of the protocol; this is similar to what we did for the idealized MVCC in Section 6.6.

Second, the original protocol in [34] requires a centralized clock which all threads have access to. There are two ways to adapt this design to a distributed environment: (1) a centralized clock server which all transactions get the timestamp from, or (2) synchronized distributed clocks. We picked the second design and used `ptp` [4] for clock synchronization.

We run both protocols with the YCSB benchmark where each transaction accesses 16 tuples and each access has 90% probability to be a read and 10% probability to be a write. Two different contention levels are tested: with low contention tuples are accessed with uniformly random distribution; with high contention tuples are accessed following a power law distribution with a skew factor of $\theta = 0.9$, meaning that 75% of accesses go to 10% of hot data.

Table 2: Performance comparison between Sundial and Lomet et al [34]

	Low Contention	High Contention
Sundial	130.3	99.6
Lomet et al. [34]	110.9	58.5

Table 2 shows the performance of the two protocols. At low contention, their performance is similar, with Sundial outperforming by 17.5%. In this setting, both protocols incur very few aborts. The performance improvement is mainly due to the lower cost of managing the metadata in Sundial, because there is no need to adjust the timestamp ranges for *other* transactions when conflicts occur. Compared to per-transaction timestamp ranges, the per-tuple logical lease is a more lightweight solution to dynamically determine transactions' commit timestamps.

At high contention, the performance difference between Sundial and [34] becomes a more significant 70%. In this setting, Sundial has lower abort rate and thus performs better. One reason of this is that [34] has to decide how to shrink the timestamp ranges of conflicting transactions at the moment the conflict occurs. Failing to choose the best way of shrinking can hurt performance. Sundial, in contrast, delay the decision to the end of the transaction in an optimistic way, thereby avoiding some unnecessary aborts.

7. CONCLUSION

We presented Sundial, a distributed concurrency control protocol that outperforms all other ones that we evaluated. Using logical leases, Sundial reduces the number of aborts due to read-write conflicts, and reduces the cost of distributed transactions by dynamically caching data from a remote server. The two techniques are seamlessly integrated into a single protocol as both are based on logical leases. Our evaluation shows that both optimizations significantly improve the performance of distributed transactions under various workload conditions.

8. ACKNOWLEDGEMENTS

This work was supported (in part) by the U.S. National Science Foundation (CCF-1438955, and CCF-1438967).

This paper is dedicated to the memory of Leon Wrinkles.
May his tortured soul rest in peace.

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