IcebergHT: High Performance PMEM Hash Tables Through Stability and Low Associativity

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ABSTRACT

Modern hash table designs strive to minimize space while maximizing speed. The most important factor in speed is the number of cache lines accessed during updates and queries. This is especially important on PMEM, which is slower than DRAM and in which writes are more expensive than reads.

This paper proposes two stronger design objectives: stability and low-associativity. A stable hash table doesn't move items around, and a hash table has low associativity if there are only a few locations where an item can be stored. Low associativity ensures that queries need to examine only a few memory locations, and stability ensures that insertions write to very few cache lines. Stability also simplifies scaling and crash safety.

We present IcebergHT, a fast, crash-safe, concurrent, and space-efficient hash table for PMEM based on the design principles of stability and low associativity. IcebergHT combines in-memory metadata with a new hashing technique, iceberg hashing, that is (1) space efficient, (2) stable, and (3) supports low associativity. In contrast, existing hash-tables either modify numerous cache lines during insertions (e.g. cuckoo hashing), access numerous cache lines during queries (e.g. linear probing), or waste space (e.g. chaining). Moreover, the combination of (1)-(3) yields several emergent benefits: IcebergHT scales better than other hash tables, supports crash-safety, and has excellent performance on PMEM (where writes are particularly expensive).

In our benchmarks, IcebergHT inserts are 50% to $3\times$ faster than state-of-the-art PMEM hash tables Dash and CLHT and queries are 20% to $2\times$ faster. IcebergHT space overhead is 17%, whereas Dash and CLHT have space overheads of $2\times$ and $3\times$, respectively. IcebergHT also exhibits linear scaling and is crash safe. In DRAM, IcebergHT outperforms state-of-the-art hash tables libcuckoo and CLHT by almost $2\times$ on insertions while offering good query throughput and much better space efficiency.

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1 INTRODUCTION

Hash tables are a core data structure in many applications, including key-value stores, databases, and big-data-analysis engines, and are included in most standard libraries. Hash-table performance can be a substantial bottleneck for many applications [14, 31, 36].

With the advent of persistent-memory (PMEM) hardware, such as Intel Optane, designing PMEM hash tables has become an active field of research [6, 10, 18, 21, 26–28, 35, 43, 47, 49]. Optane is cheaper than DRAM, enabling larger data sets, but it is slower, with write bandwidth being roughly $2-5\times$ slower than read bandwidth [19, 45]. Hash tables must be specifically designed for PMEM in order to achieve both high performance and crash safety.

Despite several years of research on PMEM hash tables, state-of-the-art PMEM hash tables such as Dash [26] and CLHT [9] utilize less than 35% of PMEM's raw throughput for at least one of insertions and queries (see Figure 4) Furthermore, Dash and CLHT have space overheads of 2–3× (see Table 3).

In this paper, we introduce a new hash table, **IcebergHT**, that is able to achieve over 60-70% of the PMEM hardware throughput on both insertions and queries, scales easily with additional threads, is crash safe, and has space efficiency of over 85% (i.e. space overhead is less than $1/0.85 \approx 17\%$). IcebergHT also integrates easily with existing PMEM software infrastructure without requiring custom allocators or PMDK implementations, whereas CLHT requires custom support libraries.

The design of PMEM (and other) hash tables typically involves developing a hash table algorithm that minimizes read and write amplification.[1] In this paper, we argue that two stricter criteria, *referential stability* and *low associativity* should be optimized to yield high performance on PMEM. As we will see, these two goals seem to be at odds with each other, and part of the innovation of our hash table design is that it simultaneously achieves both. Naturally, the third design goal for a high-performance hash table is *compactness*, but compactness also seems at odds with referential stability and low associativity.

A hash table is said to be ***stable*** if the position where an element is stored is guaranteed not to change until either the element is

[1] The ***write amplification*** is the amount of data written to PMEM per insert/delete divided by the amount of data inserted/deleted. Similarly, the ***read amplification*** is the amount of data read from PMEM per query divided by the amount of data output by the query.

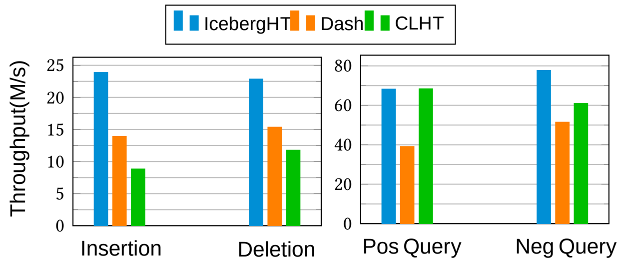


Figure 1: Throughput for insertions, deletions, and queries (positive and negative) using 16 threads for PMEM hash tables. The throughput is computed by inserting $0.95N$ keys-value pairs where N is the initial capacity of the hash table. (Throughput is Million ops/second)

deleted or the table is resized [17, 20, 42]. Stability offers a number of desirable properties. For example, stability enables simpler concurrency-control mechanisms and thus reduces the performance impact of locking. Moreover, since elements are not moved, writing is minimized, which improves PMEM performance.

The ***associativity*** of a hash table is the number of locations where an element is allowed to be stored.[2] The best known low-associative (DRAM) hash table is the cuckoo hash table [37, 38]. In the original design, each element has exactly two locations in the table where it is allowed to be stored, meaning that the associativity is two. Low associativity yields a different set of desirable properties most importantly, it helps search costs. For example, searching for an element in a cuckoo hash table is fast because there are only two locations in the table to check. In addition, low associativity can enable us to further improve query performance by keeping a small amount of metadata; see Section 2.

In combination, stability can be used to achieve high insertion throughput in PMEM, where writes are expensive, and low associativity can be use to achieve high query performance. Furthermore, we also show how stability enables locking and concurrency-control mechanisms to be simplified, leading to better multithreaded scaling and simpler designs for crash consistency.

Unfortunately, there is a tension between stability and low associativity. If a hash table has associativity α and elements cannot move once they are inserted, then an unlucky choice of α locations for α elements can block the $(\alpha + 1)$st element from being inserted. As α decreases, the probability of such an unlucky event increases. Cuckoo hashing reduces the probability of these bad events by giving up stability via ***kickout chains***, which are chains of elements that displace each other from one location to another. Practical implementations [23] generally increase the number of elements that can be stored in a given location and thus the associativity to reduce the kickout-chain length and increase the maximum-allowed ***load factor***, i.e, the ratio of the total number of keys in the table to the overall capacity of the table.

Similarly, there is a three-way tension between space efficiency, associativity, and stability. For example, cuckoo hash tables can be made stable if they are overprovisioned so much that the kickout-chain length reaches 0. Such overprovisioning directly decreases space efficiency, but it also increases associativity. Linear probing hash tables are stable (assuming they use tombstones to implement delete) but, as the load factor approaches 1, the average probe length for queries goes up, increasing associativity. Other open-addressing hash tables have a similar space/associativity trade-off. Chaining hash tables are stable, but they have large associativity and significant space overheads. CLHT [9] improves query performance despite high associativity by storing multiple items in each node, but this further reduces space efficiency.

IcebergHT is based on a new type of hash table, which we call ***iceberg hashing***. Iceberg hash tables are the first to simultaneously achieve low associativity and stability, and they also have small space consumption. To date, hash tables have had to choose between stability (e.g., chaining), low associativity (e.g., cuckoo) or neither (e.g., Robin Hood [1, 5]). The techniques introduced in this paper also have ramifications to the theoretical study of hash tables we present a detailed study of these implications, including closing various theoretical open problems, in a companion manuscript [2]. We describe Iceberg hash tables in Section 2.

Results. In this paper, we introduce Iceberg hashing and its implementation, IcebergHT. We prove that Iceberg hashing simultaneously achieves stability and low associativity. Iceberg hashing is the first hash-table design to achieve both properties. These guarantees give IcebergHT excellent performance on PMEM, as well as on DRAM, and for workloads ranging from read-heavy to write-heavy. Specifically, IcebergHT accesses very few cache lines, both for queries and insertions, has low CPU cost, and has high load factor (and thus small space), with high probability. Stability and low associativity enable simpler concurrency mechanisms, so that IcebergHT achieves nearly linear scaling with the number of threads, and it is crash safe on PMEM.

In building IcebergHT, based on our Iceberg hash table, we offer the following design contributions:

(1) We show how to achieve an efficient, practical metadata scheme that is adapted to practical hardware constraints. The metadata scheme is small enough that the metadata for a bucket fits in a cache line, improving query performance and enabling nearly lock-free concurrency, i.e., locks are needed only for resizing.
(2) A highly concurrent and thread-safe implementation of Iceberg hashing. IcebergHT can scale almost linearly with increasing threads in PMEM, as well as DRAM, experiments.
(3) Fenceless crash safety on PMEM. Achieving crash-safety on PMEM often requires controlling the order in which cache lines get flushed to persistent storage, e.g., to ensure that an undo-log entry gets persisted before the changes to the hash table get persisted. Since insertions in our hash table modify only a single cache line, we can achieve crash safety by simply persisting that cache line.
(4) A simple, high-performance and concurrent technique for efficiently resizing Iceberg hash tables in a lazy online manner, thus reducing the worst-case latency of insertions.

Performance. We evaluated IcebergHT on a system with Intel Optane memory. We find that:

[2] Associativity is often associated with caches that restrict the locations an item may be stored in. Here we refer to *data structural associativity*, which is a restriction on how many locations a data structure may choose from to put an item in, even on fully associative hardware.

