Bundled References: An Abstraction for Highly-Concurrent Linearizable Range Queries

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Abstract
We present bundled references, a new building block to provide linearizable range query operations for highly concurrent linked data structures. Bundled references allow range queries to traverse a path through the data structure that is consistent with the target atomic snapshot and is made of the minimal amount of nodes that should be accessed to preserve linearizability. We implement our technique into a skip list, a binary search tree, and a linked list data structure. Our evaluation reveals that in mixed workloads, our design improves upon the state-of-the-art techniques by 3.9x for a skip list and 2.1x for a binary search tree. We also integrate our bundled data structure into the DBx1000 in-memory database, yielding up to 20% gain over the same competitors.

Keywords: Concurrent Data Structures, Range Query

1 Introduction
Iterating over a collection of elements to return those that fall within a contiguous range (also known as a range query operation) is without contest an essential feature for data repositories. In addition to database management systems, which historically deploy support for range queries (through predicate reads or writes), recent key-value stores (e.g., RocksDB [15] and others [14, 17, 25, 29, 37]) enrich their traditional PUT and GET APIs to include range query operations.

With the high-core-count era in full swing, providing high-performance range query operations that execute concurrently with modifications is challenging. On the one hand, ensuring strong correctness guarantees of range queries, such as linearizability [22], requires that they observe a consistent snapshot of the collection regardless of any concurrent update that may take place. On the other hand, since range queries are naturally read-only operations, burdening them with synchronization steps to achieve strong correctness guarantees may significantly deteriorate their performance.

To address this trade-off, existing solutions in literature either assume relaxed guarantees for range queries [27, 30] or sacrifice providing high-performance under highly concurrent workloads, namely when hundreds of threads concurrently perform a mix of updates on single elements (so called primitive operations) and scans over a range of elements [3, 30, 35].

In this paper we propose bundled references, a new building block to design linearizable concurrent linked data structures (e.g., skip lists) optimized to scale up performance of range query operations executing concurrently with update operations. The core innovation behind bundled reference lies in adapting the design principle of Multi Version Concurrency Controls (MVCC) [40] to generic linked data structures, and improving it by eliminating the overhead of determining the appropriate version to be returned. Bundled references achieve that by augmenting each link in a data structure with a record of its previous values, each of which is tagged with a timestamp reflecting the point in (logical) time when the operation that generated that link occurred. In other words, we associate timestamps to references connecting data structure elements instead of to the pointed elements.

The bundled reference building block enables the following properties of the data structure:

- Range query operations are linearized when they start, which helps reduce the interference with ongoing and subsequent update operations;
- Each thread performing a range query only traverses the minimal amount of nodes in the range, regardless of concurrent updates. The minimality property precludes a thread from scanning multiple versions to find the one consistent with its linearizable snapshot.
- Data structure traversals, including those of contains and update operations, do not require any special treatment, permitting optimizations such as wait-free [20] traversals in the lazy data structure patterns;
- State-of-art reclamation techniques (e.g., EBR [16]) can be easily integrated into the bundled references to reclaim data structure elements, which minimizes the space overhead of bundling, making it practical.

By leveraging the bundled references, we develop three relevant ordered implementations of a Set, namely a linked list, a skip list, and a binary search tree (BST). While the linked list is a convenient data structure to illustrate all the details of our design that favors range query operations, the skip list and the BST are high-performance data structures widely used in systems (such as database indexes) where predicate reads are predominant.
In these new data structure implementations we replace the existing links with bundled references to provide linearizable range queries. The history of a link between nodes (called a bundle) is consistently updated every time a successful modification to the data structure occurs. A range query uses the bundles in each node to perform its scan on the data structure, following a path made of the latest links marked with a timestamp lower than (or equal to) the operation’s starting timestamp.

We evaluate our bundled data structures against three alternative techniques to provide linearizable range queries, namely read-log-update (RLU) and two variants of a solution based on epoch-based reclamation (EBR-RQ and EBR-RQ-LF). In a mixed workload, bundling allows for up to 3.9x and 2.1x improvement over the closest competitors. We also find that we outperform the competitors at high thread counts (i.e., 192 threads), in nearly all cases. Further, bundling achieves a more consistent performance profile across different configurations than our competitors, whose design choices lead them to prefer specific workloads. Finally, we integrate both the skip list and BST as indexes in the DBx1000 in-memory database and test them using the TPC-C benchmark, finding that bundling provides 20% better performance than the next best competitor at high numbers of threads.

To the best of our knowledge, bundling is the first approach that allows for range query operations over a linked data structure that traverse the minimal amount of nodes in their ranges without blocking concurrent update operations in the range. The source code for our bundling technique and bundled data structures can be found at https://zenodo.org/record/4402298. Refer to the README, there within for info.

2 Related Work

Linearizable range queries. Existing work has focused on providing range queries through highly-specific data structure implementations [4, 5, 8, 9, 36, 38]. While recognizing their effectiveness, their tight dependency on the data structure characteristics makes them difficult to extend to other structures, even if manually. The literature is also rich with highly effective concurrent data structure designs that lack range query support and cannot leverage the aforementioned data structure specific solutions to perform range queries. This motivates generalized solutions, which achieve linearizable range queries by applying the same technique to a variety of data structures [3, 30, 35].

Read-log-update (RLU) [30] is a technique in which writing threads keep a local log of updated objects, along with the logical timestamp when the update takes effect. When no reader requires the original version, the log is committed. It extends read-copy-update (RCU) [31] to support multiple object updates. Similar to Bundling, RLU’s range queries are linearized at the beginning of their execution, after reading a global timestamp and fixing their view of the data structure. However, in RLU, updates block while there are ongoing RLU protected operations, as it only commits its changes after guaranteeing no operation will access the old version. Bundling minimizes write overhead because new entries are added while deferring the removal of outdated ones.

Snapcollector [35] also logs changes made to the data structure during an operations lifetime so that concurrent updates are observed. A range query first announces its intention to snapshot the data structure by posting a reference to an object responsible for collecting updates. It traverses as it would in a sequential setting, then checks a report of concurrent changes it may have missed. The primary difference with respect to RLU is that range queries are linearized at the end of the operation, after disabling further reports.

