Using Nesting to Push the Limits of Transactional Data Structure Libraries

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Abstract

Transactional data structure libraries (TDSL) combine the ease-of-programming of transactions with the high performance and scalability of custom-tailored concurrent data structures. They can be very efficient thanks to their ability to exploit data structure semantics in order to reduce overhead, aborts, and wasted work compared to general-purpose software transactional memory. However, TDSLs were not previously used for complex use-cases involving long transactions and a variety of data structures.

In this paper, we boost the performance and usability of a TDSL, allowing it to support complex applications. A key idea is nesting. Nested transactions create checkpoints within a longer transaction, so as to limit the scope of abort, without changing the semantics of the original transaction. We build a Java TDSL with built-in support for nesting in a number of data structures. We conduct a case study of a complex network intrusion detection system that invests a significant amount of work to process each packet. Our study shows that our library outperforms TL2 twofold without nesting, and by up to 16x when nesting is used. Finally, we discuss cross-library nesting, namely dynamic composition of transactions from multiple libraries.

1 Introduction

1.1 Transactional Libraries

The concept of memory transactions [24] is broadly considered to be a programmer-friendly paradigm for writing concurrent code [21, 44]. A transaction spans multiple operations, which appear to execute atomically and in isolation, meaning that either all operations commit and affect the shared state or the transaction aborts. Either way, no partial effects of on-going transactions are observed.

Despite their appealing ease-of-programming, software transaction memory (STM) toolkits [6, 23, 40] are seldom deployed in real systems due to their huge performance overhead [5]. The source of this overhead is twofold. First, an STM needs to monitor all random memory accesses made in the course of a transaction (e.g., via instrumentation in VM-based languages [30]), and second, STMs abort transactions due to conflicts. Instead, programmers widely use concurrent data structure libraries [4, 20, 25, 32, 45], which are much faster but guarantee atomicity only at the level of a single operation on a single data structure.

To mitigate this tradeoff, Spiegelman et al. [47] have proposed transactional data structure libraries (TDSL). In a nutshell, the idea is to trade generality for performance. A TDSL restricts transactional access to a pre-defined set of data structures rather than arbitrary memory locations, which eliminates the need for instrumentation and allows it to exploit the data structures’ semantics and structure to get efficient transactions bundling a sequence of data structure operations. A TDSL can manage aborts on a semantic level, e.g., two concurrent transactions can simultaneously change two different locations in the same list without aborting. While the original TDSL library [47] was written in C++, we implement our version in Java. We offer more background on TDSL in Section 2.

Since its publication, quite a few works have used and extended the TDSL approach [8, 9, 27, 28, 31, 33, 46, 55, 56]. These efforts have shown good performance for fairly short transactions on a small number of data structures. Yet, despite their improved scalability compared to general purpose STMs, TDSLs have not been applied to long transactions or complex use-cases. A key challenge arising in long transactions is the high potential for aborts along with the large penalty that such aborts induce as much work is wasted.

1.2 Our Contribution

Transactional nesting. In this paper we push the limits of the TDSL concept in an attempt to make it more broadly applicable. Our main contribution, presented in Section 3, is facilitating long transactions via nesting [36]. Nesting allows the programmer to define nested child transactions as self-contained parts of larger parent transactions. This controls the program flow by creating checkpoints; upon abort of a nested child transaction, the checkpoint enables retrying only the child’s part and not the preceding code of the parent. This reduces wasted work, which, in turn, improves performance and reduces energy consumption.

We focus on closed nesting [49], which, in contrast to so-called flat nesting, limits the scope of aborts, and unlike open...
nesting [38], is generic and does not require semantic constructs. Unlike transaction chopping [33, 37, 51], nesting does not relax consistency or isolation, and continues to ensure that the entire parent transaction is executed atomically.

The flow of nesting is shown in Algorithm 1. When a child commits, its local state is migrated to the parent but is not yet reflected in shared memory. If the child aborts, then the parent transaction is checked for conflicts. And if the parent incurs no conflicts in its part of the code, then only the child transaction retries. Otherwise, the entire transaction does. It is important to note that the semantics provided by the parent transaction are not altered by nesting. Rather, nesting allows programmers to identify parts of the code that are more likely to cause aborts and encapsulate them in child transactions in order to reduce the abort rate of the parent.

Yet nesting induces an overhead which is not always offset by its benefits. We investigate this tradeoff using microbenchmarks. We find that nesting is helpful for highly contended operations that are likely to succeed if retried.

**NIDS benchmark.** In Section 4 we introduce a new benchmark of a network intrusion detection system (NIDS) [18], which invests a fair amount of work to process each packet. This benchmark features a pipelined architecture with long transactions, a variety of data structures, and multiple points of contention. It follows one of the designs suggested in [18] and executes significant computational operations within transactions, making it more realistic than existing intrusion-detection benchmarks (e.g., [29, 35]).

**Enriching the library.** In order to support complex applications like NIDS, and more generally, to increase the usability of TDSLs, we enrich our transactional library in Section 5 with additional data structures – producer-consumer pool, log, and stack – all of which support nesting. The TDSL framework allows us to custom-tailor to each data structure its own concurrency control mechanism. We mix optimism and pessimism (e.g., stack operations are optimistic as long as a child has popped no more than it pushed, and then they become pessimistic), and also fine tune the granularity of locks (e.g., one lock for the whole stack versus one per slot in the producer-consumer pool).

**Evaluation.** In Section 6, we evaluate our NIDS application. We find that nesting can improve performance by up to 8x. Moreover, nesting improves scalability, reaching peak performance with as many as 40 threads as opposed to 28 without nesting.

**Composition.** While most of this paper considers nesting in the context of a single library, programmers often wish to access data structures from multiple libraries within the same atomic transaction. Section 7 addresses this use-case and discusses dynamic composition of nested transactions from distinct libraries.

