PI : a Parallel in-memory skip list based Index

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ABSTRACT

Due to the coarse granularity of data accesses and the heavy use of latches, indices in the B-tree family are not efficient for in-memory databases, especially in the context of today's multi-core architecture.

In this paper, we present **PI**, a **P**arallel in-memory skip list based **I**ndex that lends itself naturally to the parallel and concurrent environment, particularly with non-uniform memory access. In PI, incoming queries are collected, and disjointly distributed among multiple threads for processing to avoid the use of latches. For each query, PI traverses the index in a Breadth-First-Search (BFS) manner to find the list node with the matching key, exploiting SIMD processing to speed up the search process. In order for query processing to be latch-free, PI employs a light-weight communication protocol that enables threads to re-distribute the query workload among themselves such that each list node that will be modified as a result of query processing will be accessed by exactly one thread. We conducted extensive experiments, and the results show that PI can be up to three times as fast as the Masstree, a state-of-the-art B-tree based index.

Keywords

Database index, skip list, B-tree, parallelization

1. INTRODUCTION

DRAM has orders of magnitude higher bandwidth and lower latency than hard disks, or even flash memory for that matter. With exponentially increasing memory sizes and falling prices, it is now frequently possible to accommodate the entire database and its associated indices in memory, thereby completely eliminating the significant overheads of slow disk accesses [15, 19, 20, 36, 37]. Non-volatile memory such as phase-change memory looming on the horizon is destined to push the envelope further. Traditional database indices, e.g., B^+-trees [12], that were mainly optimized for disk accesses, are no longer suitable for in-memory databases since they may suffer from poor cache utilization due to their hierarchical structure, coarse granularity of data access and poor parallelism.

The integration of multiple cores into a single CPU chip makes many-core computation a norm today. Ideally, an in-memory database index should scale with the number of on-chip cores to fully unleash the computing power. The B^+-tree index, however, is ill-suited for such a parallel environment. Suppose a thread is about to modify an intermediate node in a B-tree index. It should first prevent other concurrent threads from descending into the sub-tree rooted at that node in order to guarantee correctness, thereby forcing serialization among these threads. Worse, if the root node is being updated, all of the other threads cannot proceed to process queries. Consequently, the traditional B-tree index does not provide the parallelism required for effective use of the concurrency provided by a many-core environment.

On the other hand, *single instruction multiple data* (SIMD) is now supported by almost all modern processors. It enables performing the same computation, e.g., arithmetic operations and comparisons, on multiple data simultaneously, holding the promise of significantly reducing the time complexity of computation. However, to operate on indices using SIMD requires a non-trivial rethink since SIMD operations require operands to be contiguously stored in memory.

The aforementioned issues highlight the need for a new parallelizable in-memory index, and motivate us to re-examine the *skip list* [32] as a possible candidate as the base indexing structure in place of the B^+-tree (or B-tree). Skip list employs a probabilistic model to build multiple linked lists such that each linked list consists of nodes selected according to this model from the list at the next level. Like B^+-trees, the search for a query key in a skip list follows breadth-First traversal in the sense that it starts from the list at the top level and moves forward along this level until a node with a larger key is encountered. Thereupon, the search moves to the next level, and proceeds as it did in the previous level. However, since only one node is being touched by the search process at any time, its predecessors at the same level can be accessed by another search thread, which means data access in the skip list has a finer granularity than the B^+-tree where an intermediate tree node contains multiple keys, and should be accessed in its entirety. Moreover, with a relaxation on the structure hierarchy, a skip list can be divided vertically into disjoint partitions, each of which can be individually processed on multi-core systems. Hence, we can expect the skip list to be an efficient and much more suitable indexing technique for concurrent settings.

It is natural to use latches to implement concurrent accesses over a given skip list. Latches, however, are costly. In fact, merely inspecting a latch may require it to be flushed from other caches, and is therefore costly. Latch modification is even more expensive, as it will invalidate the latch replicas located at the caches of other cores, and force the threads running on these cores to re-read the latch for inspection, incurring significant bandwidth cost, especially in a Non-Uniform Memory Access (NUMA) architecture where accessing memory of remote NUMA nodes can be an order of magnitude slower than that of a local NUMA node.

In this paper, we propose a highly parallel in-memory database index based on a latch-free skip list. We call it **PI**, a **P**arallel in-memory skip list based **I**ndex. In PI, we employ a fine-grained processing strategy to avoid using latches. Queries are organized into batches and each batch processed simultaneously using multiple threads. Given a query, PI traverses the index in a breadth-first manner to find the corresponding list node. SIMD instructions are used to accelerate the search process. To handle the case in which two threads find the same list node for some keys, PI adjusts the query workload among execution threads to ensure that each list node that will be modified as a result of query processing is accessed by exactly one thread, thereby eliminating the need for latches.