Although the construction of Snapcollector is wait-free, this method may lead a range query to observe reports of changes that were already witnessed during its traversal. Creating and announcing reports penalizes operation performance; not to mention the memory overhead required to maintain these reports. Collectively, the cost of these characteristics is insurmountable and we experimentally verify that it is easily outperformed. With our bundling approach, a range query visits nodes only once to produce its view of the data structure and is linearized at the operation’s start.

An extension of Snapcollector enables snapshotting only a range of the data structure instead of all elements [11]. However, this approach continues to suffer many of the same pitfalls as the original design. In addition to these, concurrent range queries with overlapping key ranges are disallowed.

Arbel-Raviv and Brown [3] build upon epoch-based memory reclamation (EBR) to provide linearizable range queries. In this method, range query traversals leverage a global timestamp to determine if nodes, annotated with a timestamp by update operations, belong in their snapshot. In order to preserve linearizability, remove operations announce their intention to delete a node before physically removing them and adding them to the list of to-be-deleted nodes, or limbo list. Range queries scan the data structure, the announced deletions, and limbo list to determine which nodes to include in their view; potentially resulting in a situation where nodes are observed multiple times. Since range queries’ atomic updates to the timestamp conflict, the design also prioritizes update-mostly workloads.

Our bundling approach enhances performance of range queries by allowing them to traverse the minimal number of nodes in the range without needing to validate its snapshot and eliminating contention on a shared global counter.

MVCC. Multi-version concurrency control (MVCC) relies on timestamps to coordinate concurrent accesses to objects. It is widely used in database management systems. Many different implementations exist [6, 7, 26, 28, 33]; all rely on a multiversioned data repository where each shared object stores a list of versions, and each version is tagged with a
creation timestamp. Transactions then read the versions of objects that are consistent with their execution.

The de facto standard for version storage in MVCC systems is to maintain a linked list of versions for each object that is probed during a read [40], with recent innovations targeting this particular aspect. One example, Cicada [28], implements optimistic MVCC by making a transaction install a PENDING version for every written object as the first step in its validation phase. Readers block until this version is no longer pending. When the transaction either commits or aborts each PENDING version’s status changes accordingly.

Similar to Cicada, bundling requires updates to install pending entries to notify other operations of an ongoing change; in contrast to Cicada’s approach, updates are always successful. Furthermore, pending entries only exist for a short duration surrounding the linearization point.

Another example, X-Engine [24], is a highly optimized LSM-tree storage engine that uses a skip list variant to optimize access to recent updates stored in memory. A key is represented by a single node pointing to a list of versions. Comparable approaches (e.g. LevelDB [17] and RocksDB [15]), treat versions as independent nodes in the data structure. X-engine’s solution optimizes for index layer traversals since the path no longer includes multiple versions of the same key. Nevertheless, the version list must still be scanned for the value consistent with the operation. Unlike X-engine, bundled references ensures that the MVCC traverses only those objects that belong to the transaction’s atomic snapshot.

Persistent data structures. The Bundled reference abstraction is similar in spirit to the concept of fat nodes in persistent data structures [13]. In principle, persistent data structures are those which maintain all previous versions of the data structure. The ephemeral structure is the current state and the persistent structure encodes past ephemeral structures. The core difference is that bundling aims at providing efficient linearizable range queries in highly concurrent workloads, while persistent data structures are commonly used in functional programming languages to maintain theoretical requirements regarding object immutability [23, 34] and algorithms requiring reference to previous state [12, 39].

3 The Bundle Building Block

The principal idea behind bundling is the maintenance of a historical record of physical changes to the data structure so that range queries can traverse a consistent snapshot. As shown in details below, the idiosyncrasy of bundling is that this historical record stores links between data structure elements that are used by range query operations to rebuild the exact composition of a range at a given (logical) time.

Before detailing bundling, it is important to note that update operations are totally ordered using a global timestamp, named globalTs, which is incremented every time a modification to the data structure takes place (i.e., when an update operation reaches its linearization point).

Every link in the data structure is backed by a bundle, implemented as a linked list of bundle entries (Listing 1). Each bundle entry logs the value of the link and the value of globalTs at the time the link was added to the bundle. Whenever an update operation reaches its linearization point, meaning when it is guaranteed to complete, it prepends a bundle entry consisting of the newest value of the link and the value of the global timestamp. Because of that, the head of the bundle always reflects the link’s latest value.

Since each link’s history is preserved through the bundles, range queries simply need to read the global timestamp at the operation’s outset and traverse the linked data structure using the newest values no larger than the observed global timestamp. This design is inherently advantageous when pruning bundle entries. In fact, a bundle entry may be removed (or recycled) if an entry is no longer the newest in the bundle and no range query needs it.

Figure 1. An example of using bundled references in a linked list. The path made of solid lines represents the state of the linked list after all update operations take place. Edges are labeled with their respective timestamps.

Figure 1 shows an example on how bundles are deployed in a linked list. As shown in the figure, the next pointer of each node is replaced by a bundle object that encapsulates the history of this next pointer. The figure shows the state of the linked list and its bundles after the following sequence of operations (assuming an initially empty linked list): insert(20), insert(30), insert(10), remove(20).

To understand how this state is generated, we assume that the list is initialized with a single bundle reference whose timestamp is ”0” (the initial value of globalTs), which connects its head and tail sentinel nodes. Inserting 20 does not replace this reference. Instead, it creates a new entry in the head’s bundle with timestamp ”1” pointing to the newly inserted node as well as an entry with the same timestamp in this new node pointing to the tail node. Similarly, inserting 30 and 10 adds new bundle entries with timestamps ”2” and ”3”, respectively. The last operation that removes 20 also does not replace any reference. Instead, it creates a new bundle entry in 10’s bundle (with timestamp ”4”) that points to 30, which reflects physically deleting 20 by making its predecessor node point to its next node.
Now assume that different range queries start at different times concurrently with those update operations. For clarity, we name a range query $R_i$ if it starts when $\text{globalTs}$ is $i$, and for simplicity we assume its range matches the key range. Regardless of the times at which the different nodes are traversed, each range query is always able to traverse the proper snapshot of the list that reflects the time it started. For example, $R_0$ will skip any links in the range added after it started because all of them have timestamp greater than “0”. Also, $R_0$ will observe $20$ even if it reaches $10$ after $20$ is deleted. This is because in that case it will use the bundle entry whose timestamp is “3”, which points to $20$.

