Concurrent Hash Tables: Fast and General(?)!

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Abstract

Concurrent hash tables are one of the most important concurrent data structures which is used in numerous applications. Since hash table accesses can dominate the execution time of whole applications, we need implementations that achieve good speedup even in these cases. Unfortunately, currently available concurrent hashing libraries turn

speedup even in these cases. Unfortunately, currently available concurrent hashing libraries turn out to be far away from this requirement in particular when adaptively sized tables are necessary or contention on some elements occurs.

Our starting point for better performing data

Our starting point for better performing data structures is a fast and simple lock-free concurrent hash table based on linear probing that is however limited to word sized key-value types and does not support dynamic size adaptation. We explain how to lift these limitations in a provably scalable way and demonstrate that dynamic growing has a performance overhead comparable to the same generalization in sequential hash tables.

We perform extensive experiments comparing the performance of our implementations with six of the most widely used concurrent hash tables. Ours are considerably faster than the best algorithms with similar restrictions and an order of magnitude faster than the best more general tables. In some extreme cases, the difference even approaches four orders of magnitude.

Category: [D.1.3] Programming Techniques Concurrent Programming [E.1] Data Structures Tables [E.2] Data Storage Representation Hashtable representations

Terms: Performance, Experimentation, Measurement, Design, Algorithms

Keywords: Concurrency, dynamic data structures, experimental analysis, hash table, lock-freedom, transactional memory

1 Introduction

A hash table is a dynamic data structure which stores a set of elements that are accessible by their key. It supports insertion, deletion, find and update in constant expected time. In a concurrent hash table, multiple threads have access to the same table. This allows threads to share information in a flexible and efficient way. Therefore, concurrent hash tables are one of the most important concurrent data structures. See Section 4 for a more detailed discussion of concurrent hash table functionality.

To show the ubiquity of hash tables we give a short list of example applications: A very simple use case is storing sparse sets of precomputed solutions (e.g. [27], [3]). A more complicated one is aggregation as it is frequently used in analytical data base queries of the form SELECT FROM...COUNT...GROUP BY x [25]. Such a query selects rows from one or several relations and counts for every key x how many rows have been found (similar queries work with SUM, MIN, or MAX). Hashing can also be used for a data-base join [5]. Another group of examples is the exploration of a large combinatorial search space where a hash table is used to remember the already explored elements (e.g., in dynamic programming [36], itemset mining [28], a chess program, or when exploring an implicitly defined graph in model checking [37]). Similarly, a hash table can maintain a set of cached objects to save I/Os [26]. Further examples are duplicate removal, storing the edge set of a sparse graph in order to support edge queries [23], maintaining the set of nonempty cells in a grid-data structure used in geometry processing (e.g. [7]), or maintaining the children in tree data structures such as van Emde-Boas search trees [6] or suffix trees [21].

Many of these applications have in common that – even in the sequential version of the program – hash table accesses constitute a significant fraction

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of the running time. Thus, it is essential to have highly scalable concurrent hash tables that actually deliver significant speedups in order to parallelize these applications. Unfortunately, currently available general purpose concurrent hash tables do not offer the needed scalability (see Section 8 for concrete numbers). On the other hand, it seems to be folklore that a lock-free linear probing hash table where keys and values are machine words, which is preallocated to a bounded size, and which supports no true deletion operation can be implemented using atomic compare-and-swap (CAS) instructions [36]. Find-operations can even proceed naively and without any write operations. In Section 4 we explain our own implementation (folklore) in detail, after elaborating on some related work, and introducing the necessary notation (in Section 2 and 3 respectively). To see the potential big performance differences, consider an exemplary situation with mostly read only access to the table and heavy contention for a small number of elements that are accessed again and again by all threads. folklore actually profits from this situation because the contended elements are likely to be replicated into local caches. On the other hand, any implementation that needs locks or CAS instructions for findoperations, will become much slower than the sequential code on current machines. The purpose of our paper is to document and explain performance differences, and, more importantly, to explore to what extent we can make *folklore* more general with an acceptable deterioration in performance.

These generalizations are discussed in Section 5. We explain how to grow (and shrink) such a table, and how to support deletions and more general data types. In Section 6 we explain how hardware transactional memory can be used to speed up insertions and updates and how it may help to handle more general data types.

After describing implementation details in Section 7, Section 8 experimentally compares our hash tables with six of the most widely used concurrent hash tables for microbenchmarks including insertion, finding, and aggregating data. We look at both uniformly distributed and skewed input distributions. Section 9 summarizes the results and discusses possible lines of future research.

2 Related Work

This publication follows up on our previous findings about generalizing fast concurrent hash tables [18]. In addition to describing how to generalize a fast linear probing hash table, we offer an extensive experimental analysis comparing many concurrent hash tables from several libraries.

There has been extensive previous work on concurrent hashing. The widely used textbook "The Art of Multiprocessor Programming" [12] by Herlihy and Shavit devotes an entire chapter to concurrent hashing and gives an overview over previous work. However, it seems to us that a lot of previous work focuses more on concepts and correctness but surprisingly little on scalability. For example, most of the discussed growing mechanisms assume that the size of the hash table is known exactly without a discussion that this introduces a performance bottleneck limiting the speedup to a constant. Similarly, the actual migration is often done sequentially.

Stivala et al. [36] describe a bounded concurrent linear probing hash table specialized for dynamic programming that only support insert and find. Their insert operation starts from scratch when the CAS fails which seems suboptimal in the presence of contention. An interesting point is that they need only word size CAS instructions at the price of reserving a special empty value. This technique could also be adapted to port our code to machines without 128-bit CAS.

Kim and Kim [14] compare this table with a cache-optimized lockless implementation of hashing with chaining and with hopscotch hashing [13]. The experiments use only uniformly distributed keys, i.e., there is little contention. Both linear probing and hashing with chaining perform well in that case. The evaluation of find-performance is a bit inconclusive: chaining wins but using more space than linear probing. Moreover it is not specified whether this is for successful (use key of inserted elements) or mostly unsuccessful (generate fresh keys) accesses. We suspect that varying these parameters could reverse the result.

Gao et al. [10] present a theoretical dynamic linear probing hash table, that is lock-free. The main contribution is a formal correctness proof. Not all details of the algorithm or even an implementation is given. There is also no analysis of the complexity

of the growing procedure.

Shun and Blelloch [34] propose phase concurrent hash tables which are allowed to use only a single operation within a globally synchronized phase. They show how phase concurrency helps to implement some operations more efficiently and even deterministically in a linear probing context. For example, deletions can adapt the approach from [15] and rearrange elements. This is not possible in a general hash table since this might cause findoperations to report false negatives. They also outline an elegant growing mechanism albeit without implementing it and without filling in all the detail like how to initialize newly allocated tables. They propose to trigger a growing operation when any operation has to scan more than $k \log n$ elements where k is a tuning parameter. This approach is tempting since it is somewhat faster than the approximate size estimator we use. We actually tried that but found that this trigger has a very high variance – sometimes it triggers late making operations rather slow, sometimes it triggers early wasting a lot of space. We also have theoretical concerns since the bound $k \log n$ on the length of the longest probe sequence implies strong assumptions on certain properties of the hash function. Shun and Blelloch make extensive experiments including applications from the problem based benchmark suite [35].

Li et al. [17] use the bucket cuckoo-hashing method by Dietzfelbinger and Weidling [8] and develop a concurrent implementation. They exploit that using a BFS-based insertion algorithm, the number of element moves for an insertion is very small. They use fine grained locks which can sometimes be avoided using transactional memory (Intel TSX). As a result of their work, they implemented the small open source library libcuckoo, which we measure against (which does not use TSX). This approach has the potential to achieve very good space efficiency. However, our measurements indicate that the performance penalty is high.

The practical importance of concurrent hash tables also leads to new and innovative implementations outside of the scientific community. A good example of this is the Junction library, that was published by Preshing [31] in the beginning of 2016, shortly after our initial publication [19].

3 Preliminaries

We assume that each application thread has its own designated hardware thread or processing core and denote the number of these threads with p. A data structure is non-blocking if no blocked thread currently accessing this data structure can block an operation on the data structure by another thread. A data structure is lock-free if it is non-blocking and guarantees global progress, i.e., there must always be at least one thread finishing its operation in a finite number of steps.

Hash Tables store a set of $\langle Key, Value \rangle$ pairs (elements). A hash function h maps each key to a cell of a table (an array). The number of elements in the hash table is denoted n and the number of operations is m. For the purpose of algorithm analysis, we assume that n and m are $\gg p^2$ – this allows us to simplify algorithm complexities by hiding O(p) terms that are independent of n and m in the overall cost. Sequential hash tables support the insertion of elements, and finding, updating, or deleting an element with given key – all of this in constant expected time. Further operations compute n (size), build a table with a given number of initial elements, and iterate over all elements (forall).

Linear Probing is one of the most popular sequential hash table schemes used in practice. An element $\langle x,a\rangle$ is stored at the first free table entry following position h(x) (wrapping around when the end of the table is reached). Linear probing is at the same time simple and efficient – if the table is not too full, a single cache line access will be enough most of the time. Deletion can be implemented by rearranging the elements locally [15] to avoid holes violating the invariant mentioned above. When the table becomes too full or too empty, the elements can be migrated to a larger or smaller table respectively. The migration cost can be charged to insertions and deletions causing amortized constant overhead.

 $^{^1\}mathrm{Much}$ of what is said here can be generalized to the case when Elements are black boxes from which keys are extracted by an accessor function.

4 Concurrent Hash Table Interface and Folklore Implementation

Although it seems quite clear what a hash table is and how this generalizes to concurrent hash tables, there is a surprising number of details to consider. Therefore, we will quickly go over some of our interface decisions, and detail how this interface can be implemented in a simple, fast, lock-free concurrent linear probing hash table.

This hash table will have a bounded capacity c that has to be specified when the table is constructed. It is the basis for all other hash table variants presented in this publication. We call this table the *folklore* solution, because variations of it are used in many publications and it is not clear to us by whom it was first published.

The most important requirement for concurrent data structures is, that they should be linearizable, i.e., it must be possible to order the hash table operations in some sequence – without reordering two opperations of the same thread – so that executing them sequentially in that order yields the same results as the concurrent processing. For a hash table data structure, this basically means that all operations should be executed atomically some time between their invokation and their return. For example, it has to be avoided, that a find returns an inconsistent state, e.g. a half-updated data field that was never actually stored at the corresponding key.