(1) **Inserts and deletions:** IcebergHT insertions and deletions are roughly 50% faster than Dash and 2–$3\times$ faster than CLHT.
(2) **Queries:** IcebergHT positive queries are as fast as CLHT and negative queries are about 20% faster. IcebergHT queries are $1.5-2\times$ faster than Dash.
(3) **Space:** IcebergHT achieves a space efficiency of 85%, whereas Dash and CLHT have space efficiencies of 45% and 33%, respectively.
(4) **Scalability:** IcebergHT throughput scales nearly linearly in all our benchmarks. CLHT also scales roughly linearly to 8 threads but scales slightly less efficiently than IcebergHT from 8 to 16 threads. Dash hits a wall at 8 threads in several benchmarks.
(5) **YCSB:** IcebergHT is anywhere from $1\times$ to $8\times$ faster than Dash and CLHT in our YCSB benchmarks.

Although IcebergHT is designed for PMEM, we also compare it to libcuckoo [23], CLHT [9], and TBB [39] in DRAM. We find that IcebergHT outperforms these other state-of-the-art DRAM hash tables on insertions and offers good but not-quite-best query performance. For example, IcebergHT is almost twice as fast as the next fastest hash table on insertions in DRAM, and it nearly matches the fastest hash table on positive queries, but it is only about 75% as fast as the fastest hash table on negative queries and roughly 60% as fast on deletions. We believe this insertion optimization at the cost of queries reflects the fact that IcebergHT is optimized to minimize writes, which are expensive in PMEM, resulting in stellar insertion performance. Thus, IcebergHT is a strong choice for insertion-heavy workloads in DRAM.

Roadmap. In the rest of the paper, we discuss the various hash table designs in and we give an overview of Iceberg hashing and theoretical guarantees Section 2. In Sections 3 to 6, we present our implementation of IcebergHT in DRAM and PMEM. Section 7 evaluates IcebergHT and compares it with other hash tables. We discuss related work in Section 8.

2 ICEBERG HASHING

In this section, we begin by introducing Iceberg Hashing, a new, stable, low-associativity hash-table design. We then give the theoretical basis for Iceberg hashing, proving the theorems that establish its correctness. In subsequent sections, we show how to exploit Iceberg hashing's low associativity to implement an efficient metadata scheme, explain how to make the hashtable concurrent, how to handle resizes, and how to ensure crash safety.

The goal of this section is to establish the theoretical basis for the high performance we demonstrate in Section 7. Of particular note for PMEM is that IcebergHT enables an unmanaged backyard that results in stability, which we will show is important for both high performance and crash safety on PMEM. These theoretical guarantees hold even in the presence of deletes. Previous hash-table designs have weak or no theoretical guarantees in the presence of deletes, e.g., cuckoo hashing. An important technical challenge is to guarantee stability and low associativity, which we simultaneously achieve in a hash table for the first time.

Ave fill $= h$	Max fill $= b$	Space Efficiency $= b/h$
$O(1)$	$O(\log n/\log\log n)$	$\Theta(\log n/\log\log n) \gg \Theta(1)$
$\log n$	$O(\log n)$	$\Theta(1)$
$\gg \log n$	$h + O(\sqrt{h})$	$1 + o(1)$

Table 1: The relationship between the average fill, b, and the maximum fill, h, in a balls-and-bins system is well understood [4, 32].

2.1 From Load Balancing to Iceberg hashing

In this section, we have an overview of the design and design principles of IcebergHT. IcebergHT is a three-level hash table, where most items are hashed into a very efficient first level, some items are hashed into a less efficient second level, and a few residual items are hashed into an overflow third level. The first level is called the ***front yard*** and the second and third levels are called the ***backyard***. In the remainder of the section, we describe how each level is designed, and we give theorems to show that IcebergHT is correct and fast. Interestingly, the bounds in our main theorems are so tight that we are able to make all parameter choices in our implementation based on these theorems, as we describe below.

Consider a one-level hash table (which will correspond to the first level of IcebergHT). One way to design a hash table is to take an array and logically break it into m buckets of size b. As items are inserted, they are hashed to a random bucket and placed in any free spot of the bucket. After inserting n items, the expected number of items in each bucket will be $h = n/m$ and the ***space efficiency*** of the table will be $bm/n = bm/hm = b/h$. Thus, in order to optimize space efficiency, we want to minimize b/h. But b is a function of h, so the choices are not independent, as show in Table 1. Note that in a balls-and-bins game, b is the maximum fill of a bucket, because in our hash table, each bucket must be configured to be big enough to handle all insertions into that bucket.

The second observation is that, by using a backyard, we don't need to get the number of overflows to 0. Specifically, we configure the front yard so that the number of overflows will be $O(n/\text{polylog}(n))$. Then we can use any hash table for the back yard as long as it has $\Theta(1)$ space efficiency. In section 2.2, we show that the overall space efficiency of the hash table will be a remarkable $1 + O(1/\log n)$.

We conclude that h should be somewhat greater than $\log n$, so we set the bucket size to be 64. This bucket size is bigger than a cache line but IcebergHT does not read the whole bucket. Rather it will keep metadata to index the bucket. IcebergHT finds itself in a sweet spot because, as will show below, buckets of size 64 are small enough that the metadata needed to index the items in a bucket fits in a cache line.

A smaller bucket size offers a poorer choice. Smaller buckets would either decrease the space efficiency, by increasing the number of buckets needed to prevent overflows, or increase the number of items that land in the less efficient backyard. On the other hand, a larger bucket size does not decrease overflows but the metadata for bigger buckets no longer fits in a cache line.

2.2 Bounding the Overflows

In this section, we describe the theoretical basis for Iceberg hash tables. The primary theorem we need is a bound on the number of items that will be placed in the backyard.

As before, we have a hash table with a front yard consisting of an array broken into m equal-size buckets. Items are hashed to a single bucket and may be placed in any slot in their bucket if there is no free slot in the bucket, then the item is placed in the *backyard*. The hash table is stable: once inserted, items are not moved until they are deleted.

The following theorem bounds the size of the backyard.

Theorem 1. *Consider a frontyard/backyard hash table that can hold up to n items. Suppose further that the front yard consists of m bins. When an item x arrives, it is hashed uniformly into a bin $H(x)$. If bin $H(x)$ has room, the item is placed into the bin, and if bin $H(x)$ is full, it is placed into the backyard. The capacity of a bin is determined by two parameters: $h \leq n^{1/4}/\sqrt{\log n}$ and $j \leq \sqrt{h}$. Specifically, each bin has capacity $h + j\sqrt{h+1} + 1$. Then at any moment over the course of $poly(m)$ insertion/deletions where the table never has more than n items, the number of balls in the backyard is $O(n/2^{\Omega(j^2)} + n^{3/4}\sqrt{\log n})$ with probability $1 - 1/poly(n)$.*

Proof. For the sake of analysis, partition the bins into $K = \sqrt{n}$ collections $\mathcal{B}_1, \ldots, \mathcal{B}_K$ each of which contains m/K bins. For each time t and bin collection $\mathcal{B}_i$, define $R_{t,i}$ to be the set of balls x that are present at time t and satisfy $H(x) \in \mathcal{B}_i$. By a standard application of Chernoff bounds, we can deduce that, for any fixed i, t we have

$$\begin{aligned} |R_{i,t}| &\leq n/K + O(\sqrt{(\log n) \cdot n/K}) \\ &\leq \sqrt{n} + O(n^{1/4}\sqrt{\log n}) \end{aligned} \quad (1)$$

with high probability in n (i.e., with probability $1 - 1/\text{poly}(n)$). Applying a union bound over all i, t, we find that (1) holds with high probability in n for all i, t simultaneously. Consider any possible outcome R for the sets $\{R_{i,t}\}$, where the only requirement on R is that (1) holds for all i, t; we will show that if we condition on such an R occurring, then the size of the backyard is $O(n/2^{\Omega(j^2)} + n^{3/4}\sqrt{\log n})$ with high probability in n.

Consider some time t, and let X_i be the number of balls that are in the backyard at time t and that satisfy $H(x) \in \mathcal{B}_i$. Observe that the conditional variables $X_1|R, X_2|R, \ldots, X_K|R$ are independent (since R fully determines which x and i satisfy $H(x) \in \mathcal{B}_i$). Thus, if we define

$$X|R := \sum_{i=1}^{K} X_i|R,$$

then $X|R$ is a sum of independent random variables, each of which is (by (1)) deterministically in the range $[0, O(\sqrt{n})]$. We can therefore apply a Chernoff bound to $X|R$ to deduce that

$$\mathbb{P}[X|R \leq \mathbb{E}[X|R] + O(\sqrt{Kn\log n})] \geq 1 - 1/\text{poly}(n),$$

Recalling that $K = \sqrt{n}$, we conclude that $X|R \leq \mathbb{E}[X|R] + O(n^{3/4}\sqrt{\log n})$ with high probability in n.