Our main contributions include:

- We propose a latch-free skip list index that shows high performance and scalability. It serves as an alternative to tree-like indices for in-memory databases and suits the many-core concurrent environment due to its high degree of parallelism.
- We use SIMD instructions to accelerate query processing of the index.
- A set of optimization techniques are employed in the proposed index to enhance the performance of the index in many-core environment.
- We conduct an extensive performance study on PI as well as a comparison study between PI and Masstree [29], a state-of-the-art index used in SILO [37]. The results show that PI is able to perform up to more than 3× better than Masstree in terms of query throughput.

The remainder of this paper is structured as follows. Section 2 presents related work. We describe the design and implementation of PI in Section 3 and 4, respectively, and develop a mathematical model to analyze PI's performance of query processing in Section 5. Section 6 presents the performance study of PI. Section 7 concludes this work.

2. RELATED WORK

2.1 B$^+$-tree

The B$^+$-tree [12] is perhaps the most widely used index in database systems. However, it has two fundamental problems which render it inappropriate for in-memory databases First, its hierarchical structure leads to poor cache utilization which in turn seriously restricts its query performance. Second, it does not suit concurrent environment well due to its coarse granularity of data access and heavy use of latches. In order to solve those drawbacks, exploiting cache and removing latches become the core direction for implementing in-memory B$^+$-trees.

2.1.1 Cache Exploitation

A better cache utilization can substantially enhance the query performance of B$^+$-trees since reading a cache line from the cache is much faster than from memory. Software prefetching is used in [10] to hide the slow memory access. Rao et al. [33] presents a cache-sensitive search tree (CSS-tree), where nodes are stored in a contiguous memory area such that the address of each node can be arithmetically computed, eliminating the use of child pointers in each node. This idea is further applied to B$^+$-trees, and the resultant structure, called the CSB$^+$-tree, is able to achieve cache consciousness and meanwhile support efficient update. The relationship between the node size and cache performance of the CSB$^+$-tree is analyzed in [16]. Masstree [29] is a trie of B$^+$-trees to efficiently handle keys of arbitrary length. With all the optimizations presented in [10, 33, 34] enabled, Masstree can achieve a high query throughput. However, its performance is still restricted by the locks upon which it relies to update records. In addition, Masstree is NUMA agnostic as NUMA-aware techniques have been shown to be not providing much performance gain [29]. As a result, expensive remote memory accesses are incurred during query processing.

2.1.2 Latch and Parallelizability

There have been many works trying to improve the performance of the B$^+$-tree by avoiding latches or enhancing parallelizability. The B^{link}-tree [24] is an early attempt towards enhancing the parallelizability of B$^+$-trees by adding to each node, except the rightmost ones, an additional pointer pointing to its right sibling node so that a node being modified does not prevent itself from being read by other concurrent threads. However, Lomet [28] points out that the deletion of nodes in B^{link}-trees can incur a decrease in performance and concurrency, and addresses this problem through the use of additional state information and latch coupling. Braginsky and Petrank present a lock-free B$^+$-tree implemented with single-word CAS instructions [8]. To achieve a dynamic structure, the nodes being split or merged will be frozen, but search operations are still allowed to perform against such frozen nodes.

Due to the overhead incurred by latches, a latch-free B$^+$-tree has also attracted some attention. Sewall et al. propose a latch-free concurrent B$^+$-Tree, named PALM [35], which adopts bulk synchronous parallel (BSP) model to process queries in batches. Queries in a batch are disjointly distributed among threads to eliminate the synchronization among them and thus the use of latches. FAST [21] uses the same model, and achieves twice query throughput as PALM at a cost of not being able to make updates to the index tree. The Bw-tree [26], developed for Hekaton [15, 25], is another latch-free B-tree which manages its memory layout in a log-structured manner and is well-suited for flash solid state disks (SSDs) where random writes are costlier than sequential ones.

2.2 CAS Instruction and Skip List

Compare-and-swap (CAS) instructions are atomic operations introduced in the concurrent environment to ease the implementation of synchronization primitives, such as semaphores and mutexes. Herlihy proposes a sophisticated model to show that CAS instructions can be used in implementing wait-free data structures [17]. These instructions

are not the only means to realize concurrent data structures. Brown et al. also present a new set of primitive operations for the same purpose [9].

Skip lists [32] are considered to be an alternative to B^+-trees. Compared with B^+-trees, a skip list has approximately the same average search performance, but requires much less effort to implement. In particular, even a latch-free implementation, which is notoriously difficult for B^+ trees, can be easily achieved for skip lists by using CAS instructions [18]. Crain et al. propose new skip list algorithms [14] to avoid contention on hot spots. Abraham et al. combine skip lists and B-trees for efficient query processing [2]. In addition, skip lists can also be integrated into distributed settings. Aspnes and Shah present Skip Graph [4] for peer-to-peer systems, a novel data structure leveraging skip lists to support fault tolerance.