**Summary of contributions.** This paper is the first to bring nesting into transactional data structure libraries. We implement a Java version of TDSL with built-in support for nesting. Via microbenchmarks, we show that in some scenarios, nesting can greatly reduce abort rates and improve performance. We build a complex network intrusion detection application, while enriching our library with the data structures required to support it. We show that nesting yields significant improvements in performance and abort rates. Finally, we provide a general approach to dynamic composition of nested transactions from different libraries. Section 9 concludes the paper.

### 2 A Walk down Transactional Data Structure Lane

Our algorithm builds on ideas used in TL2 [6], which is a generic STM framework, and in TDSL [47], which suggests forgoing generality for increased efficiency. We briefly overview their modus operandi as background for our work.

The TL2 [6] algorithm introduced a version-based approach to STM. The algorithm’s building blocks are version clocks, read-sets, write-sets, and a per-object lock. A global version clock (GVC) is shared among all threads. A transaction has its own version clock (VC), which is the value of GVC when the transaction begins. A shared object has a version, which is the VC of the transaction that most recently modified it. The read- and write-sets consist of references to objects that were read and written, respectively, in a transaction’s execution.

Version clocks are used for validation: Upon read, the algorithm first checks if the object is locked and then the VC of the read object is compared to the transaction’s VC. If the object is locked or its VC is larger than the transaction’s, then we say the validation fails, and the transaction aborts. Intuitively, this indicates that there is a conflict between the current transaction, which is reading the object, and a concurrent transaction that writes to it.

At the end of a transaction, all the objects in its write-set are locked and then every object in the read-set is revalidated. If this succeeds, the transaction commits and its write-set is reflected to shared memory. If any lock cannot be obtained
or any of the objects in the read-set does not pass validation, then the transaction aborts and retries.

Opacity [17] is a safety property that requires every transaction (including aborted ones) to observe only consistent states of the system that could have been observed in a sequential execution. TL2’s read-time validation (described above) ensures opacity. If this validation fails, it means that the object was modified during the transaction’s execution. In TL2, the transaction aborts rather than observe an inconsistent system view.

In TDSL, the TL2 approach was tailored to specific data structures (skiplists and queues) so as to benefit from their internal organization and semantics. TDSL’s skiplists use small read- and write-sets capturing only accesses that induce conflicts at the data structure’s semantic level. For example, whereas TL2’s read-set holds all nodes traversed during the lookup of a particular key, TDSL’s read-set keeps only the node holding this key. In addition, whereas TL2 uses only optimistic concurrency-control (with commit-time locking), TDSL’s queue uses a semi-pessimistic approach. Since the head of a queue is a point of contention, \textit{deq} immediately locks the shared queue (although the actual removal of the object from the queue is deferred to commit time); the \textit{enq} operation remains optimistic.

Note that TDSL and TL2 provide transactional semantics at different levels: TL2 transactions span all memory accesses within a transaction; this is enabled, e.g., by instrumentation of binary code [1] and results in large read- and write-sets that are oblivious to an address’s scope or sharing status. TDSL provides transactional semantics within the confines of the library’s data structures while other memory locations are not accessed transactionally. This eliminates the need for instrumenting code. In this work, we follow the path of TDSL and provide a library of transactional data structures with support for nesting. We implement our library in Java, which is currently the most popular programming language [48]. Yet, our algorithms are not confined to a specific programming language.

3 Adding Nesting to TDSL

We introduce nesting into TDSL. Section 3.1 describes the correct behavior of nesting and offers a general scheme for making a transactional data structure (DS) nestable. Section 3.2 then demonstrates this technique in the two DSs supported by the original TDSL – queue and skiplist. We restrict our attention to a single level of nesting for clarity, as we could not find any example where deeper nesting is useful. In Section 3.3 we use microbenchmarks to investigate when nesting is useful and when less so.

3.1 Nesting Semantics and General Scheme

Nesting is a technique for defining child sub-transactions within a transaction. A child has its own local state (read- and write-sets), and it may also observe its parent’s local state. A child transaction’s commit migrates its local state to its parent but not to shared memory visible by other threads. Thus, the child’s operations take effect when the parent commits, and until then remain unobservable.

Correctness. A nested transaction implementation ought to ensure that (1) nested operations are not visible in the shared state until the parent commits; and (2) upon a child’s commit, its operations are correctly reflected in the parent’s state exactly as if all these operations would have been executed as part of the parent. In other words, nesting part of a transaction does not change its externally visible behavior.

Implementation scheme. In our approach, the child uses its parent’s VC. This way, the child and the parent observe the shared state at the same “logical time” and so read validations ensure that the combined state observed by both of them is consistent, as required for opacity.

Algorithm 2 introduces general primitives for nesting arbitrary DSs. The \textit{nTXbegin} and \textit{nCommit} primitives are exposed by the library and may be called by the user as in Algorithm 1. When user code operates on a transactional DS managed by the library for the first time, it is registered in the transaction’s childObjectList, and its local state and lockSet are initialized empty. \textit{nTryLock} may be called from within the library in the context of certain DS operations, e.g., a nested dequeue calls \textit{nTryLock}. Finally, \textit{nAbort} may be called by both the user and the library.

We offer the \textit{nTryLock} function to facilitate pessimistic concurrency control (as in TDSL’s queues), where a lock is acquired before the object is accessed. This function (1) locks the object if it is not yet locked; and (2) distinguishes newly acquired locks from ones that were acquired by the parent. The latter enables correct lock management upon a child’s abort by preventing the child from releasing a lock that was acquired by its parent.

A nested commit, \textit{nCommit}, validates the child’s read-set in all the transaction’s DSs \textit{without} locking the write-set. If validation is successful, the child migrates its local state to the parent, again, in all DSs, and also makes its parent the owner of all the locks it holds. To this end, every nestable DS must support migrate and validate functions, in addition to nested versions of all its methods.