The solid lines in the figure represent the most recent state of the linked list. Different insights can be inferred from this solid path. First, the references in this path are those with the largest timestamp in each bundle. This guarantees that any operation (including range queries) that starts after this steady state observes the most recent abstract state of the list. Second, once the reference with timestamp “4” is created, $20$ becomes no longer reachable by any operation that will start later, because this operation will observe a timestamp greater than (or equal to) “4”. Thus, unreachable elements can be concurrently reclaimed.

In the following, to simplify the description we assume that a bundle may hold an infinite number of entries, and no memory is freed. Later in Section 7, and more in detail in the supplementary material, we address memory reclamation.

### 3.1 Bundle Structure

Generally, in order to deploy bundling each link in a data structure should use our bundled reference. As an illustrative example, Listing 2 shows how the newPtr entry in a linked list node is replaced with a bundled reference, which consists of the original reference (newestNextPtr) along with a bundle to record its history (newestNextPtrBundle).

```java
Listing 1. Bundle.
1 class Bundle {
2     Node + ptr;
3     timestamp + ts;
4     BundleEntry + next;
5 }
6
7 class BundleEntry {
8     Bundle + head;
9 }
```

```java
Listing 2. Linked List Node.
1 class Node {
2     key + key;
3     val + val;
4     lock + lock;
5     bool deleted;
6     // The bundled reference
7     Node + newestNextPtr;
8     Bundle newestNextPtrBundle;
9 }
```

Our bundle is a collection of entries sorted by timestamp to facilitate determining which reference to use during range queries. Each bundle entry contains the updated pointer value, ptr, the timestamp associated with this value, ts, and a pointer to the next bundle entry, next. As we detail in the next section, since update operations annotate bundle entries using a monotonically increasing timestamp ($\text{globalTs}$), new bundle entries will always have a timestamp larger than all other entries in the bundle. Hence, bundle entries are sorted by ts.

A bundled reference consistently replicates the newest entry of the bundle (i.e., newestNextPtr). This is done because in our bundled data structures, primitive operations (i.e., add, remove, and contains) should not incur overhead due to the existence of the bundles. As a positive side effect of this decision, all traversals done to reach the desired elements of the data structure, including those performed by range queries to enter the range, execute quickly without accessing the bundled references, as in a non-bundled data structure. Meanwhile, range queries rely solely on bundles upon entering their range.

### 3.2 Bundles and Update Operations

Generally speaking, an update operation has two phases. The operation first traverses the data structure to reach the desired location where the operation should take place, then performs the necessary changes. Bundling involves augmenting only the act of changing pointers, not the traversal.

#### Algorithm 1: LinearizeUpdateOperation

```java
Input: linAddr, linNewVal, bundles, ptrs
begin
for (b, p) in (bundles, ptrs) do
    PrepareBundle(b, p)
end

\( ts \leftarrow \text{AtomicFetchAndAdd}(\text{globalTs}, 1) + 1 \)

\( \text{linAddr} \leftarrow \text{linNewVal} \) /* Linearization point. */
for b in bundles do
    FinalizeBundle(b, ts + 1)
end
```

#### Algorithm 2: PrepareBundle

```java
Input: bundle, ptr
begin
newEntry ← new BundleEntry
newEntry.ptr ← ptr
newEntry.ts ← PENDING_TS
while true do
    expected ← bundle.head
    newEntry.next ← expected
    while currEntry.ts = PENDING_TS do end
    if AtomicCompareAndSwap(&bundle.head, expected, newEntry) then
        return
    end
end
```

The role of bundling with respect to updates is to reflect the changes observable at the operation’s completion so that range queries may see a consistent view of the data structure. This is performed through four crucial steps (Algorithm 1). First, bundles are prepared by atomically prepending a new bundle entry in a pending state (Line 3). After preparing the bundles, $\text{globalTs}$ is atomically fetched and incremented and its new value is stored locally (Line 4). Next, the linearization point is executed (Line 5), making the update visible to other primitive operations. Lastly, pending bundle entries are finalized by annotating them with the newly incremented timestamp (Line 7).
Initializing new bundle entries in a pending state (Line 4 of Algorithm 2) is needed because range queries must wait until pending bundle entries are finalized to guarantee that they do not miss a concurrent update that should be included in their snapshot (see the example at the end of Section 3.3). Additionally, concurrent updates attempting to modify a currently pending bundle are blocked until the ongoing update is finalized (Line 8 of Algorithm 2). This is done so that concurrent updates to the same node are properly ordered by timestamp. It is also possible to address this problem by assuming that all nodes whose bundles will change are locked. We choose not to do so to make our design independent of data structure specific optimizations (see Section 4).

3.3 Bundles and Range Query Operations

Much like updates, a range query consists of two phases. First, it traverses the data structure to reach the entry point to its range. Next, it scans the range node by node to collect its snapshot. These two phases are represented in Algorithm 3 by the functions GetFirstNodeInRange and GetNext, respectively. These two functions are data structure specific and their details are discussed in the subsequent sections.

Before explaining how range query operations perform in a bundled data structure, let us define a bundle entry to satisfy a timestamp $t$ if it was the newest entry in the bundle when the global timestamp equaled $t$.