To complete the proof, it suffices to bound $\mathbb{E}[X|R]$ by $O(n/2^{\Omega(j^2)})$. For this, in turn, it suffices to show that each ball x present at time t (there are up to n such balls) satisfies

$$\mathbb{P}[x \text{ in backyard} \mid R] \leq 1/2^{\Omega(j^2)}. \quad (2)$$

To prove (2), consider a ball x that hashes to some collection $\mathcal{H}_i$. At the previous time $t_0 < t$ that x was inserted, we have by (1) that there were at most $\sqrt{n} + O(n^{1/4}\sqrt{\log n})$ balls present that hashed to $\mathcal{H}_i$ (i.e., balls in the set $R_{i,t_0} \setminus \{x\}$); each of these balls has probability $K/m = K/(n/h) = Kh/n$ of hashing to the same bin as x, meaning that the number Y of balls that hash to the same bin as x at time t_0 satisfies

$$\begin{aligned} \mathbb{E}[Y|R] &\leq \frac{Kh\sqrt{n} + O(Khn^{1/4}\sqrt{\log n})}{n} \\ &= h(1 + \sqrt{\log n}/n^{1/4}) \leq h + 1. \end{aligned}$$

The random variable $Y|R$ is just a sum of (up to) $n^{2/3} + O(n^{1/3}\sqrt{\log n})$ independent indicator random variables (one for each ball in $R_{i,t_0} \setminus \{x\}$). So by a Chernoff bound we have that

$$\mathbb{P}[Y \mid R \geq h + 1 + j\sqrt{h+1}] \leq 2^{-\Omega(j^2)}.$$

This implies (2), which completes the proof. □

The main consequence of this Theorem is that this simple bucketed front-yard design can hold all but $1/\text{poly}(h)$ items, and by design the front yard is also stable. For example, if we set $h = \log n$ and $j = \Omega(\sqrt{\log\log n})$, then $O(n/\log n)$ items will go to the backyard. The choice of $h = \log n$ suggests that the front-yard buckets should be of size 64, which we show in Section 7 provides excellent performance.

2.3 The Backyard

Iceberg hashing allows any of several backyard designs. For IcebergHT, we have selected a hash-table strategy based on the power-of-2-choices. We use power-of-two-choices in order to mitigating the space overhead of the backyard. The potential issue with using a power-of-two-choice hash table is that queries and inserts level 2 must examine two buckets. However, most items reside in the front yard, so most queries need to examine only the front yard, which means that the cost of checking two buckets in level 2 will not substantially impact overall performance.

To analyze the space efficiency and overflow probability of the backyard, let z be the upper bound on the number of overflowing items from Theorem 1. The backyard consists of an array of length $\Theta(z \log\log z)$, divided into z buckets of size $\Theta(\log\log z)$. Items are hashed to two buckets and are placed into a slot in the bucket with fewer items.

The following result of Vöcking provides a theoretical guarantee that the backyard will not overflow.

Theorem 2 ([44]). *Consider an infinite balls-and-bins process with z bins in which at each step a ball is either inserted using the power-of-2-choices algorithm or an existing ball is removed, such that there are at most hz balls present at any given step. Then the maximum load of any given bin is $(\ln\ln z)/\ln 2 + O(h)$.*

For level 2, the average bucket h is less than 1, so Theorem 2 tells us that the number of items that overflow at level 2 is quite small. We store these items in a third level that uses a standard chaining hash table. So few items make it to the third level that performance and space efficiency are negligible. As noted above, Theorem 2 suggests that level 2 buckets should be of size $\ln\ln n$. We use 8 as a coarse upper bound on log log n for all practical purposes.

2.4 Summary

In summary, an Iceberg hash table consists of three levels, as shown in Figure 2. Level 1 is a power-of-one-choice front yard with buckets of size $\log n + O(\sqrt{\log n \log\log n})$, level 2 is a power-of-two-choice

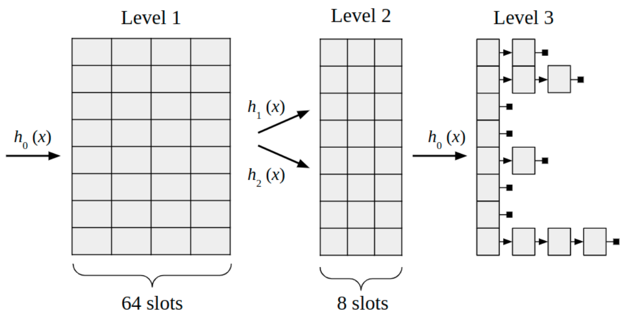


Figure 2: Iceberg hash table block structure. Iceberg table has three levels. To insert a key value pair, we first hash the key h_0(key) and determine a block in level 1. If the block in level 1 is full, we try to insert it in level 2. In level 2, we hash the key twice h_1(key) and h_2(key) and insert the key in the emptier block. If the both blocks are full in level 2 then we insert the key value pair in level 3 block h_0(key). Level 3 contains a tiny fraction of keys (see Table 4) and choice of structure in level 3 does not have an impact on the hash table performance.

table with buckets of size $O(\log \log n)$, and level 3 consists of a simple chaining hash table.

This design offers several benefits:

- Such a table is stable: items never move after they are inserted.
- The number of buckets an item can reside in is only 4 (1 bucket in level 1, 2 in level 2, and 1 in level 3).
- Most queries are satisfied by searching in level 1, so the average number of buckets accesses per query is just over 1.
- The buckets are small, so the associativity of the scheme is $\log n + \log \log n$ (plus level 3, which is rarely used). So we can encode the exact slot of an element using $O(\log \log n)$ bits.

We conclude by noting that IcebergHT offers particular advantages on PMEM. Specifically, it is stable and has low associativity and is backed by strong theoretical guarantees. This results in low read and write amplification, which are desired characteristics to achieve high performance on PMEM. Furthermore, crash safety correctness follows almost directly from stability (see Section 6). The theoretical proofs and algorithmic novelty set up the PMEM-friendly design in the next section and are backed up by strong performance results in Section 7.

3 IMPLEMENTATION

We now describe how we implement metadata scheme and operations in IcebergHT.

3.1 Metadata scheme

This section describes our in-DRAM metadata scheme that enables most queries and inserts to complete by accessing only a single PMEM cache line. Our goal is ambitious: metadata is designed so that (1) metadata for each bucket fits on a single cache line and (2) we can use vector instructions for all metadata operations. Since metadata lives in DRAM, it costs substantially less to access than PMEM. In the event of a crash, we can recompute the metadata during recovery, as explained in Section 6.

One of the impediments to storing key-value pairs in large buckets as in IcebergHT is that large buckets span multiple cache lines. This hurts the cache efficiency, because operations may need to access multiple cache lines per block.

IcebergHT addresses this concern by storing metadata for each block. The metadata for a block of k slots consists of an array of k 8-bit fingerprints, one per slot. If the slot holds a valid key, the corresponding fingerprint is a hash of the key, otherwise the metadata entry holds a special EMPTY fingerprint. Note that we do not reserve an entire bit to indicate empty/non-empty we reserve a single fingerprint value so there are 255 valid fingerprints.

The metadata scheme thus has a space overhead of 6.25% for a 16 byte key-value pair. For smaller key-value pairs, the space overhead of the metadata may be higher (e.g. 25% for 4-byte key-value pairs) but, as we will see in the evaluation section, many other PMEM hash tables have much higher space overeheads. Importantly, because the blocks in level 1 have 64 slots and the blocks in level 2 have 8 slots, the metadata for each block fits in a single cache line.

During an insert operation, probing the metadata corresponding to a block indicates which slots are empty in the block. The insert can then try to insert the new key into one of those empty slots.

During a query operation, the fingerprint of the queried key can be checked against the fingerprints in the metadata, yielding only those slots with a matching fingerprint. This filters out empty slots as well as nearly all slots with non-matching keys.

The metadata is also used to quickly compute the load in each block by counting the number of occupied slots in the metadata block.

All of these operations can be implemented using vector instructions. For example, to search for a fingerprint x in a metadata vector v, we use vector broadcast to construct a new vector q where each entry equals x and then perform a vector comparison of v and q. To find an empty slot, we do the same, except we set x to EMPTY. To count the occupancy of a bucket, we perform the search algorithm for EMPTY, which yields a bit-vector of matching entries, and then use popcount to get the number of empty slots.

Note that we do not use 2 bits for EMPTY and RESERVED. Rather, these are two values out of 2^8 (256) values. Therefore, the fingerprints support 254 values and the chance of collision is $1/254$.

3.2 Operations

Here we explain how to perform single-threaded operations in IcebergHT. Later in Section 5, we explain how to make these operations thread-safe.

Inserts. Our algorithm first searches whether k already exists and, if so, updates its associated value. For space, we omit the code for replacing an existing item and show only the code for inserting a new item.

We first try to insert the key-value pair in level 1. We hash the key using h_0 to determine a block in level 1. If there is an empty slot in the block then we insert the key-value pair and store the fingerprint in the corresponding slot in the level 1 metadata. See the pseudocode in Algorithm 1.