In case the child aborts, it releases all of its locks. Then, we need to decide whether to retry the child or abort the parent too. Simply retrying the child without changing the VC is liable to fail because it would re-check the same condition during validation, namely, Comparing read object VCs to the transaction’s VC. We therefore update the VC to the current GVC value (line 21) before retrying. This ensures that the child will not re-encounter past conflicts. But in order to preserve opacity, we must verify that the state the parent observed is still consistent at the new logical time (in which the child will be retried) because operations within a child
Algorithm 2 Nested begin, lock, commit, and abort

1: procedure \texttt{nTXbegin}
2: alloc childObjectList, init empty

3: procedure \texttt{nTryLock(obj)}
4: atomic \hfill Using CAS for atomicity
5: if obj is unlocked
6: lock obj with child id; add to lockSet
7: if obj is locked but not by parent
8: \texttt{nAbort} \hfill Abort child

9: procedure \texttt{nCommit}
10: for each obj in childObjectList do
11: validate obj with parent’s VC \hfill DS specific code
12: if validation fails
13: \texttt{nAbort}
14: for each obj in childObjectList do
15: obj.migrate \hfill DS specific code
16: for each lock in lockSet do
17: transfer lock ownership to parent

18: procedure \texttt{nAbort}
19: for each obj in childObjectList do
20: release locks in lockSet
21: parent VC ← GVC
22: for each obj in childObjectList do
23: validate parent \hfill DS specific code
24: if validation fails
25: \texttt{abort} \hfill Retry parent
26: restart child

transaction ought to be seen as if they were executed as part of the parent. To this end, we revalidate the parent’s read-set against the new VC (line 23). This is done without locking its write-set. Note that if this validation fails then the parent is deemed to abort in any case, and the early abort improves performance. If the revalidation is successful, we restart only the child (line 26).

Recall that retrying the child is only done for performance reasons and it is always safe to abort the parent. Specific implementations may thus choose to limit the number of times a child is retried.

3.2 Queue and Skiplist

We extend TDSL’s DSs with nested transactional operations in Algorithm 3.

The original queue’s local state includes a list of nodes to enqueue and a reference to the last node to have been dequeued (together, they replace the read- and write-sets). We refer to these components as the parent’s local queue, or parent queue for short. Nested transactions hold an additional child queue in the same format.

Figure 1. Nested queue operations: deq returns objects from the shared, and then parent states without dequeuing them, and when they are exhausted, dequeues from the child’s queue; enq always enqueues to the child’s queue.

The nested enq operation remains simple: it appends the new node to the tail of the child queue (line 5). The nested deq first locks the shared queue. Then, the next node to return from deq is determined in lines 8 – 12, as illustrated in Figure 1. As long as there are nodes in the shared queue that have not been dequeued, deq returns the value of the next such node but does not yet remove it from the queue (line 8). Whenever the shared queue has been exploited, we proceed to traverse the parent transaction’s local queue (line 10), and upon exploiting it, perform the actual deq from the nested transaction’s local queue (line 12). A commit appends (migrates) the entire local queue of the child to the tail of the parent’s local queue. The queue’s validation always returns true: if it never invoked dequeue, its read set is empty, and otherwise, it had locked the queue.

We note that acquiring locks within nested transactions may result in deadlock. Consider the scenario in Algorithm 4: If both $T_1$ and $T_2$ acquire the first lock before either child transaction starts, the child transactions will inevitably fail. Repeatedly retrying the nested transactions will prevent progress. To avoid this, we retry the child transaction only a bounded number of times, and if it exceeds this limit, the parent aborts as well and releases the locks acquired by it. Livelock at the parent level can be addressed using standard mechanisms (backoff, etc.).

To extend TDSL’s skiplist with nesting we preserve its optimistic design. A child transaction maintains read- and write-sets of its own, and upon commit, merges them into its parent’s sets. As in the queue, read operations of child transactions can read values written by the parent. Validation of the child’s read-set verifies that the versions of the read objects have not changed. For brevity, Algorithm 3 does not describe remove, which is similar to a put except in that it indicates in the write-set that the key is to be removed.
Nesting in Transactional Libraries

Algorithm 3 Nested operations on queues and skiplists

1. **Queue**
2.  `sharedQ` \(\triangleright\) Shared among all threads
3.  `parentQ`, `childQ` \(\triangleright\) Thread local
4.  **procedure** `nEnq(val)`
5.  `childQ.appendAll(val)`
6.  **procedure** `nDeq()`
7.  `nTryLock()`
8.  `val` ← next node in `sharedQ` \(\triangleright\) stays in `sharedQ`
9.  **if** `val = ⊥`
10.  `val` ← next node in `parentQ` \(\triangleright\) stays in `parentQ`
11.  **if** `val = ⊥`
12.  `val` ← `childQ.deq()` \(\triangleright\) Removed from `childQ`
13.  **procedure** `migrate`
14.  `parentQ.appendAll(childQ)`
15.  **procedure** `validate` return true

16. **Skiplist**
17.  `sharedSkiplist` \(\triangleright\) Shared among all threads
18.  `parentReadSet`, `parentWriteSet` \(\triangleright\) Thread local
19.  `childReadSet`, `childWriteSet` \(\triangleright\) Thread local
20.  **procedure** `nGet(key)`
21.  add key to `childReadSet`
22.  **if** `key ∈ childWriteSet`
23.  return value from `childWriteSet`
24.  **else if** `key ∈ parentWriteSet`
25.  return value from `parentWriteSet`
26.  **else if** `key ∈ sharedSkiplist`
27.  return value from `sharedSkiplist`
28.  return ⊥
29.  **procedure** `nPut(key,value)`
30.  add key to `childWriteSet`
31.  **procedure** `validate`
32.  **for each** `obj` in `childReadSet` do
33.  **if** `obj.version > parent version`
34.  abort
35.  **procedure** `migrate`
36.  `merge childWriteSet into parentWriteSet`
37.  `merge childReadSet into parentReadSet`

Algorithm 4 Potential deadlock with nesting

Transaction \(T_1\):

- `TXbegin()`
- `Q_1.dequeue()`
- `nTXbegin()`
- `Q_2.dequeue()`
- `nTXend()`
- `TXend()`

Transaction \(T_2\):

- `TXbegin()`
- `Q_2.dequeue()`
- `nTXbegin()`
- `Q_1.dequeue()`
- `nTXend()`
- `TXend()`

3.3 To Nest, or Not to Nest

Nesting limits the scope of abort and thus reduces the overall abort rate. On the other hand, nesting introduces additional overhead. We now investigate this tradeoff.