Our variant of the folklore solution ensures the atomicity of operations using 2-word atomic CAS operations for all changes of the table. As long as the key and the value each only use one machine word, we can use 2-word CAS operations to atomically manipulate a stored key together with the corresponding value. There are other variants that avoid need 2-word compare and swap operations, but they often need a designated empty value (see [31]). Since, the corresponding machine instructions are widely available on modern hardware, using them should not be a problem. If the target architecture does not support the needed instructions, the implementation can easily be switched to use a variant of the folklore solution which does not use 2-word CAS. As it can easily be deduced by the context, we will usually omit the "2-word"

prefix and use the abbreviation CAS for both single and double word CAS operations.

Initialization The constructor allocates an array of size c consisting of 128-bit aligned cells whose key is initialized to the empty values.

Modifications We propose, to categorize all changes to the hash table content into one of the following three functions, that can be implemented very similarly (does not cover deletions).

insert(k, d): Returns false if an element with the specified key is already present. Only one operation should succeed if multiple threads are inserting the same key at the same time.

update(k, d, up): Returns false, if there is no value stored at the specified key, otherwise this function atomically updates the stored value to new = up(current, d). Notice, that the resulting value can be dependent on both the current value and the input parameter d.

insertOrUpdate(k,d,up): This operation updates the current value, if one is present, otherwise the given data element is inserted as the new value. The function returns true, if insertOrUpdate performed an insert (key was not present), and false if an update was executed.

We choose this interface for two main reasons. It allows applications to quickly differentiate between inserting and changing an element – this is especially usefull since the thread who first inserted a key can be identified uniquely. Additionally it allows transparent, lockless updates that can be more complex, than just replacing the current value (think of CAS or Fetch-and-Add).

The update interface using an update function deserves some special attention, as it is a novel approach compared to most interfaces we encountered during our research. Most implementations fall into one of two categories: They return mutable references to table elements – forcing the user to implement atomic operations on the data type; or they offer an update function which usually replaces the current value with a new one – making it very hard to implement atomic changes like a simple counter (find + increment + overwrite not necessarily atomic).

In Algorithm 1 we show the pseudocode of the insertOrUpdate function. The operation com-

ALGORITHM 1: Pseudocode for the insertOrUpdate operation

```
Input: Key k, Data Element d, Update Function up: Key \times Val \times Val \rightarrow Val
 Output: Boolean true when a new key was inserted, false if an update occurred
1 i = h(k):
2 while true do
       i = i \% c;
3
       current = table[i]:
4
       if current.key == empty_key then
5
                                                                              // Key is not present yet ...
           if table[i]. CAS (current, \langle k, d \rangle) then
6
              return true
           else
8
            i--;
       else if current.key == k then
10
                                                                            // Same key already present ...
           if table[i].atomicUpdate(current, d, up) then
11
                                  // default: atomicUpdate(\cdot) = CAS(current, up(k, current.data, d))
              return false
12
           else
13
14
       i++;
15
```

putes the hash value of the key and proceeds to look for an element with the appropriate key (beginning at the corresponding position). If no element matching the key is found (when an empty space is encountered), the new element has to be inserted. This is done using a CAS operation. A failed swap can only be caused by another insertion into the same cell. In this case, we have to revisit the same cell, to check if the inserted element matches the current key. If a cell storing the same key is found, it will be updated using the atomicUpdate function. This function is usually implemented by evaluating the passed update function (up) and using a CAS operation, to change the cell. In the case of multiple concurrent updates, at least one will be successful.

In our (C++) implementation, partial template specialization can be used to implement more efficient atomicUpdate variants using atomic operations – changing the default line 11, e.g. overwrite (using single word store), increment (using fetch and add).

The code presented in Algorithm 1 can easily be modified to implement the insert (return false when the key is already present – line 10) and update (return true after a successful update – line 12 and false when the key is not found – line 5) functions. All modification functions have a

constant expected running time.

Lookup Since this folklore implementation does not move elements within the table, it would be possible for $\mathtt{find}(k)$ to return a reference to the corresponding element. In our experience, returning references directly tempts inexperienced programmers to opperate on these references in a way that is not necessarily threadsafe. Therefore, our implementation returns a copy of the corresponding cell $(\langle k, d \rangle)$, if one is found $(\langle \mathtt{empty_key}, \cdot \rangle)$ otherwise). The find operation has a constant expected running time.

Our implementation of find somewhat non-trivial, because it is not possible to read two machine words at once using an atomic instruction². Therefore it is possible for a cell to be changed inbetween reading its key and its value – this is called a torn read. We have to make sure, that torn reads cannot lead to any wrong behavior. There are two kinds of interesting torn reads: First an empty key is read while the searched key is inserted into the same cell, in this case the element is not found (consistent since it has not been fully inserted); Second

²The element is not read atomically, because x86 does not support that. One could use a 2-word CAS to achieve the same effect but this would have disastrous effects on performance when many threads try to find the same element.

the element is updated between the key being read and the data being read, since the data is read second, only the newer data is read (consistent with a finished update).

Deletions The folklore solution can only handle deletions using dummy elements – called tombstones. Usually the key stored in a cell is replaced with del_key. Afterwards the cell cannot be used anymore. This method of handling deleted elements is usually not feasible, as it does not increase the capacity for new elements. In Section 5.4 We will show, how our generalizations can be used to handle tombstones more efficiently.

Bulk Operations While not often used in practice, the folklore table can be modified to support operations like buildFrom(·) (see Section 5.5) – using a bulk insertion which can be more efficient than element-wise insertion – or forall(f) – which can be implemented embarrassingly parallel by splitting the table between threads.

Size Keeping track of the number of contained elements deserves special notice here because it turns out to be significantly harder in concurrent hash tables. In sequential hash tables, it is trivial to count the number of contained elements – using a single counter. This same method is possible in parallel tables using atomic fetch and add operations, but it introduces a massive amount of contention on one single counter creating a performance bottleneck.

Because of this we did not include a counting method in folklore implementation. In Section 5.2 we show how this can be alleviated using an approximate count.

5 Generalizations and Extensions

In this section, we detail how to adapt the concurrent hash table implementation – described in the previous section – to be universally applicable to all hash table workloads. Most of our efforts have gone into a scalable migration method that is used to move all elements stored in one table into another table. It turns out that a fast migration can

solve most shortcomings of the folklore implementation (especially deletions and adaptable size).

5.1 Storing Thread-Local Data

By itself, storing thread specific data connected to a hash table does not offer additional functionality, but it is necessary to efficiently implement some of our other extensions. Per-thread data can be used in many different ways, from counting the number of insertions to caching shared resources.

From a theoretical point of view, it is easy to store thread specific data. The additional space is usually only dependent on the number of threads (O(p)) additional space), since the stored data is often constant sized. Compared to the hash table this is usually negligible $(p \ll n < c)$.

Storing thread specific data is challenging from a software design and performance perspective. Some of our competitors use a register(·) function that each thread has to call before accessing the table. This allocates some memory, that can be accessed using the global hash table object.

Our solution uses explicit handles. Each thread has to create a handle, before accessing the hash table. These handles can store thread specific data, since they are not shared between threads. This is not only in line with the RAII idiom (resource acquisition is initialization [24]), it also protects our implementation from some performance pitfalls like unnecessary indirections and false sharing³. Moreover, the data can easily be deleted once the thread does not use the hash table anymore (delete the handle).

5.2 Approximating the Size

Keeping an exact count of the elements stored in the hash table can often lead to contention on one count variable. Therefore, we propose to support only an approximative size operation.

To keep an approximate count of all elements, each thread maintains a local counter of its successful insertions (using the method desribed in Section 5.1). Every $\Theta(p)$ such insertions this counter is atomically added to a global insertion counter I and then reset. Contention at I can be provably

³Significant slow down created by the cache coherency protocol due to multiple threads repeatedly changing distinct values within the same cache line.

made small by randomizing the exact number of local insertions accepted before adding to the global counter, e.g., between 1 and p. I underestimates the size by at most $O(p^2)$. Since we assume the size to be $\gg p^2$ this still means a small relative error. By adding the maximal error, we also get an upper bound for the table size.

If deletions are also allowed, we maintain a global counter D in a similar way. S = I - D is then a good estimate of the total size as long as $S \gg p^2$.

When a table is migrated for growing or shrinking (see Section 5.3.1), each migration thread locally counts the elements it moves. At the end of the migration, local counters are added to create the initial count for I (D is set to 0).

This method can also be extended to give an exact count – in absence of concurrent insertions/deletions. To do this, a list of all handles has to be stored at the global hash table object. A thread can now iterate over all handles computing the actual element size.

5.3 Table Migration

While Gao et al. [10] have shown that lock-free dynamic linear probing hash tables are possible, there is no result on their practical feasibility. Our focus is geared more towards engineering the fastest migration possible, therefore, we are fine with small amounts of locking, as long as it improves the overall performance.

5.3.1 Eliminating Unnecessary Contention from the Migration

If the table size is not fixed, it makes sense to assume that the hash function h yields a large pseudorandom integer which is then mapped to a cell position in 0..c-1 where c is the current capacity $c.^4$ We will discuss a way to do this by scaling. If h yields values in the global range 0..U-1 we map key x to cell $h_c(x) := \lfloor h(x) \frac{c}{U} \rfloor$. Note that when both c and U are powers of two, the mapping can be implemented by a simple shift operation.

Growing Now suppose that we want to migrate the table into a table that has at least the same size (growing factor $\gamma \geq 1$). Exploiting the properties

of linear probing and our scaling function, there is a surprisingly simple way to migrate the elements from the old table to the new table in parallel which results in exactly the same order a sequential algorithm would take and that completely avoids synchronization between threads.

Lemma 1. Consider a range a..b of nonempty cells in the old table with the property that the cells $a-1 \mod c$ and $b+1 \mod c$ are both empty – call such a range a cluster (see Figure 1a). When migrating a table, sequential migration will map the elements stored in that cluster into the range $\lfloor \gamma a \rfloor .. \lfloor \gamma (b+1) \rfloor$ in the target table, regardless of the rest of the source array.