If the block in level 1 is full, then we try to insert the key in level 2. In level 2, we use power-of-two-choice hashing to determine the block. We hash the key twice and pick the emptier block. Similar to level 1, if there is an empty slot in one of the blocks then we insert

Algorithm 1 Insert (k, v)

```
idx ← h_0(k)                                  ▷ Compute the block index in level 1
fp ← F(k)                                     ▷ Compute the fingerprint for key
Lock(lv1_metadata[idx])
if ReplaceExisting(k, v) then
    Unlock(lv1_metadata[idx])
    return False
end if
mask ← Metadata_Mask(lv1_metadata[idx], EMPTY)   ▷ mask is a bit-vector identifies empty slots in the block
count ← popcount(mask)                        ▷ Compute the number of empty slots
if 0 < popcount(mask) then
    i ← 0
    slot ← Select(mask, 0)                    ▷ Compute the index of the first empty slot
    lv1_block[idx][slot] ← (k, v)             ▷ Store(k, v) using 128-bit atomic store
    lv1_metadata[idx][slot] ← fp
else
    insert_lv2(k, v, idx)                     ▷ Level 1 block is full. Try level 2
end if
Unlock(lv1_metadata[idx])
return True
```

Algorithm 2 Insert level2 (k, v)

```
procedure insert_lv2(k, v, idx)
    idx1 ← h_1(k)       ▷ Compute primary and secondary block indexes in level 2
    idx2 ← h_2(k)
    fp1 ← F_1(k)        ▷ Compute primary and secondary fingerprints for the key
    fp2 ← F_2(k)

    mask1 ← Metadata_Mask(lv2_metadata[idx1], EMPTY)   ▷ Compute a vector identifying empty slots in primary and secondary blocks
    mask2 ← Metadata_Mask(lv2_metadata[idx2], EMPTY)
    count1 ← popcount(mask1)   ▷ Compute the number of empty slots in primary and secondary blocks
    count2 ← popcount(mask2)

    if count2 < count1 then
        idx1 ← idx2
        fp1 ← fp2
        mask1 ← mask2
        count1 ← count2
    end if
    i ← 0
    while i < count1 do
        slot ← Select(mask1, i)   ▷ Compute the index of the next empty slot
        if atomic_cas(lv2_metadata[idx1][slot], EMPTY, fp1) then   ▷ Atomically set the metadata slot before updating the table
            lv2_block[idx1][slot] ← (k, v)   ▷ Store(k, v) using 128-bit atomic store
            return
        end if
        i ← i + 1
    end while
    insert_lv3(k, v, idx)   ▷ Level 2 block is full. Try level 3
end procedure
```

the key-value pair and store the fingerprint in the corresponding slot in the level 2 metadata. See the pseudocode in Algorithm 2.

Finally, if both the blocks in level 2 are full, then we insert the key in level 3. We use the hash function from level 1 (h_0) to determine the linked list to insert the key-value pair and insert at the head of the linked list.

Queries. Similar to the insert operations, we perform queries starting from level 1 and moving to levels 2 and 3 if we do not find the key in the previous level.

During a query, we determine the block in a level in the same way as we do during the insert. In level 1 and 3, there is only one block to check and we use use hash function h_0 to determine the block. In level 2, the key can be present in either of the primary or the secondary block. Therefore, we also perform a check in the secondary block if the key is not found in the primary block.

Once we determine the block, we then perform a quick check to see if the fingerprint of the queried key is present in the metadata of the block. Checking the fingerprint requires a single memory access as all the fingerprints in a given block fit inside a cache line. If the fingerprint is not found in the metadata of the block then we can terminate the query at that level and move to the next level. Otherwise, if one or more fingerprint matches are found in the metadata of the block we then perform a complete key match in the table for all possible matches and return a pointer to the value if a key match is found.

If we are in level 3 during a query, we perform a linear search through the linked list to find the key. However, buckets in level 3 are almost always empty (<<1% please refer to Table 4) and therefore we rarely have to perform the linear search through the linked list.

Deletions. Deletions are performed similarly to queries. We first look for the key starting from level 1 and then proceed to levels 2 and 3 if the key is not yet found. Once the key is found, we first reset the corresponding fingerprint in the metadata and then reset the key-value pair slot in the table.

The pseudo-code for the query and remove operations follow the similar approach as the insert operation pseudo-code. Therefore, they are omitted from the paper to avoid redundancy.

4 RESIZING

This section describes how we resize the IcebergHT hash table when it reaches full capacity.

The three levels of the IcebergHT hash table (see Section 2) can be resized independently of each other. We invoke a resize when the load factor of the hash table reaches a predefined threshold, which in IcebergHT has the default of 85%.

In IcebergHT, we perform an in-place resize. In the in-place resize, we do not allocate a separate table of twice the current size and move existing keys over to the new table. Instead we use *mremap*[3] to remap the existing table space to twice the size. To resize a given level, we first remap the level to twice the number of current blocks. The size of each block remains the same (64 slots in level 1 and 8 slots in level 2) across resizes. This means that during a resize, the space overhead of the table will be a max $2\times$ instead of $3\times$ if we allocate a separate table of twice the size.

Doing in-place resize means that only about half the existing keys (rather than all) need to be moved to a new location because each item x's bucket is computed as $h(x) \bmod m$, where m is the number of buckets in the table. We move each key-value pair by first inserting it into its new block (in the same level) and then deleting it from its old block.

The shrink can be performed in the similar way as the doubling. The keys from the second half of the table can be moved to the first half by rehashing the keys. Once the move is complete, the second half of the table can be freed.

[3] mremap() expands (or shrinks) an existing memory mapping [34]).

4.1 Guaranteeing Balanced Levels After Resizing

In this subsection, we argue that, as the table is dynamically resized, the bounds from Section 2.2 on the number of elements that overflow from levels 1 and 2 continue to hold. The bound on the number of overflow elements from level 1 follows from essentially the same argument as in Theorem 1, so we will focus here on showing that the bins in level 2 remain balanced.

Whenever the size of level 2 doubles, from m bins to $2m$ bins, each bin i can be thought of as splitting into two bins i and $m+i$; each of the elements that were in bin i move to bin $m+i$ with probability 50% (depending on the element's hash). We are not aware of any past bounds for the maximum fill of a bin when bins are split in two from time to time. Here, we provide a lemma showing that the nice load-balancing property of power-of-2-choice bin selection (i.e., Theorem 2) is maintained, even when using our resizing scheme. The proof can be viewed as an extension of the witness-tree techniques used in [44].

Lemma 3. *Start with M_0 empty bins, and perform $N \leq poly(M_0)$ ball insertions. Double the bins whenever the current number n of balls in the system surpasses $m/4$, where m is the current number of bins. At any given moment, the number of balls in the fullest bin is guaranteed to be $O(\log \log N)$ with probability $1 - 1/poly(N)$.*

Proof Sketch. For each ball u, define n_u (resp. m_u) to be the number of balls (resp. bins) that were present when u was inserted. As an invariant, we always have $n_u \leq m_u/4$.

If a given ball x has height $\Theta(\log \log N)$ then we can construct a depth-$\Theta(\log \log N)$ ***witness tree*** T of balls, where x is the root, and where the children v_1 and v_2, of any given node u are determined as follows: if u was placed at height t when it was inserted, then v_1, v_2 are the balls that were at height $t-1$ in bins $h_1(u, m_u)$ and $h_2(u, m_u)$.

We claim that, for any given ball u, if u were to be a node in T, then the expected number of ways that we could hope to assign children to u is at most $1/4$. Indeed, there are $\binom{n_u}{2} \approx n_u^2/2$ ways to choose two nodes v_1, v_2 that were present when u was inserted, and the probability that both $v \in \{v_1, v_2\}$ satisfy $\{h_1(v, m_u), h_2(v, m_u)\} \cap \{h_1(u, m_u), h_2(u, m_u)\} \neq \emptyset$ is at most $\frac{4}{m_u^2}$. So the expected number of ways that we can assign children to u is at most

$$\frac{n_u^2}{2} \cdot \frac{4}{m_u^2} = \left(\frac{2n_u}{m_u}\right)^2 \leq \left(\frac{1}{2}\right)^2 = \frac{1}{4}.$$

Assume for simplicity that all polylog(n) of T's nodes are distinct balls.[4] We have shown that, for each ball u, the expected number of ways that we can assign children to u is $1/4$. Using this, one can argue that the expected number of valid configurations for the full tree T with polylog(N) parent/child relationships is at most $1/4^{\text{polylog}(N)} \leq 1/\text{poly}(N)$. The probability of such a T existing is therefore at most $1/\text{poly}(N)$. □

5 MULTI-THREADING

We now describe how we implement thread-safe operations in IcebergHT. We first describe how to synchronize among threads performing insert, query, and delete operations. Afterwards, we explain how to synchronize among threads when a level resizes.

[4]Formally, we can reduce to this case via standard pruning arguments, as in, e.g., [44].

5.1 Thread-safety across operations

We use one bit in the level 1 metadata as a lock. For level 1, the metadata consists of an array of 64 8-bit fingerprints. We steal one bit from one of the fingerprints to serve as the lock bit. Consequently, that fingerprint slot is only 7 bits and has a slightly higher false-positive rate.

When a thread wants to insert a key that hashes to block i in level 1, it first sets the lock bit for block i using an atomic fetch-and-or loop. It holds this lock for the entire duration of the insert, i.e. even if the element ends up inserted in level 2 or 3. This ensures that inserts/updates/deletes of the same key cannot execute concurrently, since they will both attempt to acquire the same lock.

After acquiring the lock, the thread checks whether the key already exists in any level and updates or deletes it, depending on the requested operation.

When inserting a key that does not already exist in the hash table, we first check for an empty slot in level 1 by using the metadata. If we find one, then we use a 128-bit atomic write to store the key and value in the slot and update the fingerprint in the metadata. Since we hold a lock on the level 1 block, no additional synchronization is necessary.

If the insertion goes to level 2 or 3, then we need to carefully update the bucket and metadata because the locks on level 1 do not preclude other threads operating on the same level 2 or 3 bucket (but not the same key). In level 2, we find a metadata slot holding `EMPTY`, CAS our fingerprint into the metadata slot, claiming it for our operation, and then write the key-value pair into the slot using a 128-bit atomic write. In level 3, we use an array of 1-byte integers to lock the linked list in which we want to insert the key. We acquire a lock on the linked list using an atomic *test-and-set* instruction.