Algorithm 3: RangeQuery

```
Input: low, high
Output: resultTuples
begin
while true do
    resultTuples ← ∅
    ts ← globalTs
    (curr, valid) ← GetFirstNodeInRange(low, high, ts)
    if valid then
        continue
    else if curr ≠ nullptr then
        resultsTuples ← resultTuples ∪
        (curr.key, curr.value)
        while curr ← GetNext(curr, low, high, ts) do
            resultsTuples ← resultsTuples ∪
            (curr.key, curr.value)
        return resultsTuples
    else
        return resultTuples
end
```

A range query collects a consistent snapshot of the data structure by following only references created by operations linearized before the outset of the range query. This is accomplished by first reading the current value of globalTs into a local variable $ts$ to fix its snapshot (Line 4), then traversing to the start of the range using GetFirstNodeInRange (Line 5), and finally scanning the data structure based on $ts$ using GetNext (Line 10).

The GetFirstNodeInRange function consists of two key steps. First, it performs an optimistic traversal of the data structure, without checking the bundles, until it reaches the node preceding the first node in the range. Then, it traverses using the bundles to return the first node in its range.

Note that GetFirstNodeInRange's initial traversal without bundles reflects the most recent state of the data structure, and not necessarily the snapshot that will be observed by the range query. Thus, two cases should be considered here. First, if the node preceding the range has been inserted after the range query started, then no bundle entry satisfying $ts$ exists. Since the visibility of a consistent snapshot cannot be guaranteed if no entries satisfy $ts$, the traversal is invalid and the range query starts over (Algorithm 3, Line 7) with the new value of the global timestamp. The other possibility is that a bundle entry satisfying $ts$ is found, in which case it is safe to start traversing using bundles.

The second phase of GetFirstNodeInRange traverses further only using bundles to enter the range by relying on the DereferenceBundle function. Note that, it is possible for this traversal to visit nodes not in the range, typically removed after the range query started, before reaching the first node in the range.

When GetFirstNodeInRange successfully returns the first node in the range, it is appended to the results and then the next nodes are obtained by repeated calls to GetNext (Line 10). This function must return the next node in the range, strictly accessing it through bundles, to ensure only nodes that can be included in the snapshot are traversed. Internally, all implementations of GetNext will also use DereferenceBundle, which is described next.

Given a bundle and timestamp, the DereferenceBundle function works as follows. A range query first waits for a pending bundle entry to be finalized, if any; then it scans the bundle for the first entry whose timestamp is less than or equal to $ts$, indicating whether one was found.

Blocking until the first entry is no longer pending is a necessary step to ensure that the range query waits for a concurrent update that is already linearized, but whose bundles are not yet finalized. To illustrate this scenario, consider the concurrent execution of two threads: $T_1$, which inserts the element $x$, and $T_2$, which performs a contains operation on $x$ and then executes a range query whose range includes $x$. Thread $T_1$ starts at timestamp $t$ and proceeds in isolation until it executes its linearization step, at which point it stalls indefinitely before the bundles are finalized. Then, $T_2$ executes its contains on $x$, returning True since the original linearization point has already been reached. Without waiting for pending entries to be finalized, the subsequent range query ($ts= t+1$) would not return $x$ as belonging to the range, leading to an inconsistent view of the data structure. Instead, a bundle entry's pending state stall range queries until the ongoing update completes, allowing $T_2$'s range query to observe $x$ in this example.
We now describe how to apply bundling to the well-known lazy sorted linked list [19], which provides high performance through wait-free traversals and fine-grained locking updates. We recall that Listing 2 provides a full definition of member variables of its nodes.

3.4 Bundles and Contains Operations

Since bundles are only kept to ensure correct range queries, contains operations execute independently from the bundled references. Consequently, implementations with optimized contains operations (e.g., lazy data structures with wait-free contains [2, 18, 19, 21]) can leverage bundling without restricting their execution to a more conservative progress guarantee, as we will see in Sections 4-6.

4 Bundled Linked List

We now describe how to apply bundling to the well-known highly-concurrent lazy sorted linked list [19], which provides high performance through wait-free traversals and fine-grained locking updates. We recall that Listing 2 provides a full definition of member variables of its nodes.

The wait-free contains operation is the same as the original lazy linked list without bundling [19]. Therefore, a traversal uses newestNextPtr to walk the list until it reaches the target key. At this point, it returns a reference to the first node with key greater than or equal to the target and its predecessor. It validates the current node returned from the traversal phase by checking its equivalence with the target key and if it is logically deleted. If validation passes, the contains operation returns True, otherwise it returns False.

Algorithm 4: Insert operation of Bundled Linked List

Input: key, val

\begin{algorithm}
\begin{algorithmic}
\LineComment{while true do}
\state \textbf{pred, curr} $\leftarrow$ Traverse(key)
\LineComment{Lock(pred)}
\state if ValidateLinks(pred, curr) then
\state \textbf{if curr.key} $\leftarrow$ key then
\LineComment{return false}
\LineComment{newNode $\leftarrow$ new Node(key, val)}
\LineComment{newNode.newestNextPtr $\leftarrow$ curr}
\LineComment{bundles $\leftarrow$ (newNode.bundle, pred.bundle)}
\LineComment{pts $\leftarrow$ (curr, newNode)}
\LineComment{LinearizeUpdateOperation(&pred.newestNextPtr,}
\LineComment{newNode, bundles, pts)}
\LineComment{return true}
\LineComment{Unlock(pred)}
\end{algorithmic}
\end{algorithm}

Similarly, insert operations (Algorithm 4) make use of the traversal to determine where the new node will be added. After locking the predecessor, both current and predecessor nodes are validated by checking that they are not deleted and that no node was inserted between them. If validation succeeds and the key does not already exist, a new node with its next pointer set to the appropriate node is created. If it fails, the nodes are unlocked and the operation restarts.

Up to this point we have followed the same procedure that a data structure without bundling would use. The next step is to call LinearizeUpdateOperation to perform the four steps described in Section 3.2 to linearize an update operation in a bundled data structure: installing pending bundle entries, incrementing the global timestamp, performing the linearization point, and finalizing the bundles. For an insertion, the bundles of the newly added node and its predecessor must be modified to reflect their new values and the timestamp of the operation. The linearization point remains the moment that the predecessor’s newestNextPtr is set to the new node. Finally, the locks are released and the insertion returns True.