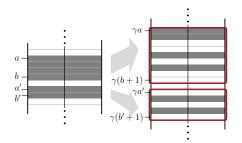
Proof. Let x be an element stored in the cluster a..b at position $p(x) = h_c(x) + d(x)$. Then $h_c(x)$ has to be in the cluster a..b, because linear probing does not displace elements over empty cells $(h_c(x) = \lfloor h(x) \frac{c}{U} \rfloor \geq a)$, and therefore, $h(x) \frac{c'}{U} \geq a \frac{c'}{c} \geq \gamma a$. Similarly, from $\lfloor h(x) \frac{c}{U} \rfloor \leq b$ follows $h(x) \frac{c}{U} < b+1$, and therefore, $h(x) \frac{c'}{U} < \gamma (b+1)$.

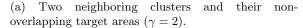
Therefore, two distinct clusters in the source table cannot overlap in the target table. We can exploit this lemma by assigning entire clusters to migrating threads which can then process each cluster completely independently. Distributing clusters between threads can easily be achieved by first splitting the table into blocks (regardless of the tables contents) which we assign to threads for parallel migration. A thread assigned block d..e will migrate those clusters that start within this range – implicitly moving the block borders to free cells as seen in Figure 1b). Since the average cluster length is short and $c = \Omega(p^2)$, it is sufficient to deal out blocks of size $\Omega(p)$ using a single shared global variable and atomic fetch-and-add operations. Additionally each thread is responsible for initializing all cells in its region of the target table. This is important, because sequentially initializing the hash table can quickly become infeasible.

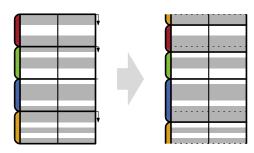
Note that waiting for the last thread at the end of the migration introduces some waiting (locking), but this does not create significant work imbalance, since the block/cluster migration is really fast and clusters are expected to be short.

Shrinking Unfortunately, the nice structural Lemma 1 no longer applies. We can still parallelize

 $^{^4\}mbox{We}$ use x..y as a shorthand for $\{x,\ldots,y\}$ in this paper.







(b) Left: table split into even blocks. Right: resulting cluster distribution (moved implicit block borders).

Figure 1: Cluster migration and work distribution

the migration with little synchronization. Once more, we cut the source table into blocks that we assign to threads for migration. The scaling function maps each block a..b in the source table to a block a'..b' in the target table. We have to be careful with rounding issues so that the blocks in the target table are non-overlapping. We can then proceed in two phases. First, a migrating thread migrates those elements that move from a..b to a'..b'. These migrations can be done in a sequential manner, since target blocks are disjoint. The majority of elements will fit into the target block. Then, after a barrier synchronization, all elements that did not fit into their respective target blocks are migrated using concurrent insertion i.e., using atomic operations. This has negligible overhead since elements like this only exist at the boundaries of blocks. The resulting allocation of elements in the target table will no longer be the same as for a sequential migration but as long as the data structure invariants of a linear probing hash table are fulfilled, this is not a problem.

5.3.2 Hiding the Migration from the Underlying Application

To make the concurrent hash table more general and easy to use, we would like to avoid all explicit synchronization. The growing (and shrinking) operations should be performed asynchronously when needed, without involvement of the underlying application. The migration is triggered once the table is filled to a factor $\geq \alpha$ (e.g. 50%), this is estimated using the approximate count from Section 5.2, and checked whenever the global count is updated. When a growing operation is triggered,

the capacity will be increased by a factor of $\gamma \geq 1$ (Usually $\gamma = 2$). The difficulty is ensuring that this operation is done in a transparent way without introducing any inconsistent behavior and without incurring undue overheads.

To hide the migration process from the user, two problems have to be solved. First, we have to find threads to grow the table, and second, we have to ensure, that changing elements in the source table will not lead to any inconsistent states in the target table (possibly reverting changes made during the migration). Each of these problems can be solved in multiple ways. We implemented two strategies for each of them resulting in four different variants of the hash table (mix and match).

Recruiting User-Threads A simple approach to dynamically allocate threads to growing the table, is to "enslave" threads that try to perform table accesses that would otherwise have to wait for the completion of the growing process anyway. This works really well when the table is regularly accessed by all user-threads, but is inefficient in the worst case when most threads stop accessing the table at some point, e.g., waiting for the completion of a global computation phase at a barrier. The few threads still accessing the table at this point will need a lot of time for growing (up to $\Omega(n)$) while most threads are waiting for them. One could try to also enslave waiting threads but it looks difficult to do this in a sufficiently general and portable way.

Using a Dedicated Thread Pool A provably efficient approach is to maintain a pool of p threads dedicated to growing the table. They are blocked

until a growing operation is triggered. This is when they are awoken to collectively perform the migration in time $\mathrm{O}(n/p)$ and then get back to sleep. During a migration, application threads might have to sleep until the migration threads are finished. This will increase the CPU time of our migration threads making this method nearly as efficient as the enslavement variant. Using a reasonable computation model, one can show that using thread pools for migration increases the cost of each table access by at most a constant in a globally amortized sense (over the non-growing folklore solution). We omit the relatively simple proof.

To remain fair to all competitors, we used exactly as many threads for the thread pool as there were application threads accessing the table. Additionally each migration thread was bound to a core, that was also used by one corresponding application thread.

Marking Moved Elements for Consistency (asynchronous) During the migration it is important that no element can be changed in the old table after it has been copied to the new table. Otherwise, it would be hard to guarantee that changes are correctly applied to the new table. The easiest solution to this problem is, to mark each cell before it is copied. Marking each cell can be done using a CAS operation to set a special marked bit which is stored in the key. In practice this reduces the possible key space. If this reduction is a problem, see Section 5.6 on how to circumvent it. To ensure that no copied cell can be changed, it suffices to ensure that no marked cell can be changed. This can easily be done by checking the bit before each writing operation, and by using CAS operations for each update. This prohibits the use of fast atomic operations to change element values.

After the migration, the old hash table has to be deallocated. Before deallocating an old table, we have to make sure that no thread is currently using it anymore. This problem can generally be solved by using reference counting. Instead of storing the table with a usual pointer, we use a reference counted pointer (e.g. std::shared_ptr) to ensure that the table is eventually freed.

The main disadvantage of counting pointers is that acquiring a counting pointer requires an atomic increment on a shared counter. Therefore, it

is not feasible to acquire a counting pointer for each operation. Instead a copy of the shared pointer can be stored locally, together with the increasing version number of the corresponding hash table (using the method from Section 5.1). At the beginning of each operation, we can use the local version number to make sure that the local counting pointer still points to the newest table version. If this is not the case, a new pointer will be acquired. This happens only once per version of the hash table. The old table will automatically be freed once every thread has updated its local pointer. Note that counting pointers cannot be exchanged in a lock-free manner increasing the cost of changing the current table (using a lock). This lock could be avoided by using a hazard pointer. We did not do this

Prevent Concurrent Updates to ensure Consistency (synchronized) We propose a simple protocol inspired by read-copy-update protocols [22]. The thread t triggering the growing operation sets some global growing flag using a CAS instruction. A thread t performing a table access sets a local busy flag when starting an operation. Then it inspects the growing flag, if the flag is set, the local flag is unset. Then the local thread waits for the completion of the growing operation, or helps with migrating the table depending on the current growing strategy. Thread t waits until all busy flags have been unset at least once before starting the migration. When the migration is completed, the growing flag is reset, signaling to the waiting threads that they can safely continue their tableoperations. Because this protocol ensures that no thread is accessing the previous table after the beginning of the migration, it can be freed without using reference counting.

We call this method (semi-)synchronized, because grow and update operations are disjoint. Threads participating in one growing step still arrive asynchronously, e.g. when the parent application called a hash table operation. Compared to the marking based protocol, we save cost during migration by avoiding CAS operations. However, this is at the expense of setting the busy flags for every operation. Our experiments indicates that overall this is only advantageous for updates using atomic operations like fetch-and-add that cannot coexist with the marker flags.

5.4 Deletions

For concurrent linear probing, we combine *tomb-stoning* (see Section 4) with our migration algorithm to clean the table once it is filled with too many *tombstones*.

A tombstone is an element, that has a del_key in place of its key. The key x of a deleted entry $\langle x, a \rangle$ is atomically changed to $\langle \text{del_key}, a \rangle$. Other table operations scan over these deleted elements like over any other nonempty entry. No inconsistencies can arise from deletions. In particular, a concurrent find-operations with a torn read will return the element before the deletion since the delete-operation will leave the value-slot a untouched. A concurrent insert $\langle x,b\rangle$ might read the key x before it is overwritten by the deletion and return false because it concludes that an element with key x is already present. This is consistent with the outcome when the insertion is performed before the deletion in a linearization.

This method of deletion can easily be implemented in the folklore solution from Section 4. But the starting capacity has to be set dependent on the number of overall insertions, since this form of deletion does not free up any of the deleted cells. Even worse, tombstones will fill up the table and slow down find queries.

Both of these problems can be solved by migrating all non-tombstone elements into a new table. The decision when to migrate the table should be made solely based on the number of insertions I (= number of nonempty cells). The count of all non-deleted elements I-D is then used to decide whether the table should grow, keep the same size (notice $\gamma=1$ is a special case for our optimized migration), or shrink. Either way, all tombstones can be removed in the course of the element migration.

5.5 Bulk Operations

Building a hash table for n elements passed to the constructor can be parallelized using integer sorting by the hash function value. This works in time O(n/p) regardless how many times an element is inserted, i.e., sorting circumvents contention. See the work of Mller et al.[25] for a discussion of this phenomenon in the context of aggregation.

This can be generalized for processing batches of size $m = \Omega(n)$ that may even contain a mix of inser-

tions, deletions, and updates. We outline a simple algorithm for bulk-insertion that works without explicit sorting albeit does not avoid contention. Let a denote the old size of the hash table and b the number of insertions. Then a+b is an upper bound for the new table size. If necessary, grow the table to that size or larger (see below). Finally, in parallel, insert the new elements.