We use a synthetic workload, where every thread runs 5000 transactions, each consisting of 10 random operations on a shared skiplist followed by 2 random operations on a shared queue. Operations are chosen uniformly at random, and so are the keys for the skiplist operations. We examine three different nesting policies: (1) flat transactions (no nesting); (2) nesting every DS operation; and (3) nesting only queue operations. We examine two scenarios in terms of contention on the skiplist. In the low contention scenario, the skiplist’s key range is from 0 to 50000. In the second scenario, it is from 0 to 50, so there is high contention on both the skiplist and the queue.

We run our experiments on an AWS m5.24xlarge instance with 2 sockets with 24 cores each, for a total of 48 physical cores. We disable hyperthreading. Every experiment is repeated 10 times. Figure 2 shows the mean results. We also plot the 95% confidence intervals for throughput.

In the low contention scenario (Figures 2a and 2b), we see that nesting reduces abort rates dramatically compared to flat transactions, and improves throughput by 2.5x on average. Moreover, nesting reduces the throughput’s variance when the number of threads increases, making performance more predictable. We further observe that while nesting all operations reduces the overall abort rate, it achieves lower throughput than nesting only queue operations. Here, the overhead induced by allocation, management, and migration of child local states outweighs the amount of work saved by reducing aborts.

In the second scenario (Figures 2c and 2d), both DSs are highly contended, and nesting is less helpful. The high contention causes the majority of transactions to abort with as little as 4 threads, regardless of nesting. Despite exhibiting the lowest abort rate, nesting all operations performs worse than the alternatives.

Aborts on queue operations occur due to failures of `nTryLock`, which has a good chance of succeeding if retried. On the other hand, aborts on nested skiplist operations are due to reading a higher version than the parent’s VC. In such scenarios, the parent is likely to abort as well since multiple threads modify a narrow range of skiplist elements, hence an aborted child is not very likely to commit even if given another chance. Overall, we find that nesting the highly contended queue operations is useful, and nesting map operations – even when contended – is useless, so contention alone is not a sufficient predictor for the utility of nesting. Rather, the key is the likelihood of the failed operation to succeed if retried.
4 NIDS Case Study

We conduct a case study of parallelizing a full-fledged network intrusion detection system using memory transactions. In this section we provide essential background for multi-threaded IDS systems, describe our NIDS software and point out candidates for nesting.

Intrusion detection is a basic security feature in modern networks, implemented by popular systems such as Snort [43], Suricata [12], and Zeek [39]. As network speeds increase and bandwidth grows, NIDS performance becomes paramount, and multi-threading becomes instrumental [18].

Multi-threaded NIDS. We develop a multi-threaded NIDS benchmark. The processing steps executed by the benchmark follow the description in [18]. As illustrated in Figure 3, our design employs two types of threads. First, producers simulate the packet capture process of reading packet fragments off a network interface. In our benchmark, we do not use an actual network, and so the producers generate the packets and push MTU-size packet fragments into a shared producer-consumer pool called the fragments pool. The rationale for using dedicated threads for packet capture is that – in a real system – the amount of work these threads have scales with network resources rather than compute and DRAM resources. In our implementation, the producers simply drive the benchmark and do not do any actual work.

Figure 2. Microbenchmark results.

Figure 3. Our NIDS benchmark: tasks and data structures.

Packet processing is done exclusively by the consumer threads, each of which consumes and processes a single
packet fragment from the shared pool. Algorithm 5 describes the consumer’s code. To ensure consistency, each consumer executes as a single atomic transaction. It begins by performing header extraction, namely, extracting information from the link layer header. The next step is called stateful IDS; it consists of packet reassembly and detecting violations of protocol rules. Reassembly uses a shared packet map associating each packet with its own shared processed fragment map. The first thread to process a fragment pertaining to a particular packet creates the packet’s fragment map whereas other threads append fragments to it. Similarly, only the thread that processes a packet’s last fragment continues to process the packet, while the remaining threads move on to process other fragments from the pool. By using atomic transactions, we guarantee that indeed there are unique “first” and “last” threads and so consistency is preserved.

**Algorithm 5** Consumer code

```java
1: f ← fragmentPool.consume()  
2: process headers of f  
3: fragmentMap ← packetMap.get(f)  ▷ Start nested TX  
4: if fragmentMap = ⊥  
5: fragmentMap ← new map  
6: packetMap.put(f, fragmentMap)  ▷ End nested TX  
7: fragmentMap.put(f)  
8: if f is the last fragment in packet  
9: reassemble and inspect packet ▷ Long computation  
10: log the result ▷ Nested TX
```

The thread that puts together the packet proceeds to the signature matching phase, whence the reassembled packet’s content is tested against a set of logical predicates; if all are satisfied, the signature matches. This is the most computationally expensive stage [18]. Finally, the thread generates a packet trace and writes it to a shared log.

As an aside, we note that our benchmark performs five of the six processing steps detailed in [18]; the only step we skip is content normalization, which unifies the representations of packets that use different application-layer protocols. This phase is redundant in our solution since we use a unified packet representation to begin with. In contrast, the intruder benchmark in STAMP [35] implements a more limited functionality, consisting of packet reassembly and naïve signature matching: threads obtain fragments from their local states (rather than a shared pool), signature matching is lightweight, and no packet traces are logged. This results in significantly shorter transactions than in our solution.