To support concurrent deletes and queries, we reserve a special "invalid" key. Deletes reset the slot to the invalid key and then set the corresponding fingerprint to `EMPTY`. Note that we can still allow the application to insert a key that is equal to our special "invalid" key. We just need to set aside a special location for storing the associated value and a bit indicating whether the key is present or not. Concurrent updates can be made safe by using `cmpxchg16b` to update the associated value and the "present" bit atomically. Queries must also special-case this key to check the designated location instead of performing the standard lookup algorithm. They must also use 128-bit loads to get the "present" bit and the value in one atomic read.

Queries are lockless on levels 1 and 2. They proceed through the levels, examining any slots with a matching fingerprint. They load the key-value pair from a candidate slot using 128-bit atomic reads and then check whether the key read from the slot is valid and actually matches the queried keys. On level 3 they check for bucket emptiness locklessly but acquire locks on buckets before searching in them. Since all slots are read and written using 128-bit atomic operations, and since buckets on level 3 are locked, queries are guaranteed to see only entries with either invalid keys (which are ignored) or with correct key-value pairs.

5.2 Multi-threaded performance analysis

Each insert, delete, or query dirties exactly one PMEM cache line, i.e. for the slot affected by the operation. As for the metadata, each mutation also dirties the level 1 metadata cache line (in DRAM) for the target key's block (to acquire the lock). If the insert does not go into level 1, then it will also access 2 metadata cache lines for level

2, and will dirty one of them. Level 3 is so rarely used that we can largely ignore it. As our evaluation shows, over 90% of the keys go in level 1, so the average number of DRAM cache lines accessed is around 1.2, and the average number dirtied is around 1.1.

Furthermore, since the cache line accesses are determined by the hash of the key, they are independent (unless there are some hot keys that get frequently updated) and therefore it is unlikely that two threads will attempt to access/dirty the same cache lines at the same time. Hot keys that are frequently updated are a genuine scaling bottleneck for almost all hash tables, including IcebergHT.

Queries are invisible, i.e. they are lock free and dirty no cache lines.

5.3 Thread-safety across resizes

Initiating resizes. When a resize is invoked, the table structure goes through the memory-doubling phase, which requires a global lock on the hash table. During the doubling phase, the insert, query, and delete operations cannot operate on the table. Thus, the table has a global reader-writer lock for synchronizing between the memory-doubling step and all other operations. All other operations grab the global lock in read-mode, a thread performing the memory-doubling step grabs it in write mode.

The global lock is implemented as a distributed readers-writer lock [22] so that threads acquiring the lock in read mode do not thrash on the cache line containing the count of the number of readers holding the lock.

Each insertion checks the current load factor of the hash table and performs a memory-doubling step if the load factor is above a configurable threshold. In order to ensure high concurrency, insertion threads first check the load factor while holding the global lock in read mode. If a thread detects that a resize is needed, it releases the global lock in read mode, reaquires it in write mode, and rechecks the load factor. If it is still above threshold, then it performs the memory-doubling step, releases the global lock, and then performs an insertion, as described below.

Recall that we ensure there is at most one operation per key by locking the level 1 block for a key being inserted, updated, or deleted. A memory-doubling step changes the mapping from keys to level 1 blocks, and hence changes the lock for each key. We need to ensure that there are not two threads operating concurrently but using different key-to-lock mappings. The global resizing lock solves this problem by waiting for all in-flight mutations to complete before beginning the resize. Thus, during the resize, there are no threads holding any locks on level 1 blocks. After the resize completes, mutations can resume, using the new key-to-lock mapping.

Concurrency of block moves and other operations. After the memory-doubling step, existing key-value pairs must be moved to their new location in the table.

We refer to blocks in the first half of the table as *old blocks* and blocks in the second half of the table as *new blocks*. Each new block has a corresponding old block.

One clearly safe way to perform this step is to freeze the world, perform all the moves, and then let other operations proceed. Rather than freezing the world, we simulate this by moving blocks the first time any insert, update, or delete operation attempts to access them. Concretely, during a resize, we maintain an additional *moved* flag for each old block. The flag can be in one of three states: `UNMOVED`, `IN-FLIGHT`, or `MOVED`. Initially all old blocks are marked as `UNMOVED`. Whenever an insert, update, or delete is about to access a block, it first checks the state of the corresponding old block. If the old block is in the `UNMOVED` state, then the thread attempts to CAS the block's state to `IN-FLIGHT`. If the CAS fails, then the thread waits until the state is `MOVED`. If the CAS succeeds, then the thread iterates over the block, moving key-value pairs to their new block. The thread then sets the block's state to `MOVED`. The operation can then continue its execution.

Queries do not check the moved flags, so we need to ensure that queries and concurrent moves will not result in incorrect answers. Queries check both the old and new locations for a key, in that order. Moves ensure that each key-value pair is written to its new location before erasing it from its old location. Thus queries will never miss an item in the table.

As an optimization, we also maintain a counter of the number of blocks that still need to be moved. Threads check this counter after acquiring the global resize lock in read mode. If the counter is 0, then threads can skip the above additional work. Thus, in the common case when there is no on-going resize, operations do not incur the overhead of checking moved flags or additional locations for a key. Furthermore, since the count of blocks to be moved is never modified when a resize is not in progress, each core can keep this counter in its local cache, making the counter check very cheap.

6 CRASH CONSISTENCY AND PERFORMANCE ON PMEM

Crash safety. Because IcebergHT is stable, crash consistency is straightforward.

Because all the data in levels 1 and 2 is accessed by computing an offset using block numbers, there are no direct pointers into them, and so there is no need for additional pointer swizzling. The linked lists in level 3 allocate nodes by offset from a fixed array, which is mapped into PMEM. These offsets are then used to reference the nodes.

Recall that all metadata is kept in volatile memory, so that only the data is kept in PMEM. This data is stored in several large preallocated sparse files on a PMEM-backed DAX file system, one each for levels 1 and 2, and 2 for level 3 (one for the linked list heads and one for allocating nodes). A specially designated value is used to indicate if a key or value is invalid, and the key-value pair is considered invalid (and therefore free) if either key or value is invalid.

An insert or deletion is persisted by writing the item into a slot (residing in a block in a level on PMEM), and then performing a cache line writeback instruction followed by an sfence, using PMDK [40]. One small issue is that persistent memory guarantees atomicity only for 8-byte stores, but we must write 16 bytes to insert a key-value pair. However, because the key-value pair is considered invalid if either key or value is invalid, we can store them in a slot in either order, or the stores can even be reordered by the CPU, and the hash table will always be in a consistent state. This eliminates the need for a fence between storing the value and storing the key.

A global metadata file is used to store the initial size of the array as well as the number of (doubling) resizes that have been performed. Note that this file is only modified when a resize is initiated. Resizes first initialize the new PMEM data region to consist of invalid key-value pairs, then updates and persists the table size in the global metadata file, before updating the size in volatile memory.

Recovery consists of reading through the data array and rebuilding the metadata for each valid key-value pair found. Because data from an in-progress resize may not have been moved, recovery must check that each key-value pair is in the correct block, and move it if it is not. Because this can be performed using a sequential scan, the process is efficient.

For example, consider a table initialized with $2^{24} = 16777216$ level 1 slots (18874368 slots total in levels 1 and 2), into which is inserted $2^{26} * 1.07 \approx 71.8$M items, which causes 2 resizes, after which the table is dismounted or crashes (dismount only performs deallocation). Recovery on a single thread then takes 0.48 s, recovering 173 M slots per second and 148 M items per second (roughly 6x faster than individual insertions). Furthermore this process is easily parallelized.

Performance. Changes to the hash table (i.e. inserts, deletes, and updates), modify a single PMEM cache line unless they go to level 3, which we show in our experiments is extremely rare. Positive queries almost always access a single PMEM cache line, plus occasional additional cache lines from false positives in the metadata. Negative queries also almost always touch only a single PMEM cache line to examine the head of the queried key's bucket in level 3 (plus, like other queries, any false positives from the metadata checks in level 1 and 2). We could eliminate even that PMEM access by maintaining in-DRAM metadata about the emptiness of each bucket in level 3, but we have not found it necessary to do so. Since inserts, deletes, and updates must query for the target key, they may also occasionally access (but not modify) extra PMEM cache lines due to metadata false positives.

So, in summary, all operations access a single PMEM cache line in the common case.

7 EXPERIMENTS

In this section, we evaluate the performance of IcebergHT hash table. We compare IcebergHT against two state-of-the-art concurrent PMEM hash tables, Dash [26] and CLHT [9] from the RECIPE library [21]. In our evaluation, we have used the Dash-Extendible Hashing (Dash-EH) variant from the Dash-enabled hash tables. Dash-EH offers faster performance compared to other Dash variants. For CLHT, we have used the CLHT_LB_RES variant which is lock-based and supports resizing. The CLHT_LB_RES variant is ported to PMEM in the RECIPE library [21].

While IcebergHT primarily targets PMEM, its design also yields strong DRAM performance. Therefore, we additionally evaluate IcebergHT on DRAM. On DRAM, we compare IcebergHT against state-of-the-art concurrent in-memory hash tables, libcuckoo [23], Intel's threading building blocks (TBB) hash table [39], and CLHT [9]. Similar to the PMEM evaluation, we use CLHT_LB_RES variant of CLHT.