More generally, processing batches of size m = $\Omega(n)$ in a globally synchronized way can use the same strategy. We outline it for the case of bulk insertions. Generalization to deletions, updates, or mixed batches is possible: Integer sort the elements to be inserted by their hash key in expected time O(m/p). Among elements with the same hash value, remove all but the last. Then "merge" the batch and the hash table into a new hash table (that may have to be larger to provide space for the new elements). We can adapt ideas from parallel merging [11]. We co-partition the sorted insertion array and the hash table into corresponding pieces of size O(m/p). Most of the work can now be done on these pieces in an embarrassingly parallel way – each piece of the insertion array is scanned sequentially by one thread. Consider an element $\langle x, a \rangle$ and previous insertion position i in the table. Then we start looking for a free cell at position $\max(h(x), i)$

5.6 Restoring the Full Key Space

Our table uses special keys, like the empty key (empty_key) and the deleted key (del_key). Elements that actually have these keys cannot be stored in the hash table. This can easily be fixed by using two special slots in the global hash table data structure. This makes some case distinction necessary but should have rather low impact on the overall performance.

One of our growing variants (asynchronous) uses a marker bit in its key field. This halves the possible key space from 2^{64} to 2^{63} . To regain the lost key space, we can store the lost bit implicitly. Instead of using one hash table that holds all elements, we use the two subtables t_0 and t_1 . The subtable t_0 holds all elements whose key does not have its topmost bit set. While t_1 stores all elements whose key does have the topmost bit set, but instead of storing the topmost bit explicitly it is removed.

Each element can still be found in constant time, because when looking for a certain key, it is immediately obvious in which table the corresponding element will be stored. After choosing the right table, comparing the 63 explicitly stored bits can uniquely identify the correct element. Notice that both empty keys have to be stored distinctly (as described above).

5.7 Complex Key and Value Types

Using CAS instructions to change the content of hash table cells makes our data structure fast but limits its use to cases where keys and values fit into memory words. Lifting this restriction is bound to have some impact on performance but we want to outline ways to keep this penalty small. The general idea is to replace the keys and or values by references to the actual data.

Complex Keys To make things more concrete we outline a way where the keys are strings and the hash table data structure itself manages space for the keys. When an element $\langle s, a \rangle$ is inserted, space for string s is allocated. The hash table stores $\langle r, a \rangle$ where r is a pointer to s. Unfortunately, we get a considerable performance penalty during table operations because looking for an element with a given key now has to follow this indirection for every key comparison - effectively destroying the advantage of linear probing over other hashing schemes with respect to cache efficiency. This overhead can be reduced by two measures: First, we can make the table bigger thus reducing the necessary search distance – considering that the keys are large anyway, this has a relatively small impact on overall storage consumption. A more sophisticated idea is to store a signature of the key in some unused bits of the reference to the key (on modern machines keys actually only use 48 bits). This signature can be obtained from the master hash function h extracting bits that were not used for finding the position in the table (i.e. the least significant digits). While searching for a key y one can then first compare the signatures before actually making a full key comparison that involves a costly pointer dereference.

Deletions do *not* immediately deallocate the space for the key because concurrent operations might still be scanning through them. The space for deleted keys can be reclaimed when the array grows. At that time, our migration protocols make

sure that no concurrent table operations are going on.

The memory management is challenging since we need high throughput allocation for very fine grained variable sized objects and a kind of garbage collection. On the positive side, we can find all the pointers to the strings using the hash function. All in all, these properties might be sufficiently unique that a carefully designed special purpose implementation is faster than currently available general purpose allocators. We outline one such approach: New strings are allocated into memory pages of size $\Omega(p)$. Each thread has one current page that is only used locally for allocating short strings. Long strings are allocated using a general purpose allocator. When the local page of a thread is full, the thread allocates a fresh page and remembers the old one on a stack. During a shrinking phase, a garbage collection is done on the string memory. This can be parallelized on a page by page basis. Each thread works on two pages A and B at a time where A is a partially filled page. B is scanned and the strings stored there are moved to A (updating their pointer in the hash table). When A runs full, B replaces A. When B runs empty, it is freed. In either case, an unprocessed page is obtained to become B.

Complex Values We can take a similar approach as for complex keys – the hash table data structure itself allocates space for complex values. This space is only deallocated during migration/cleanup phases that make sure that no concurrent table operations are affected. The find-operation only hands out *copies* of the values so that there is no danger of stale data. There are now two types of update operations. One that modifies part of a complex value using an atomic CAS operation and one that allocates an entirely new value object and performs the update by atomically setting the value-reference to the new object. Unfortunately it is not possible to use both types concurrently.

Complex Keys and Values Of course we can combine the two approaches described above. However in that case, it will be more efficient to store a single reference to a combined key-value object together with a signature.

6 Using Hardware Memory Transactions

The biggest difference between a concurrent table, and a sequential hash table is the use of atomic processor instructions. We use them for accessing and modifying data which is shared between threads. An additional way to achieve atomicity is the use of hardware transactional memory synchronization introduced recently by Intel and IBM. The new instruction extensions can group many memory accesses into a single transaction. All changes from one transaction are committed at the same time. For other threads they appear to be atomic. General purpose memory transactions do not have progress guarantees (i.e. can always be aborted), therefore they require a fall-back path implementing atomicity (a lock or an implementation using traditional atomic instructions).

We believe that transactional memory synchronization is an important opportunity for concurrent data structures. Therefore, we analyze how to efficiently use memory transactions for our concurrent linear probing hash tables. In the following, we discuss which aspects of our hash table can be improved by using restricted transactional memory implemented in Intel Transactional Synchronization Extensions (Intel TSX).

We use Intel TSX by wrapping sequential code into a memory transaction. Since the sequential code is simpler (e.g. less branches, more freedom for compiler optimizations) it can outperform inherently more complex code based on (expensive 128-bit CAS) atomic instructions. As a transaction fall-back mechanism, we employ our atomic variants of hash table operations. Replacing the insert and update functions of our specialized growing hash table with Intel TSX variants increases the throughput of our hash table by up to 28 % (see Section 8.4). Speedups like this are easy to obtain on workloads without contentious accesses (simultaneous write accesses on the same cell). Contentious write accesses lead to transaction aborts which have a higher latency than the failure of a CAS. Our atomic fall-back minimizes the penalty for such scenarios compared to the classic lockbased fall-back that causes more overhead and serialization.

Another aspect that can be improved through

the use of memory transactions is the key and value size. On current x86 hardware, there is no atomic instruction that can change words bigger than 128 bits at once. The amount of memory that can be manipulated during one memory transaction can be far greater than 128 bits. Therefore, one could easily implement hash tables with complex keys and values using transactional memory synchronization. However, using atomic functions as fall-back will not be possible. Solutions with fine-grained locks that are only needed when the transactions actually fail, are still possible.

With general purpose memory transactions it is even possible to atomically change multiple values that are not stored consecutively. Therefore, it is possible to implement a hash table that separates the keys from the values storing each in a separate table. In theory this could improve the cache locality of linear probing.

Overall, transactional memory synchronization can be used to improve performance and to make the data structure more flexible.

7 Implementation Details

Bounded Hash Tables. All of our implementations are constructed around a highly optimized variant of the circular bounded *folklore* hash table that was describe in Section 4. The main performance optimizations were to restrict the table size to powers of two – replacing expensive modulo operations with fast bit operations When initializing the capacity c, we compute the lowest power of two, that is still at least twice as large as the expected number of insertions $(2n \le size \le 4n)$.

We also built a second non growing hash table variant called *tsxfolklore*, this variant forgoes the usual CAS-operations that are used to change cells. Instead tsxfolklore uses TSX transactions to change elements in the table atomically. As described in Section 6, we use our usual atomic operations as fallback in case a TSX transaction is aborted.

Growing Hash Tables. All of our growing hash tables use folklore or tsxfolklore to represent the current status of the hash table. When the table is approximately 60% filled, a migration is started. With each migration, we double the capacity. The migration works in cell-blocks of the size 4096.

Blocks are migrated with a minimum amount of atomics by using the cluster migration described in Section 5.3.1.

We use a user-space memory pool from Intel's TBB library to prevent a slow down due to the remapping of virtual to physical memory (protected by a coarse lock in the Linux kernel). This improves the performance of our growing variants, especially when using more than 24 threads. By allocating memory from this memory pool, we ensure that the virtual memory that we receive is already mapped to physical memory, bypassing the kernel lock.

In Section 5.3.1 we identified two orthogonal problems that have to be solved to migrate hash tables: which threads execute the migration? and how can we make sure that copied elements cannot be changed? For each of these problems we formulated two strategies. The table can either be migrated by user-threads that execute operations on the table (u), or by using a pool of threads which is only responsible for the migration (p). To ensure that copied elements cannot be changed, we proposed to wait for each currently running operation synchronizing update and growing phases (s), or to mark elements before they are copied, thus proceeding fully asynchronously (a).

All strategies can be combined – creating the following four growing hash table variants: uaGrow uses enslavement of user threads and asynchronous marking for consistency; usGrow also uses user threads threads, but ensures consistency by synchronizing updates and growing routines; paGrow uses a pool of dedicated migration threads for the migration and asynchronous marking of migrated entries for consistency; and psGrow combines the use of a dedicated thread pool for migration with the synchronized exclusion mechanism.

All of these versions can also be instantiated using the TSX based non-growing table tsxfolklore as a basis.

8 Experimental Evaluation

We performed a large number of experiments to investigate the performance of different concurrent hash tables in a variety of circumstances (an overview over all tested hash tables can be found in Table 1). We begin by describing the tested competitors (Section 8.1, our variants are introduced in

Section 7), the test instances (Section 8.3), and the test environment (Section 8.2). Then Section 8.4 discusses the actual measurements. In Section 8.5, we conclude the section by summarizing our experiments and reflecting how different generalizations affect the performance of hash tables.

8.1 Competitors

To compare our implementation to the current state of the art we use a broad selection of other concurrent hash tables. These tables were chosen on the basis of their popularity in applications and academic publications. We split these hash table implementations into the following three groups depending on their growing functionality.

8.1.1 Efficiently Growing Hash Tables

This group contains all hash tables, that are able to grow efficiently from a very small initial size. They are used in our growing benchmarks, where we initialize tables with an initial size of 4096 thus making growing necessary.