**Nesting.** We identify two candidates for nesting. The first is the logging operation given that logs are prone to be highly contended. Because in this application the logs are write-only, transactions abort only when they contend to write at the tail and not because of consistency issues. Therefore, retrying the nested transaction amounts to retrying to acquire a lock on the tail, which is much more efficient than restarting the transaction.

Second, when a packet consists of multiple fragments, its entry in the packet map is contended. In particular, for every fragment, a transaction checks whether an entry for its packet exists in the map, and creates it if it is absent. Nesting lines 3 - 6 of Algorithm 5 may thus prevent aborts.

### 5 Additional Nestable DSs

Transactions may span multiple objects of different types. Every DS implements the methods defined by its type (e.g., deq for queue), as well as methods for validation, migrating a child transaction’s state to its parent, and committing changes to shared memory. We extend our Java TDSL with three widely used data structures – a producer-consumer pool (Section 5.1), a log (Section 5.2), and a stack (Section 5.3). For each, we first describe the transactional implementation and then how nesting is achieved.

#### 5.1 Producer-consumer Pool

Like many other applications, our NIDS benchmark uses a producer-consumer pool. Such pools are also a cornerstone in architectures like SEDA [53]. They scale better than queues because they don’t guarantee order [2, 13, 14]. We support a bounded-size transactional producer-consumer pool consisting of a pre-defined number of slots, K. The produce operation finds a free slot and inserts a consumable object into it, while the consume operation finds a produced object and consumes it. Our pool guarantees that if there is an available slot for consumption and any number of consumer threads, then at least one of the consumers will consume it, and similarly for free slots and producers.

Algorithm 6 presents our nestable producer-consumer pool. We assume that the consumer functions passed to the consume method do not have any side effects that are visible in shared state before the transaction commits.

Similarly to deq, consume also warrants pessimistic concurrency control, as each object can be consumed at most once. But the granularity of locking is finer-grain, namely, consume locks a single slot rather than the entire pool, which allows much more parallelism. Produce is also pessimistic at the same granularity, ensuring that the same slot is not concurrently used by multiple threads. More specifically, we assign a state to each slot in the pool, as follows: ⊥ means that the slot is free. A slot is in the locked state if there is an ongoing transaction that uses it. A ready slot is available to be consumed. We implement the methods getFreeSlot and getReadySlot, which atomically find and lock a free or ready slot, respectively, using CAS. The changeState method executes a state transition atomically using a CAS. We use these methods to ensure that a ready slot is populated by at most one transaction and a produced item is consumed at most
once: We keep track of slots that are locked by the current transaction in two sets: produced and consumed. A slot’s state changes from locked to ready upon successful commit of a parent locking transaction, and changes from locked to ⊥ either upon successful commit or upon cancellation (line 15) as we describe next. Upon abort, every slot’s state reverts to its previous state.

We now explain how we use cancellation for liveness. Consider a pool of size K and a transaction T1 that performs K + 1 produce operations, each followed by a consume operation. If every operation locks a slot until the commit time, such a transaction cannot proceed past the Kth consume, despite the fact that the transaction respects the semantics of the data structure. To mitigate this effect, our implementation consumes slots that were produced within the same transaction before locking additional ready slots, and releases the lock of any consumed slot by setting its state to ⊥. This way, consumed slots cancel out with produced slots within the same transaction. Since cancellation occurs in thread-local state, which is not accessed by more than one thread, correctness is trivially preserved.

As in other nestable data structures, the child’s local state is structured like the parent’s. When nesting, the cancellation logic is expanded. The consume operation first tries to consume from child-local produced slots (lines 25–28), then from parent-local ones (lines 29–32) and only then locks a slot (line 34). We keep track of slots that were produced by the parent and consumed by the child in childConsumedFromParent. The state of such slots changes back to ⊥ when the child commits (lines 40–42). Additionally, at the end of the child transaction, the produced and the consumed sets of the child are merged with the parent’s sets. Because access to slots is pessimistic, our pool involves no speculative execution, and so validate always returns true.

5.2 Log

Logs are commonly used for record-keeping of events in a system, as occurs in our NIDS benchmark. Recently, they are also popular for ledger transaction ordering. Logs are unique because their prefixes are immutable, whereas their tail is an ever-changing contention point among concurrent write operations. A log has 2 operations: read(i) and append(val). Read(i) returns the value in position i in the log or ⊥ if it has not been created yet. Append(val) appends val to the log.

Log reads never modify the state of the log, which lends itself to an optimistic implementation. Append, on the other hand, is more amendable to a pessimistic solution, since the semantics of the log imply that only one of any set of inter-leaving appending transactions may successfully commit.