Note that in Algorithm 4 we employ an optimization where only the predecessor is locked by insert operations (Line 4). In [19], it has been proven that this optimization preserves linearizability. However, this optimization reveals a subtle but important corner case that motivates the need for waiting for pending bundles to be finalized (Line 8 of Algorithm 2). Because the current node is not locked, it is possible that a concurrent update operation successfully locks the new node after it is reachable and before its bundles are finalized by the inserting operation. This nefarious case is protected by first waiting for the ongoing insertion to finish to ensure the bundle remains ordered (see Section 3.2).

Remove operations follow a similar pattern by first traversing to the appropriate location, locking the nodes of interest, validating them (restarting if validation fails), removing the current node if its key matches the target key, then finally unlocking the nodes and returning. Here, the removal is linearized when the node is logically deleted, not when the reference changes. However, we reflect the predecessor’s updated reference in the bundle since the physical removal of this node resides within the same critical section as its linearization point. The removed node’s bundle does not change because its ptr value reflects the physical state of the data structure immediately before the removal takes place.

We now turn our attention to the two functions required by range queries: GetFirstNodeInRange and GetNext. Recall from Section 3.3 that a range query must first traverse the list (without bundles) to the node pointing to the first node in the range, then enter the range by traversing only bundles. For a linked list, we simply scan from the head until this node is found, then traverse using the bundles up to the first node in the range. Traversing using GetNext is trivial since we simply return the node that satisfies ts in the bundle of the current node. These two functions are used by Algorithm 3 to perform linearizable range query operations.

**Correctness.** Proving the linearizability of our bundled linked list is straightforward. The linearization point of (successful) update operations is the same as the original lazy
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linked list: insertion is linearized when the newestNextPtr
of the predecessor node is changed, and removal is linearized
when the node is logically deleted. Contains operations’ lin-
earization point also matches that of the original lazy linked
list, as they use newestNextPtr in their traversal and check
for logical deletion when they reach the node.

A range query R is linearized when it snapshots the global
timestamp before starting its data structure traversal. An
update operation U that is linearized before this point will
always be observed by R because only the following two
situations can occur. First, U completely finished before R
starts, which means that the timestamps of the links added by
U are less than, or equal to, the snapshot taken by R. Second,
U is concurrent with R but executes its linearization step
before R starts. In this case, since the linearization step of U
is executed only after incrementing the global timestamp and
changing the corresponding bundles into a pending state, R
will be blocked (if needed) until the pending states of such
bundles are released and the links that reflect the updates
made by U are added with the proper timestamp.

Minimality of traversed nodes within range. One of
the powerful properties of the bundled linked list is that
range queries traverse the minimum number of nodes in the
range: starting from the first node in the range, the range
query only scans the nodes that belong to its range. It is
worth noting that this minimality would also hold for the
traversal phase (before reaching the entry node to the range)
if we would have used bundles from the beginning of the list.
However, as we mentioned before, for performance reasons
we decide to avoid using bundles to reach the first node of
the range, and instead we traverse through newestNextPtr.

Space overhead. Although space overhead may seem a
concern, it is instead acceptable in practical deployments.
Even without reclamation, insertions have an amortized con-
stant overhead since each insert operation adds two bundle
entries for each new node instead of adding one new link in
the non-bundled lazy list. This means that a list of n nodes
(assuming no removals) will have a total of 2n bundle entries.
Enabling reclamation reduces this number significantly. If a
cleanup operation is performed while all other threads are in
a quiescent state, it is guaranteed to leave only one in each
bundle (see Section 7 and the supplementary material).

5 Bundled Skiplist

The second data structure where we apply bundling is the
lazy skiplist [21], whose update operations use fine-grained
locks and contains operations are wait-free, similar to the
bundled linked list. In the following, we highlight the differ-
ences between the two designs.

The first difference is that skiplist consists of a bottom
data layer where data resides and a set of index layers to ac-
celerate traversal. Hence, given a target key, traversal returns
a set of (pred, curr) pairs for both index and data layers,
rather than a single pair. If the target key exists in the data
structure, then it also returns the highest level (level1Found
at which the node was found. A naive approach to bundling
this skiplist would be to replace all links with bundled refer-
ences, including the index layers. However, recall that range
queries are the only operations that utilize bundles and only
require them as they traverse the range of interest. As an
optimization, we therefore only bundle references at the
bottom-most layer (data layer), leaving the index layers as is
for use during traversals.

Second, because update operations manipulate multiple
links per node, they are linearized using logical flags. Specif-
ically, insert operations set a fullyLinked flag in the new
node after the links of all its pred nodes are updated to point
to it. Setting this flag is the linearization point of insert oper-
ations. Thus, it is book-ended by the preparation and final-
ization of the bundles for the predecessor and the new node,
similarly to the bundled linked list, by using Algorithm 1.

Remove operations are handled as follows. Upon a suc-
cessful removal, the logical deletion flag is set to linearize
the operation, and the bundle entry of the node immediately
preceding the target in the data layer is updated. Then, the
references of the predecessor nodes in the index and data
layer are modified to physically remove the node.

To support linearizable range queries, the skiplist def-
defines the two required functions as follows. GetFirstNodeInRange
leverages the traversal over the index layer to find a node in
the data layer that points to the first node in the range. Then
it scans to enter the range using the bundles. GetNext is then
used to scan the bottom list, using bundles, and collect the
range query’s result set, as described in Section 3.3.

6 Bundled Binary Search Tree

For our bundled tree, we reference the Citrus unbalanced
binary search tree [2], which leverages RCU and lazy fine-
grained locking to synchronize update operations while sup-
porting wait-free traversals. We modify it by replacing each
child link of the search tree with a bundled reference.

Citrus implements a traversal enclosed in a critical section
protected by RCU’s read lock, the required calls of which are
wait-free. This protects concurrent updates from overwriting
nodes required by the traversal. After the traversal, if the
current node matches the target, the operation returns a
reference to it (named curr), a reference to its parent (named
pred) and the direction of the child from pred. Otherwise,
the node is not found and the return value of curr is null.
Contains operations simply invoke this traversal then return
whether curr’s value is non-null.