Junction Linear ●, Junction Grampa ⊕, and Junction Leapfrog

The junction library consists of three different variants of a dynamic concurrent hash table. It was published by Jeff Preshing over github [31], after our first publication on the subject ([19]). There are no scientific publications, but on his blog [32] Preshing writes some insightful posts on his implementation. In theory, junction's hash tables use an approach to growing which is similar to ours. A filled bounded hash table is migrated into a newly allocated bigger table. Although they are constructed from a similar idea, the execution seems to differ quite significantly. The junction hash tables use a quiescentstate based reclamation (QSBR) protocol, for memory reclamation. Using this protocol, in order to reclaim freed hash table memory, the user has to regularly call a designated function.

Contrary to other hash tables, we used the provided standard hash function (avalanche), because junction assumes its hash function, to be invertible. Therefore, the hash function which is used for all other tables (see Section 8.3) is not usable.

The different hash tables within junction all perform different variants of open addressing. These variants are described in more detail, in one of Preshing's blogposts (see [32]).

tbbHM ★ and tbbUM ★ (correspond to the TBB maps tbb::concurrent_hash_map and tbb::concurrent_unordered_map respectively)
The Threading Building Blocks [30] (TBB) library (Version 4.3 Update 6) developed by Intel is one of the most widely used libraries for shared memory concurrent programming. The two different concurrent hash tables it contains behave relatively similar in our tests. Therefore, we sometimes only plot the results of tbbHM ★. But they have some differences concerning the locking of accessed elements. Therefore, they behave very differently under contention.

8.1.2 Hash Tables with Limited Growing Capabilities

This group contains all hash tables that can only grow by a limited amount (constant factor of the initial size) or become very slow when growing is required. When testing their growing capabilities, we usually initialize these tables with half their target size. This is comparable to a workload where the approximate number of elements is known but cannot be bound strictly.

folly + (folly::AtomicHashMap) This hash table was developed at facebook as a part of their open source library folly [9] (Version 57:0). It uses restrictions on key and data types similar to our folklore implementation. In contrast to our growing procedure, the folly table grows by allocating additional hash tables. This increases the cost of future queries and it bounds the total growing factor to ≈ 18 (× initial size).

cuckoo \bot (cuckoohash.map) This hash table using (bucket) cuckoo hashing as its collision resolution method, is part of the small libcuckoo library (Version 1.0). It uses a fine grained locking approach presented by Li et al. [17] to ensure consistency. Cuckoo is mentionable for their interesting interface, which combines easy container style access with an update routine similar to our update interface.

RCU ×/RCU QSBR × This hash table is part of the Userspace RCU library (Version 0.8.7) [29], that brings the read copy update principle to userspace applications. Read copy update is a set of protocols for concurrent programming, that are popular in the Linux kernel community [22]. The hash table uses split-ordered lists to grow in a lockfree manner. This approach has been proposed by Shalev and Shavit [33].

RCU uses the recommended read-copy-update variant called urcu. RCU QSBR uses a QSBR based protocol that is comparable to the one used by junction hash tables. It forces the user to repeatedly call a function with each participating thread. We tested both variants, but in many plots we show only RCU \times because both variants behaved very similarly in our tests.

8.1.3 Non-Growing Hash Tables

One of the most important subjects of this publication is offering a scalable asynchronous migration for the simple folklore hash table. While this makes it usable in circumstances where bounded tables cannot be used, we want to show that even when no growing is necessary we can compete against bounded hash tables. Therefore, it is reasonable to use our growing hash table even in applications where the number of elements can be bounded in a reasonable manner, offering a graceful degradation in edge cases and allowing improved memory usage if the bound is not reached.

Folklore • Our implementation of the folklore solution described in Section 4. Notice that this hash table is the core of our growing variants. Therefore, we can immediately determine the overhead that the ability for growing places on this implementation (Overhead for approximate counting and shared pointers).

Phase Concurrent ♦ This hash table implementation proposed by Shun and Blelloch [34] is designed to support only phase concurrent accesses, i.e. no reads can occur concurrently with writes. We tested this table anyway, because several of our test instances satisfy this constraint and it showed promising running times.

Hopscotch Hash ▲ Hopscotch hashing (ver 2.0) is one of the more popular variants of open addressing. The version we tested, was published by Herlihy et al. [13] connected to their original publication proposing the technique. Interestingly, the provided implementation only implements the functionality of a hash set (unable to retrieve/update stored data). Therefore, we had to adapt some tests to account for that (insert≅put and find≅contains).

LeaHash ▼ This hash table is designed by Lea [16] as part of Java's Concurrency Package. We have obtained a C++ implementation which was published together with the hopscotch table. It was previously used during for experiments by Herlihy et al. [13] and Shun and Blelloch [34]. LeaHash uses hashing with chaining and the implementation that we use has the same hash set interface as hopscotch.

As previously described, we used hash set implementations for Hopscotch hashing, as well as Lea-Hash (they were published like this). They should easily be convertible into common hash map implementations, without loosing too much performance, but probably using quite a bit more memory.

8.1.4 Sequential Variants

To report absolute speedup numbers, we implemented sequential variants of growing and fixed size tables. They do not use any atomic instructions or similar slowdowns. They outperform popular choices like google's dense hash map significantly (80% increased insert throughput), making them a reasonable approximation for the optimal sequential performance.

8.1.5 Color/Marker Choice

For practicality reasons, we chose not to print a legend with all of our figures. Instead, we use this section to explain the color and marker choices for our plots (see Section 8.1 and Table 1), hopefully making them more readable.

Some of the tested hash tables are part of the same library. In these cases, we use the same marker, for all hash tables within that library. The different variants of the hash table are then differentiated using the line color (and filling of the marker).

For our own tables, we mostly use \blacksquare and \blacksquare for uaGrow and usGrow respectively.

8.2 Hardware Overview

Most of our Experiments were run on a two socket machine, with Intel Xeon E5-2670 v3 processors (previously codenamed Haswell-EP). Each processor has 12 cores running at 2.3 Ghz base frequency. The two sockets are connected by two Intel QPI-links. Distributed to the two sockets there are 128 GB of main memory (64 GB each). The processors support Intel Hyper-Threading, AVX2, and TSX technologies.

This system runs a Ubuntu distribution with the kernel number 3.13.0-91-generic. We compiled all our tests with gcc 5.2.0 – using optimization level –03 and the necessary compiler flags (e.g. -mcx16, -msse4.2 among others).

Additionally we executed some experiments on a 32-core 4-socket Intel Xeon E5-4640 (SandyBridge-EP) machine, with 512 GB main memory (using the same operating system and compiler), to verify our findings, and show improved scalability even on 4-socket machines.

8.3 Test Methodology

Each test measures the time it takes, to execute 10^8 hash table operations (*strong scaling*). Each data point was computed by taking the average, of five separate execution times. Different tests use different hash table operations and key distributions. The used keys are pre-computed before the benchmark is started. Each speedup given in this section is computed as the *absolute speedup* over our hand-optimized sequential hash table.

The work is distributed between threads dynamically. While there is work to do, threads reserve blocks of 4096 operations to execute (using an atomic counter). This ensures a minimal amount of work imbalance, making the measurements less prone to variance.

Two executions of the same test will always use the same input keys. Most experiments are performed with uniformly random generated keys (using the Mersenne twister random number generator [20]). Since real world inputs may have recurring elements, there can be contention which can potentially lead to performance issues. To test hash

Table 1: Overview over Table Functionalities.

| name | \mathbf{plot} | std. interface | growing | atomic updates | deletion | arbitrary types |
|-----------|-----------------|-----------------|--------------|----------------|--------------|-----------------|
| xyGrow | | | | | | |
| uaGrow | | using handles | \checkmark | \checkmark | ✓ | |
| usGrow | | ,, | \checkmark | \checkmark | ✓ | |
| paGrow | | ,, | \checkmark | \checkmark | \checkmark | |
| psGrow | | " | \checkmark | \checkmark | \checkmark | |
| Junction | | | | | | |
| linear | • | qsbr function | \checkmark | only overwrite | ✓ | |
| grampa | \bigcirc | ,, | ✓ | " | \checkmark | |
| leapfrog | | ,, | \checkmark | " | \checkmark | |
| TBB | | | | | | |
| hash map | * | ✓ | \checkmark | \checkmark | \checkmark | \checkmark |
| unordered | * | ✓ | ✓ | \checkmark | unsafe | \checkmark |
| Folly | + | √ | const factor | ✓ | | |
| Cuckoo | 人 | ✓ | slow | \checkmark | \checkmark | \checkmark |
| RCU | | | | | | |
| urcu | × | register thread | very slow | \checkmark | \checkmark | \checkmark |
| qsbr | \times | qsbr function | " | \checkmark | \checkmark | \checkmark |
| Folklore | • | ✓ | | ✓ | | |
| Phase | ♦ | sync phases | | only overwrite | \checkmark | |
| Hopscotch | A | ✓ | | set interface | \checkmark | |
| Lea Hash | • | ✓ | | set interface | \checkmark | |

table performance under contention, we use Zipf's distribution to create skewed key sequences. Using the Zipf distribution, the probability for any given key k is $P(k) = \frac{1}{k^s \cdot H_{N,s}}$, where $H_{N,s}$ is the N-th generalized harmonic number $\sum_{k=1}^N \frac{1}{k^s}$ (normalization factor) and N is the universe size $(N=10^8)$. The exponent s can be altered to regulate the contention. We use the Zipf distribution, because it closely models some real world inputs like natural language, natural size distributions (e.g. of firms or internet pages), and even user behavior ([2], [4], [1]). Notice that key generation is done prior to the benchmark execution as to not influence the measurements unnecessarily (this is especially necessary, for skewed inputs).

As a hash function, we use two CRC32C x86 instructions with different seeds, to generate the upper and lower 32 bits of each hash value. Their hardware implementation minimizes the computational overhead.

8.4 Experiments

The most basic functionality of each hash table is inserting and finding elements. The performance of

many parallel algorithms depends on the scalability of parallel insertions and finds. Therefore, we begin our experiments with a thorough investigation into the scalability of these basic hash table operations.