The pseudocode of our log appears in Algorithm 7. Read-only transactions that do not reach the end of the log are not subject to aborts. A transaction that either reaches the end (i.e., read(i) returns ⊥) or appends is prone to abort. Local parent and child logs keep track of values appended during the transaction as well as the smallest location accessed by a read beyond the end of the shared log. The local log also records the length of the log at the time of the first access to the log. A read(i) operation reads through the shared and the parent logs, and in the presence of nesting, the child log

```python
Algorithm 6 Nestable producer-consumer pool
1: PCPool
2: Slots[K] \rightarrow Shared among all threads
3: parentProduced, parentConsumed \rightarrow Thread local
4: childProduced, childConsumed, childConsumedParent \rightarrow Thread local
5: for each n in parentProduced do
6:     childProduced.add(n)
7:     childConsumed.add(n)
8:     childConsumedParent.add(n)
9: for each n in parentConsumed do
10:     childProduced.add(n)
11:     childConsumed.add(n)
12:     childConsumedParent.add(n)
13: end for
14: for each n in childProduced do
15:     n.changeState(⊥)
16:     if childProduced.size > 0
17:         n ← childProduced.pop()
18:         consumer.consume(n.val)
19:     else if exists unconsumed slot from parentProduced
20:         n ← unconsumed slot from parentProduced
21:         consumer.consume(n.val)
22:         childConsumedParent.add(n)
23:     else
24:         n ← P.getReadySlot() \rightarrow Changes state to locked
25:         consumer.consume(n.val)
26:         parentConsumed.add(n)
27:     end if
28:     childProduced.add(n)
29:     childConsumed.add(n)
30:     childConsumedParent.add(n)
31:     if childProduced.size > 0
32:         n ← childProduced.pop()
33:         consumer.consume(n.val)
34:         childConsumedParent.add(n)
35:     else
36:         n ← P.getReadySlot() \rightarrow Changes state to locked
37:     end if
38:     if parentProduced.size > 0
39:         n ← parentProduced.pop()
40:         consumer.consume(n.val)
41:     else if exists unconsumed slot from parentProduced
42:         n ← unconsumed slot from parentProduced
43:         consumer.consume(n.val)
44:         childConsumedParent.add(n)
45:     else
46:         n ← P.getReadySlot() \rightarrow Changes state to locked
47:     end if
48:     if parentProduced.size > 0
49:         n ← parentProduced.pop()
50:         consumer.consume(n.val)
51:     else if exists unconsumed slot from parentProduced
52:         n ← unconsumed slot from parentProduced
53:         consumer.consume(n.val)
54:         childConsumedParent.add(n)
55:     else
56:         n ← P.getReadySlot() \rightarrow Changes state to locked
57:     end if
58:     if parentProduced.size > 0
59:         n ← parentProduced.pop()
60:         consumer.consume(n.val)
61:     else if exists unconsumed slot from parentProduced
62:         n ← unconsumed slot from parentProduced
63:         consumer.consume(n.val)
64:         childConsumedParent.add(n)
65:     else
66:         n ← P.getReadySlot() \rightarrow Changes state to locked
67:     end if
68:     if parentProduced.size > 0
69:         n ← parentProduced.pop()
70:         consumer.consume(n.val)
71:     else if exists unconsumed slot from parentProduced
72:         n ← unconsumed slot from parentProduced
73:         consumer.consume(n.val)
74:         childConsumedParent.add(n)
75:     else
6:   return true
```
Algorithm 7 Nestable transactional log

1: Log
2: sharedLog \quad \triangleright \text{Shared among all threads}
3: parentLog, childLog \quad \triangleright \text{Thread local}
4: readAfterEnd, initially false \quad \triangleright \text{Thread local}
5: initLen, initially length of sharedLog \quad \triangleright \text{Thread local}
6: procedure append(val) \quad \triangleright \text{Parent code (not nested)}
7: \quad tryLock()
8: \quad parentLog.append(val)
9: \quad procedure read(i) \quad \triangleright \text{Parent code}
10: \quad if i \in \text{sharedLog}
11: \quad \quad return \text{sharedLog}[i]
12: \quad else
13: \quad \quad readAfterEnd \leftarrow \text{true}
14: \quad \quad if i \in \text{parentLog}
15: \quad \quad \quad return \text{parentLog}[i]
16: \quad \quad else
17: \quad \quad \quad return \bot
18: \quad procedure nAppend(val) \quad \triangleright \text{Nested (child) code}
19: \quad nTryLock()
20: \quad childLog.append(val)
21: \quad procedure nRead(i) \quad \triangleright \text{Nested (child) code}
22: \quad if i \in \text{sharedLog}
23: \quad \quad return \text{sharedLog}[i]
24: \quad else
25: \quad \quad readAfterEnd \leftarrow \text{true}
26: \quad \quad if i \in \text{parentLog}
27: \quad \quad \quad return \text{parentLog}[i]
28: \quad \quad else if i \in \text{childLog}
29: \quad \quad \quad return \text{childLog}[i]
30: \quad \quad else
31: \quad \quad \quad return \bot
32: \quad procedure migrate \quad \triangleright \text{Occurs on child commit}
33: \quad append childLog to parentLog
34: \quad procedure validate
35: \quad if readAfterEnd \land \text{sharedLog exceeds initLen}
36: \quad return abort
37: \quad return true

as well. Append(val) locks the log and appends val to the current transaction’s local log.

The correctness of our log stems from the following observations: first, two writes cannot interleave, since a write is performed only if a lock had been acquired. Second, a transaction will commit if it either hadn’t read or modified (by appending to) the end of the log, or if there hadn’t been later writes. Finally, since the log is modified at commit time, opacity is preserved, i.e., no transaction sees inconsistent partial updates.

5.3 Stack

Like the queue, our stack combines pessimistic and optimistic concurrency control. But unlike the queue, the concurrency control type is not determined by the type of operation. Rather, we observe that as long as the number of pushed objects is greater than or equal to the number of popped objects in every prefix of a given transaction, locking the shared stack and migrating any remaining pushed objects to it can be deferred. This is because every pop operation observes a locally pushed object at the head of the stack. But if at any time during the execution of a transaction the number of locally popped objects exceeds the number of locally pushed ones, a pessimistic approach is preferred. Thus, once a pop operation needs to read from the shared stack, the transaction tries to lock the stack. As in the queue and pool, a value obtained from the shared stack is not removed from it until commit.

With nesting, a child transaction may observe the shared object’s and the parent’s local states, but only modifies the parent’s local state upon commit. Commit-time migration appends the parent’s stack on top of the shared stack and removes popped values from it. A nested commit migrates the child’s stack on top of its parent’s and pops values from it when needed. The stack’s pseudocode is straightforward and omitted for space limitations.

6 NIDS Evaluation

We now experiment with nesting in the NIDS benchmark. We detail our evaluation methodology in Section 6.1 and present quantitative results in Section 6.2.

6.1 Experiment Setup

Our baseline is TDSL without nesting, which is the starting point of this research. We also compare to the Java implementation of TL2 by Korland et al. [30]. We did not find any other available Java STM implementation; in particular, Synchrobench is currently unavailable for Java 8 and up [42].