As argued earlier, skip lists are more parallelizable than B^+-trees because of the fine-grained data access and relaxed structure hierarchy. However, naïve linked list based implementation of skip lists have poor cache utilization due to the nature of linked lists. In PI, we address this problem by separating the Index Layer from the Storage Layer such that the layout of the Index Layer is optimized for cache utilization and hence enables an efficient search of keys.

2.3 Single Instruction Multiple Data

Single Instruction Multiple Data (SIMD) processing has been extensively used in database research to boost the performance of database operations. Chhugani et al. [11] show how the performance of mergesort, a classical sort algorithm, can be improved, when equipped with SIMD. Similarly, it has been shown in [38, 6, 5] that the SIMD-based implementation of many database operators, including scan, aggregation, indexing and join, perform much better than its non-SIMD counterpart.

Recently, tree-based in-memory indices leveraging SIMD have been proposed to speed up query processing [21, 35]. FAST [21], a read only binary tree, can achieve an extremely high throughput of query processing as a consequence of SIMD processing and enhanced cache consciousness enabled by a carefully designed memory layout of tree nodes. Another representative of SIMD-enabled B^+-trees is PALM [35], which overcomes the FAST's limitation of not being able to support updates at the expense of decreased query throughput.

2.4 NUMA-awareness

NUMA architecture opens up opportunities for optimization in terms of cache coherence and memory access, which can significantly hinder the performance if not taken into design [27] [7]. Since accessing the memory affiliated with remote (non-local) NUMA nodes is substantially costlier than accessing local memory, the major direction for NUMA-aware optimization is to reduce the accesses of remote memory, and meanwhile keep load balancing among NUMA nodes [31]. Many systems have been proposed with NUMA aware optimizations. ERIS [22] is an in-memory storage engine which employs an adaptive partitioning mechanism to realize NUMA topology and hence reduce remote memory accesses. ATraPos [30] further avoids commutative synchronizations among NUMA nodes during transaction processing.

There are also many efforts devoted to optimizing database operations with NUMA-awareness. Albutiu et al. propose a NUMA-aware sort-merge join approach, and leverage prefetching to further enhance the performance [3]. Lang et al. explore how various implementation techniques for NUMA-aware hash join [23]. Li et al. study data shuffling algorithms in the context of NUMA architecture [7].

3. INDEX DESCRIPTION

In a traditional skip list, since nodes with different heights are dynamically allocated, they do not reside within a contiguous memory area. Non-contiguous storage of nodes causes cache misses during key search and limits the exploitation of SIMD processing, which requires the operands to be stored within a contiguous memory area. We shall elaborate on how PI overcomes these two limitations and meanwhile achieves latch-free query processing.

3.1 Structure

Like a typical skip list, PI also consists of multiple levels of sorted linked lists. The bottommost level is a list of data nodes, whose definition is given in Definition 1; an upper-level list is composed of the keys randomly selected with a fixed probability from those contained in the linked list of the next lower level. For the sake of expression, these composing linked lists are logically separated into two layers: the *storage layer* and the *index layer*. The storage layer is merely the linked list of the bottommost level, and the index layer is made up of the remaining linked lists.

DEFINITION 1. *A data node α is a triplet*

$$(\kappa, p, \Gamma)$$

where κ is a key, p is the pointer to the value associated with κ, and Γ is the height of κ, representing the number of linked lists where key κ is present. We say a key $\kappa \in S$ if there exists a data node α in the storage layer of the index, S, such that $\alpha.\kappa = \kappa$.

The difference between a traditional skip list and PI lies in the index layer. In a traditional skip list, the node of a composing linked list of the index layer contains only one key. In contrast, a fixed number of keys are included in a list node of the index layer, which we shall call an *entry* hereafter. The reason for this arrangement of keys is that it enables SIMD processing, which requires operands to be contiguously stored. An instance of PI with four keys in an entry is shown in Figure 1, where three different operations are collectively processed by two threads, which are represented by the two arrows colored purple and green, respectively.

Given an initial dataset, the index layer can be constructed in a bottom up manner. We only need to scan the storage layer once to fill the high-level entries as well as the associated data structure, i.e., routing table, which will be discussed in the next section in detail. This construction process is $O(n)$ where n is the number of records at the storage level, typically taking less than 0.2s for 16M records when running on a 2.0 GHz CPU core. Further, the construction process can be parallelized, and hence can be sped up using more computing resources.

3.2 Queries and Algorithms

PI, like most indexing structures, supports three types of queries, namely search, insert and delete. Their detailed descriptions are as follows, and an abstraction of them is further given in Definition 2.