Because the Citrus tree is unbalanced, insertions are straight-
forward and always insert a leaf node. Otherwise adhering to
the original tree algorithm, insertions are linearized by first
preparing the bundle of pred corresponding to the direction
of the new node; then by setting the appropriate child, incrementing the global timestamp, and finalizing the bundles. Lastly, the insert unlocks pred and returns.

The more interesting case is a remove operation, which should address three cases, assuming that the target node curr is found and will be removed. In the first case, curr has no children and the child of pred pointing to curr is updated along with its bundle. In the second case, the node to be removed has a child, but only one. In this scenario, the only child of curr replaces curr as the child of pred. Again, the bundle corresponding to pred’s child is also updated accordingly. The last, and more subtle, case is when curr has two children, in which we should replace the removed node with its successor (the left-most node in its right subtree).

In this last case, both the curr’s successor and its parent are locked. Then, following RCU’s methodology, a copy of the successor node is created and initialized in a locked state with its children set to curr’s children. The effect of this behavior is that possibly four bundles must be modified to reflect the new physical state after the operation take effect. First, pred’s left or right bundle are modified with an entry referencing the copy of curr’s successor. Next, both bundles in the copy are also set to curr’s children. Finally, if the parent of curr’s successor is not curr then its bundle is updated to be null, as the successor is being moved.

In all cases, the remove operation is linearized at the moment the child in pred is changed, making the update visible, and bundles are adjusted along with this linearization point.

Range queries slightly differ from the previous two implementations. For trees, unlike lists, the node preceding the range (found by GetFirstNodeInRange) is not necessarily a node whose key is lower than the lower bound of the range. Instead, it is the first node discovered through a depth-first traversal whose child is in the range. This child is the root of the sub-tree that includes all nodes belonging to the range.

Similar to before, the node reached by the optimistic traversal may not be the correct entry point to the range, and subsequent traversal using bundles may be needed.

Traversing the range follows a depth-first traversal using GetNext. We keep a stack of nodes to help traverse the subtree rooted at the node returned by GetFirstNodeInRange. The stack is initialized with the first node in the range. GetNext pops a node and checks whether its key is lower than, within, or greater than the range. Next, it adds the node’s corresponding children to the stack according to this check. Finally, if the node is within the range it returns its value to be added to the result set. Otherwise, it pops another node and performs the above procedure again.

7 Memory Reclamation

We rely on EBR to cleanup both physically removed nodes and no longer needed bundle entries because, as already assessed by [3], quiescent state memory reclamation [31] (a generalized form of EBR) mirrors the need for a range query to observe a snapshot of the data structure. A complete discussion of the details regarding memory reclamation can be found in the supplemental material. Although the experiments in Section 8 were performed without enabling memory reclamation, the same conclusions are drawn with respect to competitors when memory is reclaimed.

8 Evaluation

In each of the following experiments we compare our approach (named Bundle hereafter) with RLU [50] and two variants of Arbel-Raviv and Brown’s technique based on epoch-based reclamation [3] (referred to as EBR-RQ and EBR-RQ-LF hereafter). EBR-RQ uses a readers-writer lock to protect its global epoch counter and EBR-RQ-LF is lock-free.
The lock-free version still locks data structure nodes, but the infrastructure supporting linearizable range queries is lock-free. Note that our technique uses EBR but strictly for memory management; whereas, EBR-RQ and EBR-RQ-LF rely on EBR’s internals in order to support linearizable range queries (see Section 2).

As a reference for performance we implement Unsafe, a version of each data structure whose range queries traverse without performing any consistency checks, while still providing linearizable primitive operations. For readability, we do not include the performance of Snapcollector because its throughput is significantly slower than all other competitors.

We integrate our data structures into an existing framework [3] to develop and benchmark a variety of data structures supporting linearizable range queries, including RLU-base linked list and Citrus tree, and the EBR-base variants of all three data structures. The code is written in C++ and compiled with -std=c++11 -O3 -mcx16. All tests are performed on a machine equipped with four Xeon Platinum 8160 processors, for a total of 96 physical cores and 192 hyper-threaded cores, running Red Hat Enterprise Linux 7.6.

8.1 Bundled Data Structure Performance

For each of the following experiments the data structure is first initialized with half of the keys in the key range; all updates are evenly split between inserts and removes to ensure size stability. Threads execute a given mix of update, contains, and range query operations. Workloads are reported as $U - C - RQ$, where $U$ is the percentage of updates, $C$ is the percentage of contains and $RQ$ is the percentage of range queries. Target keys are procured atomically and uniformly. All reported results are an average of three runs of three seconds each, except where noted. The key range of each data structure is as follows: the lazy list is 10,000 and the skip list and BST are both 100,000.

Varying Workload Mix. A side effect of logarithmic traversals in the skip list and Citrus tree is that the costs of supporting linearizable range queries is more visible compared to the linked list, which have linear asymptotic bounds.

Thus, we defer an analysis of our bundled linked list until later. We report the operation throughput of different workload mixes as a function of thread count. The range query percentage is fixed at 10%, while varying the update and contains percentages. We plot the total throughput for both the skip list and Citrus tree in Figures 2a-2e and Figures 2f-2j, respectively.

Our first general observation is that our bundled data structure outperform all linearizabe competitors when the workload is mixed (the first three columns of Figure 2). These three configurations represent a wide class of workloads, contrasted with the two right-most columns that represent corner case workloads and are discussed separately. Under mixed loads, Bundle achieves maximum speedups over the nearest competitor of 3.9x (skip list, Figure 2a) and 2.1x (Citrus tree, Figure 2g). Both maximums occur when the workload is dominated by reads and occur at the highest number of threads tested.

The above behavior is the result of two design characteristics of bundling. First, single element contains are not instrumented in any way. Second, range queries only wait for ongoing updates that are localized in the target key range. In low update percentage workloads, this provides bundling with the advantage. Both EBR-RQ and EBR-RQ-LF incur significant overhead in this particular configuration. The former due contention on a global lock; the latter due to the use of a costly double-compare single-swap primitive (DCSS), which impacts both range queries and contains operations.