We experiment with nesting each of the candidates identified in Section 4 (put-if-absent to the packetMap and updating the log), and also with nesting both. Our baseline executes flat transactions, i.e., with no nesting. In TDSL, the packet pool is a producer-consumer pool, the map of processed packets is a skiplist of skiplists, and the output block is a set of logs. For TL2, the packet pool is implemented with a fixed-size queue, the packet map is an RB-tree of RB-trees, and the output log is a set of vectors. We use the implementations provided in [29] without modification.

The experiment environment is the same as for the microbenchmark described in Section 3.3. We repeated the experiment on an in-house 32-core Xeon machine and observed similar trends; these results are omitted. We run each experiment 5 times and plot all data points, connecting the median values with a curve.
We conduct two experiments. In the first, each packet consists of a single fragment, there is one producer thread, and we scale the number of consumers. In the second experiment, there are 8 fragments per packet and as we scale the number of threads, we designate half the threads as producers. We experimented also with different ratios of producers to consumers, but this did not seem to have a significant effect on performance or abort rates, so we stick to one configuration in each experiment. The number of fragments per packet governs contention: If there are fewer fragments then more threads try to write to logs simultaneously. With more fragments, on the other hand, there are more put-if-absent attempts to create maps.

6.2 Results

**Performance.** Figures 4a and 4b show the throughput and abort rate in a run with 1 fragment per packet and a single producer. Whereas the performance of all solutions is similar when we run a single consumer, performance differences become apparent as the number of threads increases. For flat transactions (red diamonds), TDSL’s throughput is consistently double that of TL2 (purple octagons), as can be observed in Figure 5, which zooms in on these two curves in the same experiment. We note that the TDSL work [47] reported better performance improvements over TL2, but they ran shorter transactions that did not write to a contended log at the end, where TDSL’s abort rate remained low. In contrast, our benchmark’s long transactions result in high abort rates in the absence of nesting. Nesting the log writes (green squares) improves throughput by an additional factor of up to 6, which is in line with the improvement of TDSL over TL2 reported in [47], and also reduces the abort rate by a factor of 2. The packet map is not contended in this experiment, and so transactions with nested insertion to the map behave similarly to flat ones (in terms of both throughput and abort rate).

Figures 4c and 4d show the results in experiments with 8 fragments per packet. For clarity, we omit TL2 from this graph because it performs 6 times worse than the lowest alternative. Here, too, the best approach is to nest only log updates, which in this scenario improves throughput only by about 20%. Nevertheless, its effect is more significant as it...
reduces the number of aborts by a factor of 3, and thus saves work and energy consumption. At first, it might be surprising that flat transactions perform better than ones that nest the put-if-absent despite their higher abort rate. However, the abort reduction has a fairly low impact since this operation is performed early in the transaction. Thus, the overhead induced by nesting exceeds the benefit of not repeating the earlier part of the computation. The effect of this overhead is demonstrated in the difference in performance between nesting both candidates (black circles) and nesting only the log writes (green squares).

Scaling. Not only does nesting have a positive effect on performance, it improves scalability as well. For instance, Figure 4a shows that throughput increases linearly all the way up to 40 threads when nesting the logging operation, whereas flat nesting, as can be seen in Figure 5, peaks at 28 threads but saturates already at 16. Table 1 summarizes the scaling factor in both experiments.

### 7 Composition and Closed Nesting

Until this point, we considered nesting in the context of a single library. We now examine nesting as a special case of dynamic composition, where a transaction may be comprised of multiple sub-transactions, possibly executing in different transactional libraries. Such dynamic composition of libraries is a desired capability for programmers who wish to use multiple libraries in their code or provide a library to be used by others.

TDSL [47] presented a composition scheme allowing transactions to span multiple libraries. However, it couples between composed libraries by forcing them to begin and end their transactions at the same time; the former results in nested dynamic composition. For correctness, commits of all sub-transactions must indeed occur together. Nevertheless, coupling aborts as in [47] is excessive. Note that each transaction’s execution is sequential, so an abort arising from a conflict in one library’s scope is not likely to indicate a conflict in another library. In what follows we first overview TDSL’s static composition guidelines, and then relax them to allow dynamic composition, where sub-transactions may be transactions.

**Static composition.** TDSL [47] defined an interface that transactional libraries must expose to allow composition. It consists of the following methods: TX-begin, TX-lock, TX-verify, TX-finalize, and TX-abort. As we saw in the previous sections, TX-begin is realized by writing the value of GVC to the transaction’s VC. The methods TX-lock, TX-verify, and TX-finalize are used in the commit phase: the TX-lock method makes the transaction’s updates committable by locking all objects in the write-set. TX-verify validates all objects in the read-set. The TX-finalize method then commits the current transaction by writing all updates to the locked objects and releasing their locks. Any library operation may throw an abort exception, in which case the TX-abort method is invoked in all libraries so as to abort the current transaction.

We refer to calls to TX-begin, TX-lock, TX-verify, TX-finalize, and TX-abort on library \( l \) as \( B^l \), \( L^l \), \( V^l \), \( F^l \), and \( A^l \), respectively, as shown in Table 2. According to [47], a composite transaction should start by calling TX-begin in all participating libraries. At the end, the transaction is committed by: (i) calling all TX-lock methods; (ii) calling all TX-verify methods; and (iii) calling all TX-finalize methods. Hence a history of a successful transaction on libraries \( l_1 \) and \( l_2 \) has the following form:

\[ B^{l_1}, B^{l_2}, \text{operations on } l_1 \text{ and } l_2, L^{l_1}, L^{l_2}, V^{l_1}, V^{l_2}, F^{l_1}, F^{l_2}. \]

A transaction may abort at any point before calling the finalize methods. For example, in the following history the transaction aborts before it starts calling the verification methods:

\[ B^{l_1}, B^{l_2}, \text{operations on } l_1 \text{ and } l_2, A^{l_1}, A^{l_2}. \]

**Cross-library nesting for dynamic composition.** The requirement to call TX-begin in all participating libraries together may limit the programmers’ ability to realize composite transactions in cases where the identity of the required libraries is unknown at the outset. And the requirement to abort all transactions when one aborts may hamper performance. Instead, we propose to use cross-library nesting for dynamic composition. Here, the child transaction may execute in a distinct library from the parent.