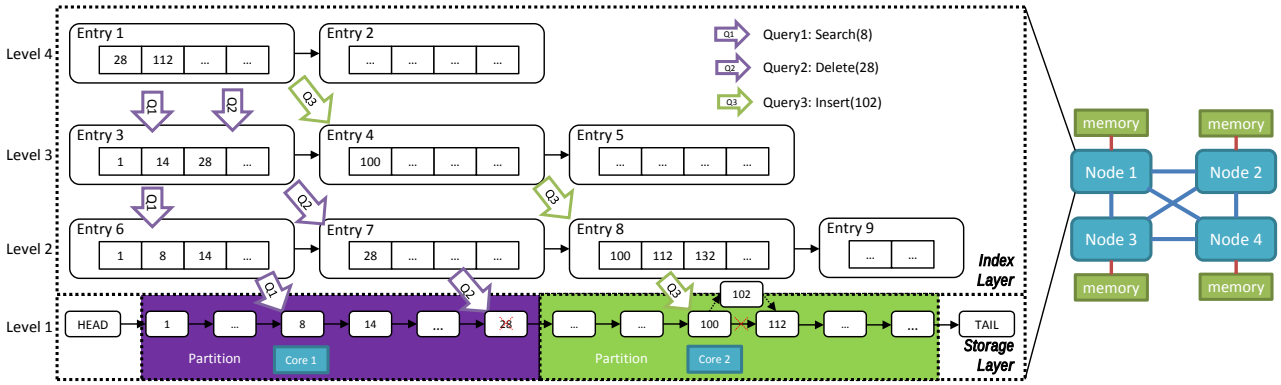


Figure 1: An instance of PI

- **Search(κ):** if there exists a data node α in the index with $\alpha.\kappa = \kappa$, $\alpha.p$ will be returned, and null otherwise.
- **Insert(κ, p):** if there exists a data node α in the index with $\alpha.\kappa = \kappa$, update the this data node by replacing $\alpha.p$ with p; otherwise insert a new data node (κ, p, Γ) into the storage layer, where Γ is drawn from a geometrical distribution with a specified probability parameter.
- **Delete(κ):** if there exists a data node α in the index with $\alpha.\kappa = \kappa$, remove this data node from the storage layer and return 1; otherwise return *null*.

Definition 2. *A query, denoted by q, is a triplet*

$$(t, \kappa, [p])$$

where t and κ are the type and key of q, respectively, and if t is insert, p provides the pointer to the new value associated with key κ.

We now define the query set Q in Definition 3. There are two points worth mentioning in this definition. First, the queries in a query set are in non-decreasing order of the query key k, and the reason for doing so will be elaborated in Section 3.2.4. Second, a query set Q only contains point queries, and we will show how such a query set can be constructed and leveraged to answer range queries in Section 3.2.5.

Definition 3. *A query set Q is given by*

$$Q = \{q_i | 1 \leq i \leq N\}$$

where N is the number of queries in Q, q_i is a query defined in Definition 2, and $q_i.\kappa \leq q_j.\kappa$ iff $i < j$.

Definition 4. *For a query q, we define the corresponding interception, I_q, as the data node with the largest key among those in $\{\alpha | \alpha.\Gamma > 1, \alpha.\kappa \leq q.\kappa\}$.*

PI accepts a query set as input, and employs a batch technique to process the queries in the input. Generally, batch processing may increase the latency of query processing, as queries may need to be buffered before being processed. However, since batch processing can significantly improve the throughput of query processing, as shown in Section 6.2, the average processing time of queries are not much affected.

Algorithm 1: Query processing

Input : S, PI index
Q, query set
$t_1, ..., t_{N_T}$, N_T threads
Output: R, Result Set

```
1  R = ∅;
2  for i = 1 → N_T do
3      Q_i = partition(Q, N);
4  /* traverse the index layer to get interceptions */
5  foreach Thread t_i do
6      Π_i = traverse(Q_i, S);
7  waitTillAllDone();
8  /* redistribute query workload */
9  for i = 1 → N_T do
10     redistribute(Π_i, Q_i, i);
11 /* query execution */
12 foreach Thread t_i do
13     R_i = execute(Π_i, Q_i);
14 waitTillAllDone();
15 R = ∪R_i;
16 return R;
```

The detailed query processing of PI is given in Algorithm 1. First, the query set Q is evenly partitioned into disjoint subsets according to the number of threads, and the i-th subset is allocated to thread i for processing (line 3). The ordered set of queries allocated to a thread is also a query set defined in Definition 3, and we call it a query batch in order to differentiate it from the input query set. Each thread traverses the index layer and generates for each query in its query batch an interception which is defined in Definition 4 (line 5 and 6). After this search process, the resultant interceptions are leveraged to adjust query batches among execution threads such that each thread is able to *safely* execute all the queries assigned to it after the adjustment (line 9 and 10). Finally, each thread individually executes the queries in its query batch (line 12 and 13). The whole procedure is exemplified in Figure 1, where three queries making up a query set are collectively processed by three threads. Following the purple arrows, thread 1 traverses downwards to

Algorithm 2: Traversing the index layer

Input : S, PI index
Q, query batch
Output: Π, interception set

```
1  Π = ∅;
2  foreach q ∈ Q do
3      e_next = getTopEntry(S);
4      v_b = _simd_load(q.κ);
5      while isStorageLayer(e_next) == false do
6          v_a = _simd_load(e_next);
7          mask = _simd_compare(v_a, v_b);
8          /* R_next is the routing table of e_next */
9          e_next = findNextEntry(e_next, mask, R_next);
10     Π = Π ∪ {e_next};
11 return Π;
```