We evaluate hash table performance on three fundamental operations: insertions, lookups, and deletions. We evaluate lookups both for keys that are present and for keys that are not present in the hash table. We also evaluate these hash tables on multiple application workloads from YCSB [8], as well as for space efficiency and scalability. In IcebergHT, we use MurmurHash to compute the h_0, h_1, and h_2.

The goal of this section is to answer the following questions:

(1) How does IcebergHT performance compare to other hash tables when hash tables are on PMEM?
(2) How does IcebergHT scale with increasing number of threads compared to other hash tables?
(3) How does IcebergHT compare to other hash tables in terms of space efficiency and instantaneous throughput?
(4) What is the impact of hash table resizing on the latency of operations in IcebergHT?
(5) How does IcebergHT compare to libcuckoo, TBB, and CLHT when hash tables are in DRAM?

7.1 Other hash tables

CLHT [9] and TBB [39] are both chaining-based hash tables. They use a linked list to handle collisions. They dynamically allocate a new a node and add it to the linked list to insert a key if the head bin is already occupied. Their space usage is also suboptimal compared to other hash table designs. Dash [26] is based on extendible hashing [13]. A directory is used to index (or store pointers to) the blocks that store key-value pairs. Similar to chaining-based hash tables, Dash also perform dynamic allocation of nodes at run time to add new keys. In cuckoo hash table [23], a pre-allocated array of blocks is maintained where each block can store up to four key-value pairs. Cuckoo hashing [37, 38] is used to perform insertions. Unlike chaining-based or extendible hashing, there is not dynamic allocation in cuckoo hash table.

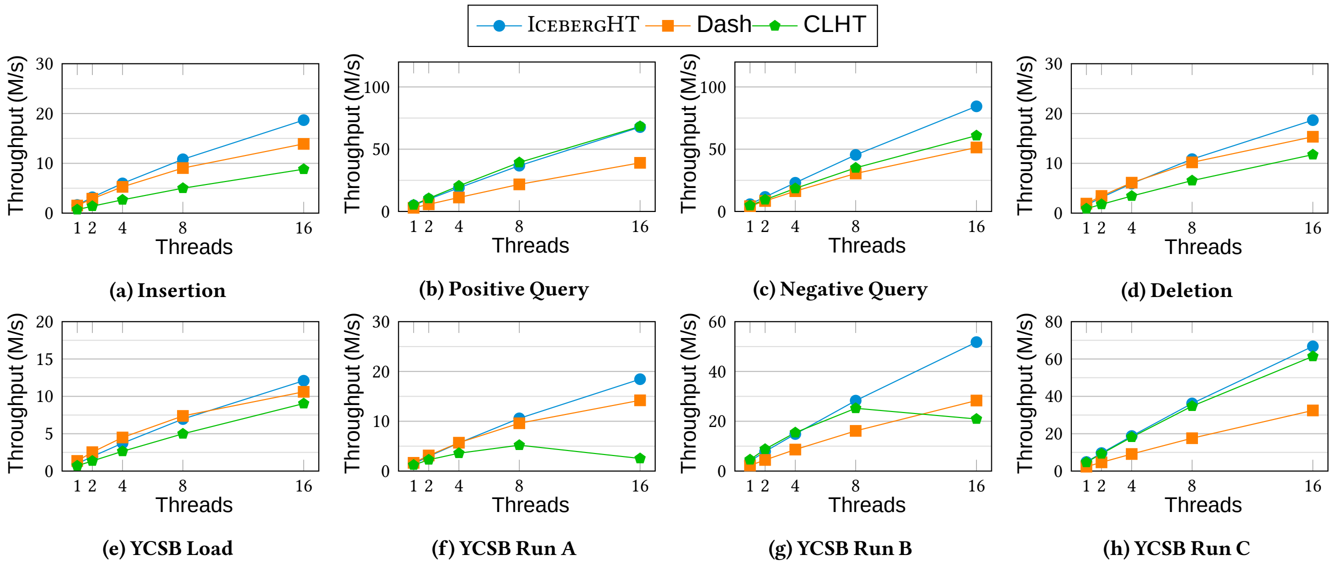
7.2 Experimental setup

In our evaluation, we perform two sets of benchmarks: micro benchmarks and application workloads. For both types of benchmarks, we evaluate the scalability of hash table operations with increasing number of threads.

Microbenchmarks. We measure performance on insertions, deletions, and lookups which are performed as follows. We generate 64-bit keys and 64-bit values from a uniform-random distribution to be inserted, removed or queried in the hash table. We configured each hash table to have as close to 2^{26} slots as possible, and we filled each hash table to its maximum recommended load factor. Specifically, we configured CLHT to use 2^{25} buckets, each with 3 slots[5]. Dash and TBB were initialized with a target size of 2^{26}, libcuckoo was initialized with 2^{26} slots, and IcebergHT was initialized with a front yard of 2^{26} slots, for a total of $(1 + 1/8)2^{26}$ slots, when also counting level 2. We then inserted $0.95N$ keys into each hash table, where N is the number of slots in the table (e.g. $N = 3 \times 2^{25}$ for CLHT, $(1 + 1/8)2^{26}$ for IcebergHT, and 2^{26} for all other hash tables). We report the aggregate throughput going from empty to 95% full as the insertion throughput.

Once the data structure is 95% full, we perform queries for keys that exist and keys that do not exist in the hash table to measure the query throughput for both positive and negative queries. For positive lookups, we query keys that are already inserted and for negative lookups we generate a different set of 64-bit keys than the set used for insertion. The negative lookup set contains almost entirely non-existent keys because the key space is much bigger than the number of keys in the insertion set. Empirically, 99.9989% of keys in the negative lookup query set were non-existent in the

[5]We also tried configured CLHT with $2^{26}/3$ slots, but its performance is much worse when the number of slots is not a power of 2.



(a) Insertion (b) Positive Query (c) Negative Query (d) Deletion

(e) YCSB Load (f) YCSB Run A (g) YCSB Run B (h) YCSB Run C

Figure 3: Performance of hash tables on PMEM on micro and YCSB workloads. (Throughput is Million ops/second)

input set. We then remove a random selection of existing keys from the hash table until its load factor reaches $\approx 50\%$ and report the aggregate deletion throughput.

In order to isolate the performance differences between the hash tables, we do not count the time required to generate the random inputs to the hash tables.

Application workloads. We also measure the hash table performance on YCSB [ ] workloads. We use YCSB workloads A, B, and C in our evaluation. Workload A has a mix of 50/50 reads and writes. Workload B has a 95/5 reads/write mix. Workload C is 100% read. We do not include other YCSB workloads as operations required by other workloads are not supported by these hash tables. The YCSB workloads consist of a load and a run phase. In the load phase, we insert 64M keys and values (64-bit keys and 64-bit values same as in the micro benchmark) generated using a uniform random distribution. The load phase configuration is the same for all three workloads. The keys are generated using the YCSB workload generator. All the hash tables are configured as in the microbenchmarks, except we target $2^{24} \approx 17M$ slots instead of 2^{26}. This ensures that they resize twice during the load phase of 64M keys. In the run phase, we perform a mixed workload depending upon the workload type. In order to make the performance in the run phase a representative of the actual performance of the hash tables, we make sure that the run phase is large enough so that the table doubles its size. Doing this enables us to include the impact of a resize on the insert and query operations in the hash table and ensures that resizes do not unfairly bias the benchmarks.

We achieve this by keeping the number of keys inserted in the run phase the same as the number of keys that are present in the hash table at the start of the run phase. Therefore, the run phase in workload A consists of 128M operations out of which 64M (50/50 reads and writes) are inserts. Similarly, the run phase in workload B consists of 1.28B operations out of which 64M are inserts (95/5 reads/write mix). Workload C does not have any inserts and only contains 64M read operations.

Speed/space tradeoff. To measure how different hash tables can trade space efficiency for speed, we fill the hash table from empty to 95% full in increments of 5%. Data items are generated as in the microbenchmarks. We record the throughput and max RSS (resident-set size) in each increment. To report the memory usage of the hash table we subtract the total memory allocated by the driver process from the Max RSS reported by *getrusage*.

To measure the space usage of PMEM hash tables, we measure the size of the file created by the hash tables on PMEM. In IcebergHT, the PMEM files are created using a sparse flag therefore the space can be measured by counting number of allocated blocks in the file. For Dash and CLHT, the files created are not sparse. Therefore, we measure the space of the hash tables by computing the minimum file size required by Dash and CLHT to complete the benchmark without complete doubling. We start with sizing the file equal to the size of the dataset and keep increasing the size in increments of 100M until the benchmarks completes successfully. We report the space usage as *space efficiency* which is the ratio of the size of the dataset over the size of the hash table. All the instantaneous performance benchmarks are performed using a single thread.

System specification. All the experiments were run on an Intel(R) Xeon(R) Gold 5218 CPU @ 2.30GHz with two NUMA nodes, 16 cores per nodes, and 44M L3 cache. The machine has 192GiB of DRAM running Linux kernel 5.4.0-70-generic. We restrict our runs to all the cores on a single NUMA node to avoid NUMA effects in the performance. For all the benchmarks, we increase the number of threads by powers of two starting from 1 up to 16 (i.e., 1, 2, 4, 8, and 16) which is the maximum number of cores on a NUMA node.