Cross-library nesting incurs a cost: it necessitates using additional calls to TX-verify in order to validate the parent when the child is invoked. More formally, each transaction must satisfy the following two rules: (1) \( B^l \) is called before any operation on library \( l \); (2) if \( B^b \) is called after an operation on library \( l_a \), then \( V^l \) is called between \( B^b \) and all operations on library \( l_b \). Thus a legal successful transaction...
Table 2. Composition API of library $l$.

| $B_l$ | $nB_l$ | $L_l$ | $nL_l$ | $V_l$ | $nV_l$ | $F_l$ | $nF_l$ | $A_l$ | $nA_l$ |
|-------|--------|-------|--------|-------|--------|-------|--------|-------|--------|
| TX-begin() | start a transaction | TX-lock() | make transaction’s updates committable | TX-verify() | verify earlier optimistic operations | TX-finalize() | commit and end the current transaction | TX-abort() | abort and end the current transaction |
| $nTX-begin()$ | start a nested child transaction | $nTX-commit()$ | commit the current nested child transaction |

on libraries $l_a$ and $l_b$ may have the following form ($OP_l^i$ represents an operation on library $l$): $B_l^{a,b}$, $OP_1^{a,b}$, $OP_2^{a,b}$, $B_l^{a,b}$, $V_l^{a,b}$, $OP_3^{a,b}$, $OP_4^{a,b}$, $L_l^{a,b}$, $L_l^{a,b}$, $V_l^{a,b}$, $V_l^{a,b}$, $F_l^{a,b}$, $F_l^{a,b}$.

Notice that the above rules ensure that the read-set of $l_a$ is validated after $B_l^{a,b}$. This means that all operations of $l_a$ that precede $B_l^{a,b}$ can be seen as if they are executed immediately after $B_l^{a,b}$.

The need for verifying the parent arises because disjoint libraries do not share clocks. Whereas a nested sub-transaction within a library adheres its parent clock, initiating sub-transactions from multiple libraries at different times may cause them to validate their read-sets against different logical times. By revalidating the parent when the child begins, we assure that the transaction observes a consistent states of the shared memory, satisfying opacity.

As a form of nesting, dynamic composition also restricts the scope of abort: when a child transaction aborts, the parent may be validated, and if it succeeds, the child transaction may retry. Note that if the parent spans multiple libraries, TX-verify needs to be called in all of them. For example:

$B_l^{a,b}$, $OP_1^{a,b}$, $B_l^{a,b}$, $V_l^{a,b}$, $OP_2^{a,b}$, $OP_3^{a,b}$, $L_l^{a,b}$, $L_l^{a,b}$, $V_l^{a,b}$, $V_l^{a,b}$, $F_l^{a,b}$, $F_l^{a,b}$.

8 Related Work

Transactional data structures. Since the introduction of TDSL [47] and STO [26], transactional libraries got a fair bit of attention [8, 9, 27, 28, 31, 33, 34, 45, 55, 56], some works introduce transactional implementations of specific data structures [46], though not the ones we introduce in this work. Other works focused on wait-free [31] and lock-free [9, 55, 56] implementations (as opposed to TDSL and STO’s lock-based approach). Such algorithms are interesting from a theoretical point of view, but provide very little performance benefits, and in some cases can even yield worse results than lock-based solutions [7, 10].

Other follow up works suggest different concurrency control mechanisms. For example, [28] uses a multi-version technique to implement a read-log-update mechanism. They achieve great performance but provide only snapshot isolation guarantees.

In [27], the authors tailor the STO version management for in-memory databases; in contrast, our approach is general purpose, and our evaluation focuses on other use cases. In [33], the authors introduce a trade-off between low abort rate and high computational overhead. By restricting their attention to static transactions they are able to perform scheduling analyses in order to reduce the overall system abort rate. We, in contrast, support dynamic transactions.

Transactional boosting and its follow-ups [8, 19, 22] offer generic approaches for making concurrent data structures transactional. However, they do not exploit the structure of the transformed data structure, and instead rely on semantic abstractions like compensating actions and abstract locks.

In this paper we choose to extend the original TDSL algorithm [47]. To the best of our knowledge, none of the previous works on transactional data structures provide nesting.

Splitting up transactions and composition. In databases, nesting has been suggested many years ago [16, 34, 36]. More recent works introduced the concept of chopping [11, 50, 54], which also splits up transactions in order to reduce abort rates. Chopping was recently adopted in transactional memory [33, 37, 51]. The high-level idea of chopping is to divide a transaction into a sequence of smaller ones and commit them one at a time. While atomicity is eventually satisfied (provided that all transactions eventually commit), this approach forgoes isolation and consistency, which nesting preserves.

While some previous work on supporting nesting in generic STMs was done in the past [3, 38, 49, 52], our solution is the first to introduce nesting into transactional data structure libraries, and thus the first to exploit the specific structure and semantics of data structures for efficient nesting implementations.

Composition of transactional libraries was discussed in the past by [15, 41, 47], but without support for nesting.

9 Conclusion

The TDSL approach enables high-performance software transactions by restricting transactional access to a well-defined set of data structure operations. Yet in order to be usable in practice, a TDSL needs to be able to sustain long transactions, to offer a variety of data structures, and to allow composition
with other libraries. In this work, we took a step towards boosting the performance and usability of TDSLs, allowing them to support complex applications. A key enabler for long transactions is nesting, which limits the scope of aborts without changing the semantics of the original transaction.

We have implemented a Java TDSL with built-in support for nesting in a number of data structures, and explained how it could be composed with other libraries. We conducted a case study of a complex network intrusion detection system running long transactions. We found that nesting improves performance by up to 8x, and the nested TDSL approach outperforms the general-purpose TL2 STM by up to 16x. We plan to make our code (both the library and the benchmark) available in open-source.

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