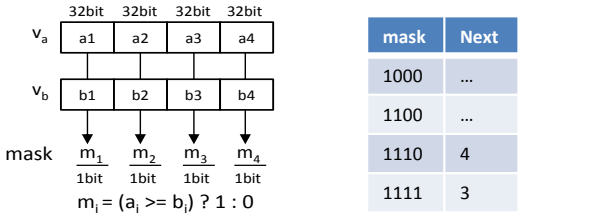
fetch the data node with key 8 and delete the data node with key 26 in storage layer, and thread 2 moves along with the green arrows to insert the data node with key 102.

3.2.1 Traversing the Index Layer

Algorithm 2 shows how the index layer is traversed to find the interceptions for queries. For each query key, the traversal starts from the top level of the index layer and moves forward along this level until an entry containing a larger key is encountered, upon which it moves on to the next level and proceeds as it does in the previous level. The traversal terminates when it is about to leave the bottom level of the index layer, and records the first data node that will be encountered in the storage layer as the interception for the current query.

We exploit Single Instruction, Multiple Data (SIMD) processing to accelerate the traversal. In particular, multiple keys within an entry can be simultaneously compared with the query key using an _simd_compare instruction, which significantly reduces the number of comparisons, and this is the main reason we put multiple keys in each entry. In our implementation, keys in an entry exactly occupy a whole SIMD vector, and can be loaded into an SIMD register using a single _simd_load instruction.

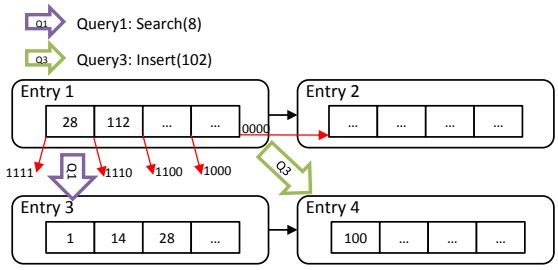
Since each _simd_compare instruction compares multiple keys in an entry, the comparison result can be diversified, and hence an efficient way to determine the next entry to visit for each comparison result is needed. To this end, we generate a routing table for each entry during the construction of PI. For each possible result of SIMD comparison, the routing table contains the address of the next entry to visit. Figure 2(a) gives an example of SIMD comparison. As shown in this figure, each SIMD comparison leads to a 4-bit mask, representing five potential results indicated by the red arrows shown in Figure 2(c). This mask is then indexed into the routing table, which is also shown in Figure 2(b), to find the next entry for comparison.



(a) SIMD comparison

mask	Next
1000	...
1100	...
1110	4
1111	3

(b) Routing table for Entry 1



(c) Routing process for Entry 1

Figure 2: Querying with a routing table

3.2.2 Redistribute Query Workload

Given the interception set output by Algorithm 2, a thread can find for each allocated query q the data node with the largest key that is less than or equal to $q.\kappa$ by walking along the storage layer, starting from I_q. However, it is possible that two queries allocated to two adjacent threads have the same interception, leading to contention between the two threads. To handle this case, we slightly adjust the query workload among the execution threads such that each interception is exclusively accessed by a single thread, and so are the data nodes between two adjacent interceptions. To this end, each thread iterates backward over its interception set until it finds an interception different from the first interception of the next thread, and hands over the queries corresponding to the iterated interceptions to the next thread. The details of this process are summarized in Algorithm 3 and exemplified in Figure 3. After the adjustment, a thread can individually execute the allocated query workload without contending for data nodes with other threads.

Algorithm 3: Redistribute query workload

Input : $Q = \{q_1, q_2, ...\}$, query batch
$\Pi = \{I_{q_1}, I_{q_2}, ...\}$, interception set
T_{last}, last execution thread
T_{next}, next execution thread

```
1  /* exchange the key of the first interception*/
2  sendKey(T_last, I_q1.κ);
3  κ = recvKey(T_next);
4  /* wait for the adjustment from last thread */
5  Q' = recvQuery(T_last), Q = Q' ∪ Q;
6  foreach q ∈ Q' do
7      /* I_q is same as I_q1 */
8      Π = I_q1 ∪ Π
9  Q' = ∅;
10 for i = |Q| → 1 do
11     if I_qi.κ = κ then
12         Q' = Q' ∪ {q_i}, Q = Q \ {q_i}, Π = Π \ {I_qi};
13     else
14         break;
15 sendQuery(T_next, Q');
```

3.2.3 Query Execution

The query execution process at each thread is demonstrated in Algorithm 4. For each query q, an execution thread iterates over the storage layer, starting from the corresponding interception, and executes the query against the data node with the largest key that is less than or equal to