PMEM setup. The machine has 1536GiB of Intel Optane 100 series persistent memory in 12 128GiB DIMMs, 6 per socket. The PMEM is configured to use AppDirect mode and is accessed using fsdax on an ext4 filesystem. This filesystem is configured with a 2MiB stride to enable 2MiB huge page faults, and mounted using dax. IcebergHT stores its data to PMEM by creating large sparse files at initialization

	Insertions			Positive Queries		
Percentile	**IcebergHT**	**Dash**	**CLHT**	**IcebergHT**	**Dash**	**CLHT**
50	353ns	830ns	1.29μs	602ns	834ns	974ns
95	1.11μs	2.39μs	2.63μs	1.49μs	2.16μs	2.14μs
99	1.97μs	3.50μs	3.72μs	1.96μs	2.74μs	3.41μs
99.9	249.88μs	78.4μs	5.68μs	2.42μs	4.35μs	5.24μs
99.99	277.52μs	103μs	16.49μs	5.24μs	7.91μs	15.60μs
max	37.09ms	8.62ms	12.31s	259.65μs	16.0ms	153.21μs

Table 2: Percentile latencies in IcebergHT, Dash and CLHT for YCSB workload A run on PMEM using 16 threads.

Hash table	Space Efficiency
IcebergHT	85%
Dash	69%
CLHT	33%

Table 3: Space efficiency of PMEM hash tables. Space efficiency is the ratio of Data size over hash table size. We compute the space efficiency after inserting $0.95N$ keys-value pairs in the hash table where N is the initial capacity.

for each level, and only using (and therefore populating) a prefix of each file.

7.3 PMEM benchmarks

Micro benchmarks. Figure 3 shows the performance and scaling of IcebergHT, Dash, and CLHT on microbenchmarks in PMEM.

IcebergHT always performs faster than Dash and CLHT. Specifically, it is $1.1\times$ $2.7\times$ faster for insert, query, and remove operations.

For all four operation types, all the hash tables scale almost linearly. The scaling ratio (i.e., the ratio of the relative throughput and the relative number of threads for a system) of IcebergHT is 0.67, Dash is 0.56, and CLHT is 0.77.

YCSB workloads. Figure 3 shows the performance of IcebergHT, Dash, and CLHT for three YCSB workloads on PMEM.

For the load phase of these workloads, IcebergHT is faster than other hash tables. Specifically, it is between $1.1\times$ and $2.5\times$ faster than Dash and CLHT. For the run phase all three workloads, IcebergHT is faster compared to both Dash and CLHT. CLHT performance for workload C is closer to IcebergHT. Workload C consists of 100% queries. And this observation is consistent with the positive query performance in microbenchmarks.

The YCSB benchmarks show that IcebergHT performs better than other hash tables when the workload also involves resizing the hash table as the YCSB load phase and workloads A and B require the hash tables to resize at least twice. Moreover, similar to the microbenchmarks, the load performance of IcebergHT scales almost linearly with increasing number of threads.

For different workload types (A, B, and C), the performance of IcebergHT is always better than other hash tables and also scales almost linearly with increasing number of threads.

Discussion. The high performance of IcebergHT both on the micro and YCSB workloads is primarily due to the small number of PMEM accesses during insert, query, and delete operations. During insert and delete operations, we only perform a single PMEM write. During query operations, we usually perform at most a single PMEM read (unless there is a false positive in the metadata). Furthermore, since most items are in level 1, most inserts, deletes, and positive queries access only a single DRAM cache line, as well. Negative queries must access 4 DRAM cache lines (1 metadata cache line for level 1, 2 for level 2, and 1 for level 3), but they usually do not have to access a PMEM cache line at all. Finally, metadata searches are implemented using vector instructions, so they take constant time even though our buckets are larger than a cache line.

Insert and query latency. Table 2 shows the 50, 95, 99, 99.9, and 99.99 percentiles and the worst case for insert and positive query operations in the benchmarked hash tables.

On PMEM, Dash has slower latency up to 99.99 percentile compared to IcebergHT for both inserts and queries. However, Dash is $2\times$ faster for the worst-case insert latency and about 50% slower for the worst-case query latency.

CLHT has the worst-case insert latency of 12 seconds. This is because during a resize operation all active inserts are stopped and insert threads help to move the keys from the old hash table to the new one. In CLHT, the query latency is always good. This is because the queries can always perform probes on the old copy of the hash table even when the resize is active. Queries are never blocked in CLHT. CLHT performs resizes by allocating a new hash table of twice the size and moving key-value pairs from the old hash table to the new one.

The latency of operations is computed during the YCSB workload A run that contains insert and positives queries (50/50). The workload is configured so that hash tables must perform at least one resize during the run. All the hash tables are run using 16 threads. Comparing the latency of operations during a workload run helps explain the impact of a resize on the worst case latency of operations.

Space efficiency in PMEM. Table 3 shows the space efficiency of PMEM hash tables. Both Dash and CLHT have low space efficiency compared to IcebergHT. IcebergHT PMEM representation is 1.2GB for a dataset size of 1.06GB ($2^{26} * 1.07$ 8 Byte keys and values) and in-memory representation is ≈ 80MB.

7.4 DRAM performance

Micro and YCSB benchmarks.. Figure 4 shows the performance of IcebergHT, cuckoo, TBB, and CLHT on microbenchmarks and YCSB workloads using 16 threads in DRAM.

IcebergHT is $2.3\times$ $9.1\times$ faster for insertions and $1.7\times$ $2.6\times$ faster for lookups than the libcuckoo and TBB. For deletions, IcebergHT is up to $5.3\times$ faster than TBB but $\approx 50\%$ slower than libcuckoo. IcebergHT is also faster than CLHT for insertions. However, CLHT has faster deletions and query operations compared to IcebergHT. This is due the extra overhead of one metadata probe in level 1 and two probes in level 2 in IcebergHT in DRAM. These metadata probes are essential to avoid multiple cache line access in the main table, especially on PMEM where accessing multiple locations in the table can hurt performance.

Figure 4 shows the performance of IcebergHT and other hash tables for YCSB workloads. For the load phase of these workloads, IcebergHT is faster than other hash tables. It is up to $2.2\times$ faster than libcuckoo, $4.4\times$ faster than TBB, and $1.9\times$ faster then CLHT in DRAM. For workload C which contains all queries, CLHT is faster than IcebergHT. This is similar to the query workload results in the microbenchmarks.

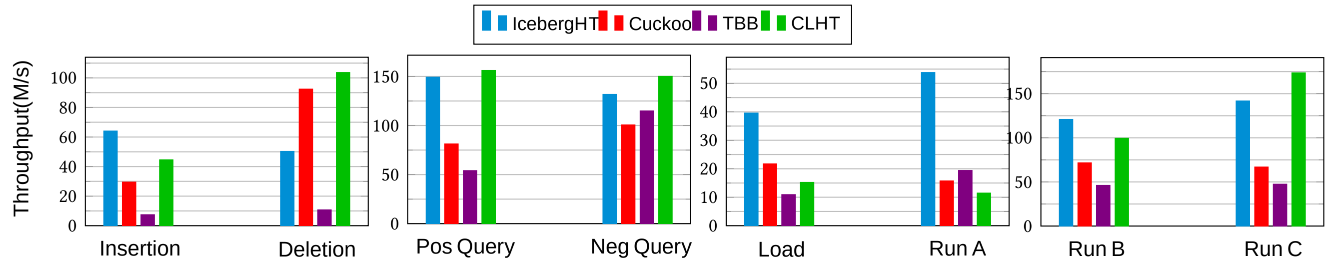


Figure 4: Throughput for insertions, deletions, and queries (positive and negative) using 16 threads for DRAM hash tables. The throughput is computed by inserting $0.95N$ keys-value pairs where N is the initial capacity of the hash table. (Throughput is Million ops/second)

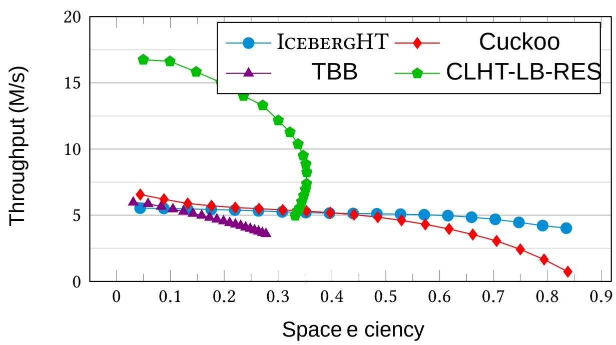


Figure 5: Insertion throughput and space efficiency performance of hash tables in DRAM. (Throughput is Million ops/second)

The faster query performance of CLHT comes at a high space overhead. Specifically, CLHT uses $3\times$ more space than IcebergHT.

Insert and query latency in DRAM. Table 5 shows the 50, 95, 99, 99.9, and 99.99 percentiles and the worst case for insert and positive query operations in various hash tables in DRAM. The latency of operations is computed in the same way as it was done for the PMEM benchmarks.

IcebergHT and libcuckoo have similar median insert latency but the worst case latency is three orders of magnitude slower in libcuckoo. This is due to the fact that IcebergHT performs resizing in a lazy dynamic manner which helps to avoid stalling other operations during a big resize. TBB's median insert latency is $2\times$ higher than IcebergHT and libcuckoo. But TBB's worst-case latency is an order of magnitude faster than libcuckoo. This is because resizes can be done fairly efficiently by splitting buckets in TBB and do not require a complete rehashing of items.

libcuckoo has the lowest median query latency compared to IcebergHT and TBB. However, the worst-case latency is again about three orders of magnitude slower than IcebergHT. TBB has the lowest worst-case query latency due to the fact the splitting a bucket is fairly fast and can be achieved using a pointer swing. However, in IcebergHT a few queries may have to wait if the block they want to look into is getting fixed during a resize.