The performance gap between Bundle and its competitors narrows as the percentage of updates increases to 50% and 90%. While RLU is faced with additional dereference logic for reads, its primary bottleneck lies in the synchronization step required by writes waiting for ongoing reads to finish. This behavior leads to poor performance in update-intensive workloads. EBR-RQ and EBR-RQ-LF perform better relative to RLU under these circumstances and barely outperforms bundling in a 90% update workload on the skip list. In bundling, the primary source of overhead is updates containing on an atomically incremented global timestamp and

![Figure 3. Throughput, relative to Unsafe, for different range query lengths for skip list (top) and Citrus tree (bottom) with a $50 - 0 - 50$ workload. Results at each cluster are first organized by competitor (in the following order: EBR-RQ, EBR-RQ-LF, RLU, Bundle), then ordered by thread count $n$; the right-most bar of each group being the highest thread count.](image-url)
temporarily stalling range queries. Regardless, it performs comparably or better in all but one of these configurations.

To better understand the cases in which Bundle performance is surpassed, we note that RLU and EBR-RQ prefer workloads at opposing ends of the configurations spectrum. In the read-only setting (Figure 2e and 2j), RLU performs well in contrast with EBR-RQ and EBR-RQ-LF. Of particular note, RLU achieves performance nearly equivalent to Unsafe in the Citrus Tree. In the absence of updates, RLU’s execution pays little cost for reads and range queries. However, recall that even a low percentage of updates is enough to cause this impressive performance to collapse (see Figure 2f), namely from the synchronization enforced by writers (i.e., RLU-sync). Hence, when a workload is primarily updates (Figure 2d and 2i), RLU incurs even higher overhead. On the other hand, EBR-RQ and EBR-RQ-LF increment a global epoch counter and validate their snapshot, which leads to the degradation of performance in read-only workloads to be more than for update-intensive ones.

Bundling manages the trade-off between update-intensive and read-only workloads effectively. The overhead of updating bundles is relatively low, and is fine-grained, which improves upon RLU’s synchronization. Only traversing the necessary nodes improves upon both EBR-RQ and EBR-RQ-LF. Hence, performance stability across different workloads is an important byproduct of bundled data structures.

Unlike RLU and the EBR-based techniques, bundling does not concentrate overhead, but distributes the responsibility of linearization between updates and range queries.

**Varying Range Query Size.** Figures 3 shows the relative throughput over Unsafe for a skip list (top) and Citrus tree (bottom) when performing equal percentages of updates and range queries at increasing range query sizes (from 1 to 500). The workload roughly corresponds to the middle column in Figure 2, having a 50 – 0 – 50 mix with the intention of avoiding bias toward either competitor.

Under the given workload, bundling outperforms all linearizable competitors at large numbers of threads, regardless of range query size. For all numbers of threads, we outperform EBR-RQ and EBR-RQ-LF. In fact, regardless of the length of the range query EBR-RQ-LF, on average, checks an additional 300 nodes in the limbo at 96 threads (and 600 nodes at 192 threads), accounting for the majority of its execution time. Since RLU’s synchronization overhead is smaller at fewer threads, the relative cost of traversing bundles is apparent, but only when range queries are long. Regardless, when the thread count is high, the impact of the use of bundles is less than the synchronization required by RLU’s updates and Bundle regains its dominance.

**Linked Lists.** Because traversals dominate the runtime of linked lists they provide less insight into algorithm behavior. The linear asymptotic bound causes the best competitors to behave nearly identically to Unsafe. This includes Bundle and the two EBR variants. The worst competitor (i.e., RLU), on the other hand, has a relative performance of 0.97x (0 – 90 – 10), 0.87x (2 – 88 – 10), 0.70x (10 – 80 – 10), 0.42x (50 – 40 – 10) and 0.40x (90 – 0 – 10) when compared to Unsafe at 96 threads.

**Weakening Linearizability.** In additional experiments, included in the supplementary material for space constrains, we measured the performance gains for range queries when linearizability is relaxed by only updating the global timestamp every T operations. In majority update workloads this strategy offers 2x better performance when T = 5 and nearly 3x when T = 50.

### 8.2 Database Integration Performance

The following results were collected for TPC-C benchmark with 10 warehouses using DBx1000 [41], an in-memory database system, integrated with our bundled skip list and Citrus tree. The data structures implement the database indexes.

Specifically, we use the NEW_ORDER (50%), PAYMENT (45%) and DELIVERY (5%) transaction profiles. The DELIVERY profile is particularly interesting since its logic includes a range query over the index representing the new order table, ordered by order_id, with the goal of selecting the oldest order to be delivered. Next, the order is deleted to prevent subsequent DELIVERY transactions from delivered the same order again. In our experiments, the range query selects the oldest order in the last 100 orders. A PAYMENT transaction performs a range query on the customer index to look up a customer by name with 60% probability. NEW_ORDER modifies multiple tables and updates their indexes accordingly, including the new order index.

![Figure 4. Throughput (Mops/s) of index operations in DBx1000 running the TPC-C benchmark.](image)

We report the total throughput across all indexes for the skip list and Citrus tree in Figure 4. Note that we elide a comparison against the baseline DBx1000 index since it is a hashmap and does not support range queries. When isolating performance metrics to indexes only, bundling outperforms all competitors regardless of the number of threads used. In both data structures, EBR-RQ and EBR-RQ-LF follow trends observed previously. We also measure the overall system throughput (i.e., transactions committed per second), but do not include the plots due to space constraints. Summarizing the findings, the performance of Bundle over an Unsafe index (non-serializable) is on average 3.6% worse for the skip list and 12.5% for the Citrus tree. These results show the
effectiveness of bundling when integrated in large systems even under skewed workloads, as is the case for TPC-C.

In the TPC-C application workload, RLU can take advantage of its highly efficient range queries while EBR-RQ and EBR-RQ-LF may benefit from 100% updates on some indexes. Unlike its competitors however, Bundle does not sacrifice performance in one case for higher performance in the other, which leads to overall better throughput. This demonstrates that our more performance-stable design is better suited for systems that have different workloads on different internal data structures, as is typical in database systems, without the need for multiple implementations each targeting specific workload distributions.