Algorithm 4: Query execution

Input : $Q = \{q_1, q_2, ...\}$, adjusted query batches
$\Pi = \{I_{q_1}, I_{q_2}, ...\}$, adjusted interception set
Output: R, result set

```
1  R = ∅;
2  for i = 1 → |Q| do
3      /* walk along the storage layer, */
4      /* starting from the corresponding interception */
5      node = getNode(q_i, I_{q_i});
6      r_i = null;
7      if q_i.t == "Search" then
8          if node.κ == q_i.κ && !node.F_del then
9              r_i = node.p;
10     else if q_i.t == "Insert" then
11         if node.κ == q_i.κ then
12             node.p = q_i.p;
13         else
14             node = insertNode(node, q_i.κ, q_i.p, Γ);
15         node.F_del = false;
16     else
17         if node.κ == q_i.κ then
18             node.F_del = true;
19     R = R ∪ {r_i}
20 return R;
```

$q.\kappa$. If the query type is delete, we do not remove the data node immediately from the storage layer, but merely set a flag F_{del} instead, which is necessary for latch-free query processing, as we shall explain in Section 3.2.4. For the search query, the F_{del} flag of the resultant data node will be checked to decide the validity of its pointer. For the update query, a new data node will be inserted into the storage layer if the query key does not match that of the resultant data node. Unlike a typical skip list, PI only allocates a random height for the new node, but does not update the index layer immediately. With more and more updates made to the storage layer, the index layer should be updated accordingly to guarantee the performance of query processing. Currently, a background process monitors the updates to the storage layer, and asynchronously rebuild the whole index layer when the number of updates exceeds a certain threshold. The detail is given in Section 4.3.5.

3.2.4 Naturally Latch-free Processing

It is easy to see that query processing in PI is latch-free. In the traversal of the index layer, since the access to each entry is read-only, the use of latches can be avoided at this stage. For the adjustment of query workload, each thread communicates with its adjacent threads via messages and thus does not rely on latches. In addition, each query q allocated to thread i after the adjustment of query workload satisfies $I^i_{q_1}.\kappa \leq q.\kappa < I^{i+1}_{q_1}.\kappa$, where $I^i_{q_1}$ and $I^{i+1}_{q_1}$ are the first element in the interception sets of thread i and $i+1$, respectively. Consequently, thread i can individually execute without latches all its queries except those which require reading $I^{i+1}_{q_1}$ or inserting a new node directly before $I^{i+1}_{q_1}$, since the data nodes that will be accessed during the execution of these queries will never be accessed by other threads. The remaining queries can still be executed without latches as the first interception of each thread will never be deleted, as described in Section 3.2.3.

In our algorithm, a query set Q is ordered mainly due to two reasons. First, cache utilization can be improved by processing ordered queries in Algorithm 1, since the entries and/or data nodes to be accessed for a query may have already been loaded into the cache during the processing of previous queries. Second, a sorted query set leads to sorted interception sets (ordered by query key), which is necessary for interception adjustment and query execution to work as expected.

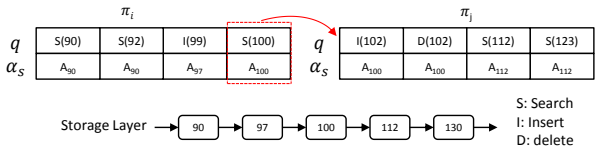


Figure 3: Interception adjustment

3.2.5 Range Query

Range query is supported in PI. Given a set of range queries (a normal point query defined in Definition 2 is also a range query with the upper and lower bound of the key range being the same), we first sort them according to the lower bound of their key range and then construct a query set defined in Definition 3 using these lower bounds. This query set is then distributed among a set of threads to find the corresponding interceptions, as in the case of point queries. The redistribution of query workload, however, is slightly different. Denote the first element in the interception set of thread i, i.e., the interception corresponding to the first query in the query batch of thread i, by $I^i_{q_1}$. For each allocated query with a key range of $[\kappa_s, \kappa_e]$, where $\kappa_e \geq I^{i+1}_{q_1}$, thread i partitions it into two queries with the key ranges being $[\kappa_s, I^{i+1}_{q_1}.\kappa)$ and $[I^{i+1}_{q_1}.\kappa, \kappa_e]$, respectively, and hands over the second query to thread $i+1$. As in Algorithm 3, this redistribution process must be performed in the order of thread *id* in order to handler the case where the key range of a range query is only covered by the union of the interception sets of three or more threads. After the redistribution of query workload, each thread then executes the allocated queries one by one, which is quite straightforward. Starting from the corresponding interception, PI iterates over the storage layer to find the first data node within the key range, and then executes the query upon it and each following data node until the upper bound of the key range is encountered. The final result of an original range query can be acquired by combining the result of corresponding partitioned queries.