Insert Performance We begin with the very basic test of inserting 10⁸ different uniformly random keys, into a previously empty hash table. For this first test, all hash tables have been initialized to the final size making growing unnecessary. The results presented in Figure 2a show clearly, that the folklore ◆ solution is optimal in this case. Since there is no migration necessary, and the table can be initialized large enough, such that long search distances become very improbable. The large discrepancy between the folklore ◆ solution, and all previous growable hash tables is what motivated us, to work with growable hash tables in the first place. As shown in the plot, our growing hash table uaGrow ■ looses about 10% of performance over folklore \bullet (9.6× Speedup vs. 8.7×). This performance loss can be explained with some overheads that are necessary for eventually growing the table (e.g. estimating the number of elements). All hash tables that have a reasonable performance (> 50%

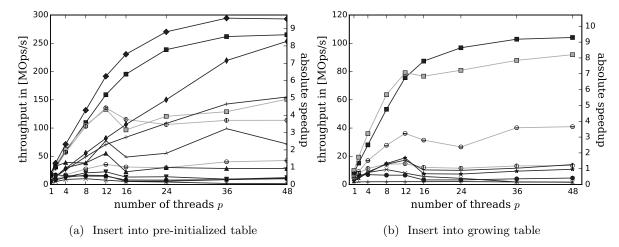


Figure 2: Throughput while inserting 10⁸ elements into a previously empty table (Legend see Table 1).

of folklore \blacklozenge performance), are variants of open addressing (junction leapfrog $\mathbb O$ 4.4 at p=12, folly + 5.1, phase \blacklozenge 8.3) that have similar restrictions on key and value types. All hash tables that can handle generic data types are severely outclassed (\bigstar , \bigstar , \curlywedge , \times , and \times).

After this introductory experiment, we take a look at the growing capability of each table. We again insert 10^8 elements into a previously empty table. This time, the table has only been initialized, to hold 4092 elements $(5 \cdot 10^7)$ for all semi growing tables). We can clearly see from the plots in Figure 2b, that our hash table variants are significantly faster than any comparable tables. The difference becomes especially obvious once two sockets are used (> 12 cores). With more than one socket, none of our competitors could achieve any significant speedups. On the contrary, many tables become slower when executed on more cores. This effect, does not happen for our table.

The speedup in this growing instance is even better than the speedup in our non-growing tests. Overall we reach absolute speedups of $> 9 \times$ compared to the sequential version (also with growing). This is slightly better then the absolute speedup in the non-growing test (≈ 8.5), suggesting that our migration is at least as scalable as hash table accesses. Overall the insert performance of our implementation behaves as one would have hoped. It performs similar to folklore \spadesuit in the non-growing case, while performing similarly well in tests where growing is necessary.

Find Performance When looking for a key in a hash table there are two possible outcomes, either it is in the table or it is not. For most hash tables not finding an element takes longer than finding said element. Therefore, we present two distinct measurements for both cases Figure 3a and Figure 3b. The measurement for successful finds has been made by looking for 10^8 elements, that have previously been inserted into a hash table. For the unsuccessful measurement, 10^8 uniformly random keys are searched in this same hash table.

All the measurements made for these plots were done on a preinitialized table (preinitialized before insertion). This does not make a difference for our implementation, but it has an influence on some of our competitors. All tables that grow by allocating additional tables (namely cuckoo \bot and folly +) have significantly worse find performance on a

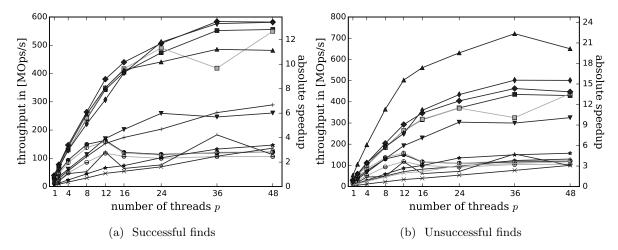


Figure 3: Performance and scalability calling 10^8 unique find operations, on a table, containing 10^8 unique keys (Legend see Table 1).

grown table, as they can have multiple active tables at the same time (all of them have to be checked).

Obviously, find workloads achieve bigger throughputs than insert heavy workloads – no memory is changed and no coordination is necessary between processors (i.e. atomic operations). It is interesting that find operations seem to scale better with multiple processors. Here, our growable implementations achieve speedups of 12.8 compared to 9 in the insertion case.

When comparing the find performance between different tables, we can see that other implementations with open addressing narrow the gap towards our implementation. Especially, the hopscotch hashing \blacktriangle and the phase concurrent approach \blacklozenge seem to perform well when finding elements. Hopscotch hashing \blacktriangle performs especially well in the unsuccessful case, here it outperforms all other hash tables, by a significant margin. However, this has to be taken with a grain of salt, because the tested implementation only offers the functionality of a hash set (contains instead of find). Therefore, less memory is needed per element and more elements can be hashed into one cache line, making lookups significantly more cache efficient.

For our hash tables, the performance reduction between successful and unsuccessful finds is around 20 to $23\,\%$ The difference of absolute speedups between both cases is relatively small – suggesting that sequential hash tables suffer from the same

performance penalties. The biggest difference has been measured for folly + (51 to 55% reduced performance). Later we see that the reason for this is likely that folly + is configured to use only relatively little memory (see Figure 10). When initialized with more memory, its performance gets closer to the performance of other hash tables using open addressing.

Performance under Contention Up to this point, all data sets we looked at contained uniformly random keys sampled from the whole key space. This is not necessarily the case in real world data sets. For some data sets one keys might appear many times. In some sets one key might even dominate the input. Access to this key's element can slow down the global progress significantly, especially if hash table operations use (fine grained) locking, to protect hash table accesses.

To benchmark the robustness of the compared hash tables on these degenerated inputs, we construct the following test setup. Before the execution, we compute a sequence of skewed keys using the Zipf distribution described in Section 8.3 (10^8 keys from the range $1..10^8$). Then the table is filled with all keys from the same range $1..10^8$.

For the first benchmark we execute an update operation for each key of the skewed key sequence, overwriting its previously stored element (Figure 4a). These update operations will create

contending write accesses to the hash table. Note that updates perform simple overwrites, i.e., the resulting value of the element is not dependent on the previous value. The hash table will remain at a constant size for the whole execution, making it easy to compare different implementations independent of effects introduced through growing. In the second benchmark, we execute find operations instead of updates, thus creating contending read accesses.

For sequential hash tables, contention on some elements can have very positive effects. When one cell is visited repeatedly, its contents will be cached and future accesses will be faster. The sequential performance is shown in our figures using a dashed black line. For concurrent hash tables, contention has very different effects.

Unsurprisingly, the effects experienced from contention are different between writing and reading operations. The reason is that multiple threads can read the same value simultaneously, but only one thread at a time can change a value (on current CPU architecture). Therefore, read accesses can profit from cache effects – much like a sequential hash table, while write accesses are hindered by the contention. This goes so far, that for workloads with high contention no concurrent hash table can achieve the performance of a sequential table.

Appart from slowdown because of exclusive write accesses, there is also the additional problem of cache invalidation. When a value is repeatedly changed by different cores of a multi-socket architecture, then cached copies have to be invalidated whenever this value is changed. This leads to bad cache efficiency and also to high traffic on QPI Links (connections between sockets).

From the update measurement shown in Figure 4a it is clearly visible, that the serious impact through contention begins between s=0.85 and 0.95. Up until that point contention has a positive effect even on update operations. For a skew between s=0.85 and 0.95, about 1% to 3% of all accesses go to the most common element (key k_1). This is exactly the point where $1/p \approx P(k_1)$, therefore, on average there will be one thread changing the value of k_1 .

It is noteworthy that the usGrow ■ version of our hash table is more efficient when updating than the uaGrow ■ version. The reason for this is that usGrow uses 128 bit CAS operations to update elements while simultaneously making sure, that the

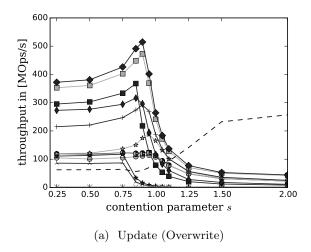
marked bit of the element has not been set before the change. This can be avoided using the usGrow variant by specializing the update method to use atomic operations on the data part of the element. This is possible because updates and grow routines cannot overlap in this variant.

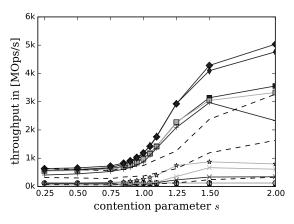
The plot in Figure 4b shows that concurrent hash tables achieve performance improvements similar to sequential ones when repeatedly accessing the same elements. Our hash table can even increase its speedups over uniform access patterns, the highest speedup of uaGrow \blacksquare is 17.9 at s=1.25. Since the speedup is this high, we also included scaled plots showing $5\times$ and $10\times$ the throughput of the sequential variant. Unfortunately, our growable variants cannot improve as much, with contention as the non-growing folklore \spadesuit and phase concurrent \spadesuit tables (both 23.2 at s=1.25). This is probably due to minor overheads compared to the folklore \spadesuit implementation which get pronounced since the overall function execution time is reduced.

Overall, we see that our folklore ◆ implementation which our growable variants are based upon, outperforms all other competitors. Our growable variant usGrow ■ is consistently close to folklore's performance – outperforming all hash tables that have the ability to grow.

Aggregation – a common Use Case Hash tables are often used for key aggregation. The idea is that all data elements connected to the same key are aggregated using a commutative and associative function. For our test, we implemented a simple key count program. To implement the key count routine with a concurrent hash table, an insert-or-increment function is necessary. For some tables, we were not able to implement an update function, where the resulting value depends on the previous value, within the given interface (junction tables, rcu tables, phase concurrent, hopscotch, and leahash). This was mainly a problem of the used interfaces, therefore, it could probably be solved by reimplementing a more functional interface. For our table this can easily be achieved with the insertOrUpdate interface using an increment as update function (see Section 4).

The aggregation benchmark uses the same Zipf key distribution as the other contention tests. For 10^8 skewed keys, the insert-or-increment function





(b) Successful Finds $(1\times, 5\times \text{ and } 10\times \text{ seq.})$

Figure 4: Throughput executing 10⁸ operations using a varying amount of skew in the key sequence (all keys were previously inserted; using 48 threads; Legend see Table 1). The sequential performance is indicated using dashed lines.

is called. Contrary to the previous contention test, there is no pre-initialization. Therefore, the number of distinct elements in the hash table is dependent on the contention of the key sequence (given by s). This makes growable hash tables even more desirable, because the final size can only be guessed before the execution.