9 Conclusion

In this paper we presented three concurrent linked data structure implementations deploying a novel building block, called bundled references, to enable range query support. Bundling data structure links with our building block shows that the coexistence of range query and update operations does not forgo achieving high-performance.

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Supplementary Material

A  Weakening Linearizability

By reducing the frequency with which threads increment the global timestamp, we can measure the impact of contention on the global timestamp required by bundling. To do so, we record the throughput with threads modifying globalTs only after performing a configurable number of updates $T$. Similar to the previous experiment, the workload has a $50 - 0 - 50$ distribution.

![Figure 5. Throughput relative to the linearizable implementation of a bundled skip list for various threshold values ($T$), represented by shade, at 96 threads.](image)

Figure 5 shows the results of our experiments for the bundled skip list under different workload distributions at 96 threads. For read-mostly workloads, changing the threshold $T$ has little benefit since most of the operations do not increment the global timestamp. At 50% updates, however, the effects of reducing the frequency of writes to globalTs lead to a 2x improvement when $T = 50$. The improvement decreases at lower thresholds, reaching roughly 25% when $T = 2$. For write intensive workloads, this improvement is amplified, and close to 3x improvement is observed. Similar conclusions have been reached for different numbers of threads, as well as for the bundled Citrus tree.

For each group of bars, the right most one illustrates performance when relaxation is at its most extreme (i.e. $T = \infty$). The effect is an ideal range query that never waits for pending timestamps and always utilize the first entry. Interestingly, when compared to $T > 50$, there is little performance gain for complete relaxation.

Clearly, if update operations do not always increment the global timestamp linearizability is weakened because range queries may be prevented from observing the freshest snapshot of their range. As a side effect of our design, if an application tolerates such a relaxation, our bundled data structure design allows for a simple and tunable mechanism to adjust the level of freshness of range queries. Further investigation about the correctness guarantees of such a weakened relaxed version of our bundled data structures is left as future work.
B Memory Reclamation

In this section we show: i) how a well-known memory reclamation technique, such as epoch-base memory reclamation (EBR) [16], can be easily integrated into our bundled data structures to safely manage memory after physically removing nodes; and ii) a simple policy (enabled by our design) to recycle no longer needed bundle entries.

We decide to rely on EBR because, as already assessed by [3], quiescent state memory reclamation [31] (a generalized form of EBR) mirrors the need for a range query to observe a snapshot of the data structure. In fact, this reclamation technique waits for a grace period to elapse before freeing memory, thus allowing range queries to safely reference nodes removed concurrently. Specifically, we use a variant of EBR, called DEBRA [10], that stores per-thread limbo lists which also reduces contention on shared resources by recording removed nodes locally for each thread. When compared with other memory reclamation algorithms (e.g., Hazard Pointers [32], StackTrack [1]), DEBRA demonstrates lower overhead and is applicable to many data structures [10].

EBR Overview. EBR guarantees that unreachable objects are freed by maintaining a collection of references to recently retired objects. It operates under the assumption that threads cannot save references to objects outside of the scope of an operation (i.e., during quiescence). To ensure that an object can be freed without problems, EBR monitors the epoch observed by each thread and the objects retired during each epoch. The epoch is only incremented after all active threads have announced that they have observed the current epoch value. When a new epoch is started, any objects retired two epochs prior can be safely freed.

Freeing Data Structure Nodes. EBR guarantees that no node is freed while concurrent range queries (as well as any concurrent primitive operation) may access it; and, bundling guarantees that no range query that starts after physically removing a node will traverse to this node. As an example, consider the two following operations: i) a range query, \( R \), whose range includes node \( x \); and ii) a removal operation, \( U_t \), which is linearized at time \( t \) and removes \( x \). If \( R \) is concurrent with \( U_t \), then EBR will guarantee that \( x \) is not freed since \( R \) was not in a quiescent state and a grace period has not passed. In this case, \( R \) may safely traverse to \( x \) based on its observed timestamp, without concern that the node may be freed. On the other hand, if \( R \) starts after \( U_t \), then trivially \( x \) will never be referenced by \( R \) and is safe to be reclaimed since \( R \) observed a timestamp greater than or equal to \( t \).

Freeing Bundle Entries. Bundle entries are reclaimed in two cases. The first, trivial, case is that bundle entries are reclaimed when a node is reclaimed. The second case is more subtle. After a node is freed, there may still exist references to it (in other nodes’ bundles) that are no longer necessary and should be freed. Bundle entries that have a timestamp older than the oldest active range query can be retired only if there also exists a more recent bundle entry that satisfies the oldest range query. This cleanup process may be performed during operations themselves or, as we implement, delegated to a background thread.

To keep track of active range queries we augment the global metadata with activeRqTsArray, an array of timestamps that maintains their respective starting timestamp. During cleanup, this array is scanned and the oldest timestamp is used to remove outdated bundle entries. Reading the global timestamp and setting the corresponding slot in activeRqTsArray must happen atomically to ensure that a snapshot of the array does not miss a range query that has read the global timestamp but not yet announced its value. This is achieved by first setting the slot to a pending state, similar to they way we protect bundle entries, which blocks the cleanup procedure until the range query announces its starting timestamp. Second, the cleanup thread has to be protected by EBR as well, just like other operations.

| Delay (d) | 0% | 10% | 50% | 90% | 100% |
|-----------|----|-----|-----|-----|------|
| 0ms       | 4  | 11  | 14  | 12  | 13   |
| 1ms       | 0  | 10  | 13  | 10  | 13   |
| 10ms      | 2  | 9   | 11  | 7   | 8    |
| 100ms     | 0  | 8   | 8   | 0   | 0    |

Table 1. % overhead when enabling memory reclamation.

Experiments. Instead of repeating experiments, we focus on performance relative to the leaky bundled data structures while adjusting the delay (\( d \)) between cleanup iterations, as shown in Table 1. For mixed and update heavy workloads, freeing nodes and bundle entries entails a maximum of 14% degradation in performance with an aggressive cleanup delay (\( d = 0 \)).