4. IMPLEMENTATION

4.1 Storage Layout

As we have mentioned, PI logically consists of the index layer and the storage layer. The index layer further comprises multiple levels, each containing the keys appearing at that level. Keys at the same level are organized into entries to exploit SIMD processing, and each entry is associated with a routing table to guide the traversal of the index layer. For better cache utilization, entries of the same level are stored in a contiguous memory area. The storage layer of PI is implemented as a typical linked list of data nodes to support efficient insertions. Since entries contained in each level of the index layer are stored compactly in a contigu-

ous memory area, PI cannot immediately update the index layer upon the insertion/deletion of a data node with height $h > 1$. Currently, we implement a simple strategy to realize these deferred updates. Once the number of insertions and deletions exceeds a certain threshold, the entire index layer is rebuilt from the storage layer in a bottom-up manner. Although this strategy seems to be time-consuming, it is highly parallelizable and the rebuilding process can thus be shortened by using more threads. Specifically, each thread can be assigned a disjoint portion of the storage layer and made responsible to construct the corresponding part of the index layer. The final index layer can then be obtained by simply concatenating these parts level by level.

4.2 Parallelization and Serializability

We focus on two kinds of parallelization in the implementation, i.e., data-level parallelization and scale-up parallelization. It is also worth noting that serializability should be guaranteed in the parallel process.

Data-level parallelization is realized through the use of SIMD instructions during the traversal of the index layer. As mentioned before, in our implementation, each entry contains multiple keys, and their comparison with the query key can be done using a single SIMD comparison instruction, which substantially accelerates the search process of interceptions. Moreover, SIMD instructions can be introduced in sorting the query set Q to improve the performance. In our implementation, we use Intel Intrinsic Library to implement SIMD related functions.

We exploit scale-up parallelization provided in multi-core systems by distributing the query workload among different cores such that the execution thread running at each core can independently process the queries assigned to it. Serializability issues may arise as a result of coexistence of search and update queries in one batch, and we completely eliminate these issues by ensuring that only one thread takes charge of each data node at any time.

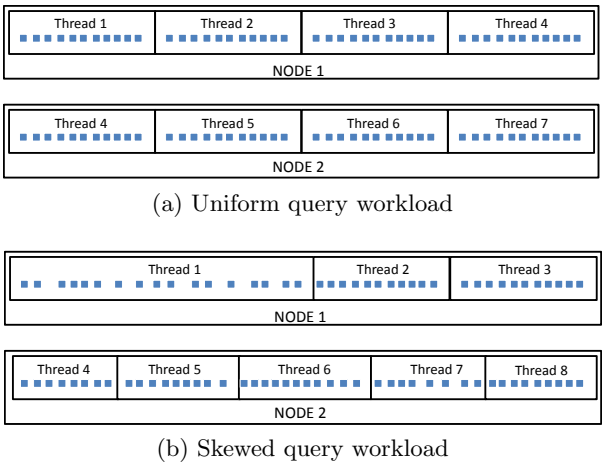
4.3 Optimization

4.3.1 NUMA-aware Optimization

The hierarchical structure of a modern memory system, such as multiple cache levels and NUMA (Non-Uniform Memory Access) architecture, should be taken into consideration during query processing. In our implementation, we organize incoming queries into batches, and process the queries batch by batch. The queries within one batch are sorted before processing. In this manner, cache locality can be effectively exploited, as the search process for a query key is likely to traverse the entries/data nodes that have just been accessed during the search of the previous query and thus have already been loaded into the cache.

A NUMA architecture is commonly used to enable the performance of a multi-core system to scale with the number of processors/cores. In a NUMA architecture, there are multiple interconnected NUMA nodes, each with several processors and its own memory. For each processor, accessing local memory residing in the same NUMA node is much faster than accessing remote memory of other NUMA nodes. It is thus extremely important for a system running over a NUMA architecture to reduce or even eliminate remote memory access for better performance.

PI evenly distributes data nodes among available NUMA nodes such that the key ranges corresponding to the data nodes allocated to each NUMA node are disjoint. One or more threads will then be spawned at each NUMA node to build the index from the data nodes of the same NUMA node, during which only local memory accesses are incurred. As a result, for each NUMA node, there is a separate index, which can be used to independently answer queries falling in the range of its key set. Each incoming query will be routed to the corresponding NUMA node, and get processed by the threads spawned in that node. In this way, there is no remote memory access during query processing, which will translate into significantly enhanced query throughput, as shown in the experiments. Moreover, the indices at different NUMA nodes also collectively improve the degree of parallelism since they can be used to independently answer queries. This idea of parallelism is aptly illustrated in Figure 1, where two threads are spawned in the first NUMA node and the other three nodes can have multiple threads running in parallel as well.