Like in previous tests, we make two distinct measurements. One with growing (Figure 5a) and one without (Figure 5b). In the test without growing, we initialize the table with a size of 10⁸ to ensure that there is enough room for all keys, even if they are distinct. We excluded the semi-growing tables from Figure 5b as approximating the number of unique keys can be difficult. To set the growing performance into relation, we show some non-growing tests. Growing actually costs less in the presence of contentious updates, because the resulting table will be smaller than without contention, therefore, fewer growing steps can be amortized over the same number of operations.

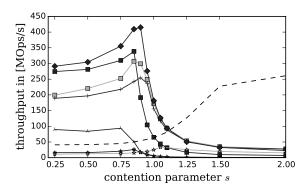
The result of this measurement is clearly related to the result of the contentious overwrite test shown in Figure 4a. However, changing a value by increment has some slight differences to overwriting it, since the updated value of an insert-or-increment is dependent on its previous value. In the best case, this increment can be implemented using an atomic fetch-and-add operation (i.e. usGrow \blacksquare , folklore \spadesuit ,

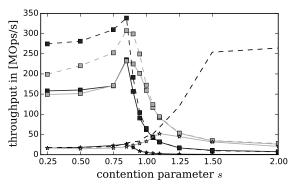
and folly +). However this is not possible for in all hash tables, sometimes dependent updates are implemented using a read-modify-CAS cycle (i.e. uaGrow \blacksquare) or fine grained locking (i.e. tbb hash map \bigstar or cuckoo \curlywedge).

Until s=0.85, ua
Grow \blacksquare seems to be the more efficient option, since it has an increased writing performance and the update cycle will be successful most of the time. From that point on, us
Grow \blacksquare is clearly more efficient because fetch-and-add behaves better under contention. For highly skewed workloads, it comes really close to the performance of our folklore implementation \spadesuit which again performs the best out of all implementations.

Deletion Tests As described in Section 5.4, we use migration, not only to implement an efficiently growing hash table, but also to clean up the table after deletions. This way all tombstones are removed, and thus freed cells are reclaimed. But how does this fare against different ways of removing elements. This is what we investigate with the following benchmark.

The test starts on a prefilled table (10^7 elements) and consists of 10^8 insertions – each immediately followed by a deletion. Therefore, the table remains at approximately the same size throughout the test ($\pm p$ elements). All keys used in the test are generated before the benchmark execution (uniform dis-





- (a) Aggregation using a pre-initialized size of 10^8 (\Rightarrow size = |operations|).
- (b) Aggregation with growing. Dashed plots (\blacksquare and \blacksquare) indicate non-growing performance.

Figure 5: Throughput of an aggregation executing 10^8 insert-or-increment operations using skewed key distributions (using 48 threads; Legend see Table 1). The dashed black line indicates sequential performance. Some tables are not shown because their interface does not support insert-or-increment in a convenient way.

tribution). As described in Section 8.3, all keys are stored in one array. Each insert uses an entry from this array distributed in blocks of 4096 from the beginning. The corresponding deletion uses the key that is 10^7 elements prior to the corresponding insert. The keys stored within the hash table are contained in a sliding window of the key array.

We constructed the test to keep a constant table size, because this allows us to test non-growing tables without significantly overestimating the necessary capacity. All hash tables are initialized with 1.5×10^7 capacity, therefore, it is necessary to reclaim deleted cells to successfully execute the benchmark.

The measurements shown in Figure 6 indicate, that only the phase concurrent hash table ♠ by Shun and Blelloch [34] can outperform our table. The reason for this is pretty simple. Their table performs linear probing comparable to our technique, but it does not use any tombstones for deletion. Instead, deleted cells are reclaimed immediately (possibly moving elements). This is only possible, because the table does not allow concurrent lookup operations, thus, removing the possibility for the so called ABA problem (a lookup of an element while it is deleted returns wrong data, if there is also a concurrent insert into the newly freed cell).

From all remaining hash tables that support fully concurrent access, ours is clearly the fastest, even though there are other hash tables like cuckoo \land

and hopscotch \blacktriangle that also get around full table migrations.

Mixed Insertions and Finds It can be argued that some of our tests are just micro-benchmarks which are not representative of real world workloads that often mix insertions with lookups. To address these concerns, we want to show that mixed function workloads (i. e. combined find and insert workloads) behave similarly.

As in previous tests, we generate a key sequence for our test. Each key of this sequence is used for an insert or a find operation. Overall, we generate 10^8 keys for our benchmark. For each key, insert or find is chosen at random according to the write percentage wp. In addition to the keys used in the benchmark, we generate a small number of keys $(pre=8192 \cdot p=2 \text{ blocks} \cdot p)$ that are inserted prior to the benchmark. This ensures that the table is not empty and there are keys that can be found with lookups.

The keys used for insertions are drawn uniformly from the key space. Our goal for find keys is to preconstruct the find keys in a way that makes find operations successful and is also fair to all data structures. If all find operations were executed to the pre-inserted keys then linear probing hash tables would have an unfair advantage, because elements that are inserted early have very short probing dis-

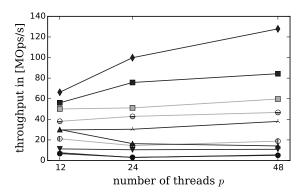


Figure 6: Throughput in a test using deletion. Some tables have been left out of this test, because they do not support deletion with memory reclamation (Legend see Table 1). By alternating between insertions and deletions, we keep the number of elements in the table at approximately 10^7 elements. For the purpose of computing the throughput, 10^8 such alternations are executed, each counting as one operation (1 Op = insert + delete).

tances, while later elements can take much longer to find. Therefore any find will look for a random key, that is inserted at least $8192 \cdot p$ elements earlier in the key sequence. This key is usually already in the table when the find operation is called. Looking for a random inserted element is representative of the overall distribution of probing distances in the table.

Notice that this method does not strictly ensure that all search keys are already inserted. In our practical tests we found, that the number of keys which were not found was negligible for performance purposes (usually below 1000).

Comparable to previous tests, we test all hash tables with and without the necessity to grow the table. In the non-growing test the size of each table is pre-initialized to be $c = pre + (wp \cdot 10^8)$. In the growing tests semi-growing hash tables are initialized with half that capacity.

Similar to previous tests it, is obvious that our non-growing linear probing hash table folklore \bullet outperforms most other tables especially on find-heavy workloads. Overall, our hash tables behave similar to the sequential solution with a constant speedup around a factor of $10\times$. Interestingly, the running time does not seem to be a linear function (over wp). Instead, performance decreases super-

linearly. One reason for this could be that for find-heavy workloads, the table remains relatively small for most of the execution. Therefore, cache effects and similar influences could play a role, since lookups only look for a small sample of elements that is already in the table.

Using Dedicated Growing Threads In Section 5.3.2 and 7 we describe the possibility, to use a pool of dedicated migration threads which grow the table cooperatively. Usually the performance of this method does not differ greatly from the performance of the enslavement variant used throughout our testing. This can be seen in Figure 8. Therefore, we omitted these variants from most plots.

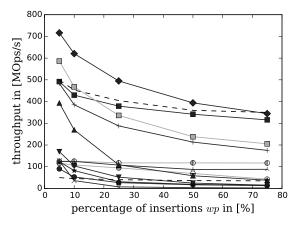
In Figure 8a one can clearly see the similarities between the the variants using a thread pool and their counterparts (uaGrow $\blacksquare \cong paGrow \blacksquare$ and usGrow $\blacksquare \cong psGrow \blacksquare$). The biggest consistent difference we found between the two options has been measured during the deletion benchmark in Figure 8b. During this benchmark, insert and delete are called alternately. This keeps the actual table size constant. For our implementation, this means that there are frequent migrations on a relatively small table size. This is difficult when using additional migration threads, since the threads have to be awoken regularly, introducing some operating system overhead (scheduling and notification).

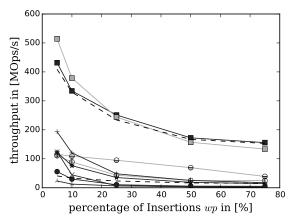
Using Intel TSX Technology As described in Section 6, concurrent linear probing hash tables can be implemented using Intel TSX technology to reduce the number of atomic operations. Figure 9 shows some of the results using this approach.

The implementation used in these tests changes only the operations within our bounded hash table (folklore) to use TSX-transactions. Atomic fallback implementations are used, when a transaction fails. We also instantiated our growing hash table variants, to use the TSX-optimized table as underlying hash table implementation.

We tested this variant with a uniform insert workload (see "Insert Performance"), because the lookup implementation does not actually need a transaction. We also show the non-TSX variant, using dashed lines, to indicate the relative performance benefits.

In Figure 9a one can clearly see that TSX-





- (a) Mixed insertions and finds on a pre-initialized table $(wp \cdot 10^8 + pre)$.
- (b) Mixed insertions and finds on a growing table.

Figure 7: Executing 10^8 operations mixed between insertions and finds (using 48 threads; Legend see Table 1). Dashed lines indicate sequential performance ($1 \times$ and $10 \times$). Find keys are generated in a fair way, that ensures that most find operations are successful.

optimized hash tables offer improved performance as long, as growing is not necessary. Unfortunately, Figure 9b paints a different picture for instances where growing is necessary. While TSX can be used to improve the usGrow wariant of our hash table especially when using hyperthreading, it offers no performance benefits in the uaGrow variant. The reason for this is that the running time in these measurements is dominated by the table migration which is not optimized for TSX-transactions.

In theory, the migration algorithm can make use of transactions similarly to single operations. It would be interesting whether an optimized migration could further improve the growing instances of this test. We have not implemented such a migration, as it introduces the need for some complex parameter optimizations – partitioning the migration into smaller blocks or executing each blockmigration into multiple transactions. We estimate that a well optimized TSX-migration can gain performance increases on the order of those witnessed in the non-growing case.

Memory Consumption One aspect of parallel hash tables, that we did not talk about until now is memory consumption. Overall, a low memory consumption is preferable, but having less cells means that there will be more hash collisions. This

leads to longer running times especially for nonsuccessful find operations.