Benchmark	Level 1	Level 2	Level 3
Micro	91.2%	8.7%	0.000082%
YCSB load	95.9%	4.0%	0%
YCSB Workload A	95.8%	4.1%	0%
YCSB Workload B	95.8%	4.1%	0%

Table 4: Distribution of keys across the three levels in IcebergHT hash table.

7.5 Speed/space tradeoff

Figure 5 shows the instantaneous DRAM insertion throughput of IcebergHT, libcuckoo, TBB, and CLHT versus their space efficiency. We compare instantaneous throughput versus space efficiency only in DRAM only because it is not always possible to measure the instantaneous space usage of PMEM-based hash tables (see discussion above), whereas in DRAM we can always get the MaxRSS. The point of these experiments is to uncover the general relationship between insertion performance and space usage.

As Figure 5 shows, CLHT's insertion performance in DRAM comes at a high price in terms of space efficiency. CLHT never gets a space efficiency higher than 40%.

CLHT space efficiency improves initially as the 3-entry bucket-heads fill but then begins to decline as bucket-heads overflow, necessitating the allocation of 3-entry overflow links in its chains. In Figure 5, the change in the space efficiency of the CLHT is marginal after 30% and therefore these points are clustered together.

Figure 5 also shows that IcebergHT offers both high space efficiency and high insertion throughput. IcebergHT also has consistent insertion throughput irrespective of the space usage. Interestingly, the throughput increases (beyond 80%) as more keys end up in level 2 and 3. For example, going from 85% to 90% load, 47% of the keys end up in level 2 and from 90% to 95% load, almost 65% keys end up in level 2. Inserting keys in level 2 is comparatively faster than level 1 as level 2 is much smaller in size compared to level 1. Due to the smaller size, a major fraction of the level 2 can be cached in the last level cache (LLC).

The insertion throughput for both libcuckoo and TBB drops as the space efficiency increases. For libcuckoo, the drop in the throughput is fairly sharp above 70% space efficiency. For TBB, the drop is consistent and gradual up to 95% space efficiency.

7.6 Distribution of keys in IcebergHT

Table 4 shows the distribution of keys across the three levels in IcebergHT. Most of the keys (>90%) reside in level 1 across all the

	Insertions			Positive Queries		
Percentile	**IcebergHT**	**libcuckoo**	**TBB**	**IcebergHT**	**libcuckoo**	**TBB**
50	336ns	264ns	819ns	290ns	198ns	494ns
95	671ns	2.02µs	1.59µs	548ns	429ns	955ns
99	1.09µs	5.99µs	2.24µs	687ns	562ns	1.22µs
99.9	22.03µs	19.8µs	6.52µs	979ns	836ns	1.57µs
99.99	29.08µs	219µs	9.27µs	1.93µs	218µs	4.97µs
max	345.34ms	2.05s	734ms	38.35µs	1.01s	42.8µs

Table 5: Percentile latencies in IcebergHT, libcuckoo and TBB for YCSB workload A run on DRAM using 16 threads.

Block size	Insertions	Neg Queries	Pos queries	Deletions	%L2	%L3
L1 64 L2 8	62.94	128.71	144.23	50.48	8.7	0.00007
L1 64 L2 6	65.58	129.27	149.27	53.77	7.0	0.007
L1 64 L2 4	64.36	115.07	152.12	51.60	5.4	0.27
L1 32 L2 8	53.99	109.28	129.54	45.97	17.7	0.03
L1 32 L2 6	54.75	109.15	133.71	49.31	13.7	0.06
L1 32 L2 4	53.20	95.99	140.08	46.33	10.38	0.64

Table 6: Performance of IcebergHT for different front/backyard block sizes on DRAM using 16 threads. Throughput in Million/sec. Each instance is filled to 95% capacity.

benchmarks and workloads. A small percentage of keys (<10%) reside in level 2 and almost no keys are found in level 3. This shows that the empirical distribution of keys across different levels follows the theoretical guarantees of Iceberg hashing.

Level 3 sees a tiny number of keys in the microbenchmark because, in the microbenchmarks, we fill the table to 95% load factor without resizing. However, even at 95% load factor, the number of keys in level 3 is negligible and does not impact the query or deletion performance.

For YCSB workloads, we report the distribution after the load phase (which is the same across the three workloads) and also after the run phase for workloads A and B that contain new insertions. The IcebergHT hash table has default load factor threshold of 85% which means a resize is invoked when the hash table reaches an 85% load factor. This makes the hash table always have enough space in levels 1 and 2 so level 3 remains empty.

7.7 Configuring front yard and back yard

Table 6 shows the performance of IcebergHT with different block sizes in front and back yards. The goal of these experiments is to determine the best configuration of front and back yard to achieve high performance and fill capacity. We vary the block sizes in front and back yard and fill up each instance to 95% load factor and evaluate the performance.

Reducing the number of blocks in L2 to 6 results in more items going into L3. This results in faster operations overall. However, reducing the L2 blocks to 4 slows down the negative queries considerably due to a high fraction of items in L3 which require pointer chasing during queries. Reducing the block size in L1 to 32 increases the fraction of items going into L2 and L3. This results in slowdown across the board. This also means that if we size front and back yards equally then the performance would be worse as more items would end up in L2/L3 causing extra cache misses.

8 RELATED WORK

In this section, we will discuss various hash table implementations and their applications. A discussion of various hash table designs used in our evaluation is given in Section 7.1.

In-memory hash tables. There are numerous in-memory hash table implementations such as sparse and dense hash maps from Google [16], the F14 hash table from Facebook [12], the FASTER hash table from Microsoft [7], the hash table in Intels' TBB library [39], the cuckoo hash table [23], the linear probing-based fast hash table [28, 29], and the unordered map in C++ STL. However, most of these hash tables only support single threaded operations.

MemC3 [15] supports multiple readers but only a single writer. It is based on optimistic concurrent cuckoo hashing. MemC3 also supports variable-length keys and optimizes accesses using fingerprinting. FASTER [7] further optimizes the implementation by storing the tag in the higher order bits of the pointer. It also supports scaling out of memory to a secondary storage device and supports crash safety using logging. Libcuckoo [23] extends MemC3 to support multiple readers and writers.

Persistent-memory hash tables. Persistent memory offers byte-addressability and high capacity compared to other traditional storage mediums. This makes PMEM an attractive medium for building dynamic hash tables. Recently numerous hash tables have been developed for PMEM [6, 10, 21, 26, 35, 43, 49]. The main goal of PMEM-based hash tables is to reduce the number of write operations during an insert/remove while still support efficient queries.

PFHT [10] reduces the number of writes using a two-level scheme similar to IcebergHT where the second level acts as a stash (or backyard). Similar to level 3 in IcebergHT PFHT also uses linked lists to store items in the stash. Path hashing [46] optimizes the storage in the stash by reorganizing it into a tree structure. This lowers the search costs in the stash. Level hashing [48, 49] is another two-level scheme that bounds the search cost to at most four buckets.

CCEH [35] is based on extendible hashing [13]. It is crash-consistent and the extendible design helps to avoid rehashing all the items after a resize. The queries tend to be slower due to random memory access. Therefore, it bounds the probing length to a few cache-lines but that in turn leads to low load factors. NVC-hashmap [43] presents a lock-free design for a PMEM-based hash table. The lock-free design though suitable for PMEM has added implementation complexity and makes searching slower due to pointer chasing.

Applications. Hash tables are widely used to maintain symbol tables in compilers, implement caches, index databases, manage memory pages in Linux, implement routing tables, and to build inverted indexes for document search. Examples of such systems are Redis [41], Memcached [30], Cassandra [3], DynamoDB [11], MongoDB [33], etc. These implementations have been further improved in follow up works such as MemC3 [15], MICA [25], and SILT [24].

9 DISCUSSION

We attribute the high performance and space-efficiency to stability and low associativity. Stability helps in achieving a faster inserts. Low associativity helps in getting faster query performance. Iceberg hashing achieves both stability and low associativity at the same time.

IcebergHT insertion performance with 16 threads is about 70% of the hardware limit. The 30% overhead in the insert operation is due the overhead of maintaining transient information, e.g., to update the metadata and increment counters for resize checks. We were able to get to 85% of the hardware limit by commenting out counter-maintenance code and using huge pages. For query performance, the overhead is about 50%. Some of this overhead is due to the same factors as in the insert operation. However, the query operation has other overheads that results in extra PMEM access. For example, there is a 25% chance of a collision in the metadata ngerprints that results in extra PMEM accesses during the query operation.

In the DRAM setting (where the hash table resides in DRAM), the cost of metadata accesses is a non-trivial fraction of the overall operation cost. Therefore, each query operation incurs at least two cache line misses. CLHT on the other hand performs a single cache line miss for most of the keys. This results in IcebergHT having a slightly slower query and deletion performance compared to CLHT.

Our implementation supports 8-byte keys and 8-byte values. As in other hash-table designs, such as Dash, this core functionality can be extended to variable-length keys and values by storing pointers to the actual keys and values in the hash table.

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