Most hash tables do not allow the user to set a specific table size directly. Instead they are initialized using the expected number of elements. We use this mechanism to create tables of different sizes. Using these different hash tables with different sizes, we find out how well any one hash table scales when it is given more memory. This is interesting for applications where the hash table speed is more important than its memory footprint (lookups to a small or medium sized hash table within an application's inner loop).

The values presented in the followplot are aquired by initializing ing with different table capacities $(4096, 0.5 \times, 1.0 \times, 1.25 \times, 1.5 \times, 2.0 \times, 2.5 \times, 3.0 \times 10^{8})$ expected elements; semi- and non-growing hash tables start at $0.5\times$ and $1\times$ respectively). During the test, the memory consumption is measured by logging the size of each allocation, and deallocation during the execution (done by replacing allocation methods, e.g. malloc and memalign). Measurements with growing (initial capacity $< 10^8$) are marked with dashed lines. Afterwards the table is filled with 10^8 elements. The plotted measurements show the throughput that can be achieved when doing 10⁸ unsuccessful lookups on

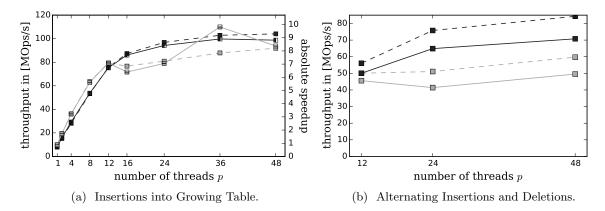


Figure 8: Comparison between our regular implementation and the variant using a dedicated migration thread pool (dashed lines mark variants enslaving user-threads; Legend see Table 1).

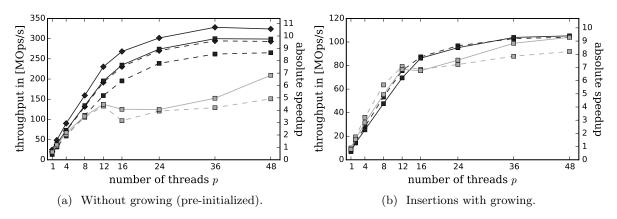


Figure 9: Comparison between our regular implementation and the variant using TSX-transactions in place of atomics (dashed lines are regular variants without TSX).

the preinitialized table. This throughput is plotted over the amount of allocated memory each hash table used.

The minimum size for any hash table should be around $1.53\,\mathrm{GiB}\approx 10^8\cdot(8\,\mathrm{B}+8\,\mathrm{B})$ (Key and Value each have $8\,\mathrm{B}$). Our hash table uses a number of cells equal to the smallest power of 2 that is at least two times as large as the expected number of elements. In this case this means we use $2^{28}\approx 2.7\cdot 10^8$, therefore, the table will be filled to $\approx 37\,\%$ and use exactly 4GiB. We believe that this memory usage is reasonable, especially for heavily accessed tables where the performance is important. This is supported by our measurements as all hash tables that use less memory have bad performance.

Most hash tables round the number of cells in

some convenient way. Therefore, there are often multiple measurement points using the same amount of memory. As expected, using the same amount of memory will usually achieve a comparable performance. Out of the tested hash tables only the folly + hash table grows linearly with the expected final size. It is also the hash table, that gains the most performance by increasing its memory. This makes a lot of sense considering that it uses linear probing and is by default configured to use more than $50\,\%$ of its cells.

The plot also shows that some hash tables do not gain any performance benefits from the increased size. Most notable for this are cuckoo \bot , all variations of junction $\bullet \bullet \bullet \bullet$ and the urcu hash tables \times . The TBB hash tables \bigstar and \bigstar seem to use a con-

stant amount of memory, independently from the preinitialized number of elements. This might be a measurement error, caused by the fact that they use different memory allocation methods (not not logged in our test).

There are also some things that can be learned about growing hash tables from this plot. Our migration technique ensures, that our hash table has the exact same size when growing is required as when it is preinitialized using the same number of elements. Therefore, lookup operations on the grown table take the same time as they would on a preinitialized table. This is not true, for many of our competitors. All Junction tables and RCU produce smaller tables when growing was used, they also suffer from a minor slowdown, when using lookups on these smaller tables. Using Folly is even worse, it produces a bigger table – when growing is needed – and still suffers from significantly worse performance.

Scalability on a 4-Socket Machine Bad performance on multi-socket workloads is recurring theme throughout our testing. This is especially true for some of our competitors where 2-Socket running times are often worse than 1-Socket running times. To further expand the understanding of this problem we made some tests on the 4-Socket machine described in Section 8.2.

The used test instances are generated similar to the insert/find tests described in the beginning of this section (10^8 executed operations with uniformly random keys). The results can be seen in Figure 11a (Insertions) and Figure 11b (unsuccessful finds).

Our competitor's hash tables seem to be a lot more effective when using only one of the four sockets (compared to one of two sockets on the two-socket machine). This is especially true for the Lookup workload where the junction hash tables • start out more efficient than our implementation. However this effect seems to invert once multiple sockets are used.

In the test using lookups, there seems to be a performance problem using our hash table. It seems to scale sub-optimally on one socket. On two sockets however, the hash table seems to scale significantly better.

Overall the four-socket machine reconfirms our

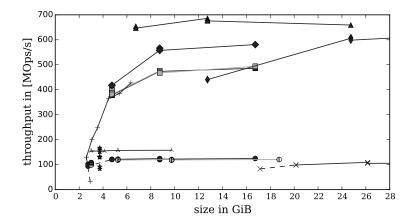
observations. None of our competitors scale well when a growing hash table is used over multiple sockets. On the contrary, using multiple sockets will generally reduce the throughput. This is not the case for our hash table. The efficiency is reduced when using more then two sockets but the absolute throughput at least remains stable.

8.5 The Price of Generality

Having looked at many detailed measurements, let us now try to get a bigger picture by asking which hash table performs well for specific requirements and how much performance has to be sacrificed for additional flexibility. This will give us an intuition, where performance is sacrificed on our way to a fully general hash table. Seeing that all tested hash tables fail to scale linearly on multi-socket machines we try to answer the question if concurrent hash tables are worth their overhead at all.

At the most restricted level – no growing/deletions and word sized key and value types – we have shown that common linear probing hash tables offer the best performance (over a number of operations). Our implementation of this "folklore" solution outperforms different approaches consistently, and performs at least as good as other similar implementations (i.e. the phase concurrent approach). We also showed, that this performance can be improved by using Intel TSX technology. Furthermore, we have shown that our approach to growing hash tables does not affect the performance on known input sizes significantly (preinitialized table to the correct size).

Sticking to fixed data types but allowing dynamic growing, the best data structures are our growing variants ({ua, us, pa, ps}Grow). The difference in our measurements between pool growing (pxGrow) and the corresponding variants with enslavement (uxGrow) are not very big. Growing with marking performs better than globally synchronized growing except for update heavy workloads. The price of growing compared to a fixed size is less than a factor of two for insertions and updates (aggregation) and negligible for find-operations. Moreover, this slowdown is comparable to the slowdown experienced in sequential hash tables when growing is necessary. None of the other data structures that support growing comes even close to our data structures. For insertions and updates we are an or-



(a) Performance of unsuccessful find operations over the size of the data structure.

Figure 10: For these tests 10^8 keys are searched (unsuccessfully) on a hash table containing 10^8 elements. Prior to the setup of the benchmark, the tables were initialized with different sizes (there can be many points on one (x-)coordinate) (Legend see Table 1).

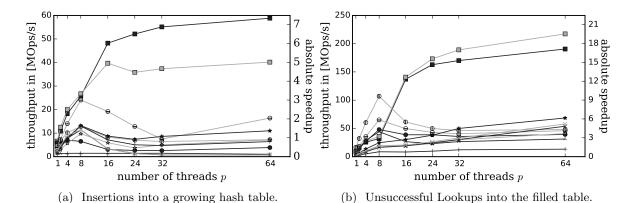


Figure 11: Basic tests made on our 4-Socket machine, consisting of four eight core E5-4640 processors with 2.4 GHz each (codenamed Sandybridge) and 512 GB main memory (Legend see Table 1).

der of magnitude faster then many of our competitors. Furthermore, only one competitor achieves speedups above one when inserting into a growing table (junction grampa).

Among the tested hash tables, only TBB, Cuckoo, and RCU have the ability to store arbitrary key-/value-type combinations. Therefore, using arbitrary data objects with one of these hash tables can be considered to cost at least an order of magnitude in performance (TBB[arbitrary] \leq TBB[word sized] $\approx 1/10 \cdot \text{xyGrow}$). In our opinion, this restricts the use of these data structures to situations where hash table accesses are not a computational bottleneck. For more demanding appli-

cations the only way to go is to get rid of the general data types or the need for concurrent hash tables altogether. We believe that the generalizations we have outlined in Section 5.7 will be able to close this gap. Actual implementations and experiments are therefore interesting future work.

Finally let us consider the situation where we need general data types but no growing. Again, all the competitors are an order of magnitude slower for insertion than our bounded hash tables. The single exception is cuckoo, which is only five times slower for insertion and six times slower for successful reads. However, it severely suffers from contention being an almost record breaking factor of

5 600 slower under find-operations with contention. Again, it seems that better data structures should be possible.

9 Conclusion

We demonstrate that a bounded linear probing hash table specialized to pairs of machine words has much higher performance than currently available general purpose hash tables like Intel TBB, Leahash, or RCU based implementations. This is not surprising from a qualitative point of view given previous publications [36, 14, 34]. However, we found it surprising how big the differences can be in particular in the presence of contention. For example, the simple decision to require a lock for reading can decrease performance by almost four orders of magnitude.

Perhaps our main contribution is to show that integrating an adaptive growing mechanism into that data structure has only a moderate performance penalty. Furthermore, the used migration algorithm can also be used to implement deletions in a way that reclaims freed memory. We also explain how to further generalize the data structure to allowing more general data types.

The next logical steps are to implement these further generalizations efficiently and to integrate them into an easy to use library that hides most of the variants from the user, e.g., using programming techniques like partial template specialization.

Further directions of research could be to look for a practical growable lock-free hash table.

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