(a) Uniform query workload

(b) Skewed query workload

Figure 4: Self-adjusted threading

4.3.2 Load Balancing

It can be inferred from Algorithm 3 that PI ensures the data nodes between two adjacent interceptions are handled by the same thread. As long as the queried keys of a batch are not limited to a very short range, PI is able to distribute the query workload evenly among multiple threads (within a NUMA node) due to the fact that queries of a batch are sorted and the way we partition the queries. However, it is more likely that the load among multiple NUMA nodes is unbalanced, which occurs when most incoming queries should be answered by the data nodes located at a single NUMA node. To address this problem, we use a self-adjusted threading mechanism. In particular, when a query batch has been partitioned and each partitioned sub-query has been assigned to the corresponding NUMA node, we spawn threads in each NUMA node to process its allocated queries such that the number of threads in each NUMA node is proportional to the number of queries assigned to it. Consequently, a NUMA node that has been allocated more queries will also spawn more threads to process queries. An example and its further explanation on the threading mechanism are given in Section 4.3.3.

4.3.3 Self-adjusted threading

In this section, we shall elaborate on our self-adjusted threading mechanism, which allocates threads among NUMA nodes for query processing such that query performance can be maximized within a given budget of computing resource. As mentioned in Section 4.3.2, if there are several NUMA nodes available, PI will allocate the data nodes among them, build a separate index in each NUMA node from its allocated data nodes, and route arriving queries to the NUMA node with matching keys in order not to incur expensive remote memory accesses. Given the query workload at each NUMA node, our mechanism dynamically allocates execution threads among NUMA nodes such that the number of threads running on each NUMA node is proportional to its query workload, i.e., the number of queries routed to it. In the cases where a NUMA node has used up its hardware threads, our mechanism will offload part of its query workload to other NUMA nodes with available computing resource.

4.3.4 Group Query Processing and Prefetching

Since entries at the same level of the index are stored in a contiguous memory area, it is thus more convenient (due to fewer translation lookaside buffer misses) to fetch entries of the same level than to fetch entries locating at different levels. In order to realize this location proximity, instead of processing queries one by one, PI organizes the queries of a batch into multiple query groups, and processes all queries in a group simultaneously. At each level of the index layer, PI traverses along this level to find the first entry at the next level to compare with and then moves downward to the next lower level to repeat this process.

Moreover, this way of group query processing naturally calls for the use of prefetching. When the entry to be compared with at the next level is located for a query, PI issues a prefetch instruction for this entry before turning to the next query. Therefore, the requested entries at the next level may have already been loaded into L1 cache before the comparison between them and the queried keys, thereby overlapping the slow memory latency.

4.3.5 Background Updating

We use a daemon thread running in background to update index layer. If the number of update operations meets a predefined threshold, the daemon thread will start rebuilding the index layer. The rebuilding of the index layer is fairly straightforward. The daemon thread traverses the storage layer, put the key of each valid data node with height > 1 encountered into an array sequentially, and updates the associated route table with the address of this data node. The new index layer will be put into use after all running threads complete the processing of current query batch, and meanwhile the old index layer will be discarded.

5. PERFORMANCE MODELING

In this section, we develop a performance model for query processing of PI. The symbols used in our analysis are summarized in Table 1.

5.1 Key Search

Table 1: Notations for Analysis

Symbol	Description
H	index height
P	probability parameter
M	number of keys contained in an entry
L	memory access latency
N	number of the initial data nodes
R	ratio of insert queries
S_e	entry size
S_n	data node size
S_l	size of a cache line
S_c	size of the last level cache
T_c	time to read a cache line from the last level cache

The key search process is to locate the data node with matching key at Storage Layer. The time spent in this process is dominated by the number of entries and data nodes that need to be read for key comparison.

Given the number of initial data nodes, N, the height of PI, H, is about $\lceil -\log_P N \rceil$. At each level of PI, the number of keys between two adjacent ones that also appear at a higher level follows a geometric distribution, and has an expected value of $1/P$. Therefore, the average number of entries needed to compare with at each level of the index layer is approximately $\lceil \frac{1+P}{2PM} \rceil$, where $\frac{1+P}{2P}$ is the average number of keys that need to be compared with. The number of cache lines that need to be read at each level is thus $\lceil \frac{S_e}{S_l} \rceil \lceil \frac{1+P}{2PM} \rceil$. Consequently, the total number of cache lines during the traversal of the index layer is $(H-1)\lceil \frac{S_e}{S_l} \rceil \lceil \frac{1+P}{2PM} \rceil$. This is however a slight over-estimate, since the top levels of the index layer may already have been read into L1 cache.

When the interception has been located in the storage layer for a given query, the search process proceeds by iterating over the data nodes from the one contained in the interception until the node with matching key is encountered. The number of data nodes scanned during this phase is about half of the number of data nodes contained between two adjacent ones with their key appearing at the index layer, which is given by $\lceil \frac{1+P}{2PM} \rceil$, and the number of cache lines read during this stage is $\lceil \frac{S_n}{S_l} \rceil \lceil \frac{1+P}{2PM} \rceil$.

The number of data nodes read during the scanning of the storage layer is not affected by the delete queries because of the PI query processing strategy. However, insert queries do impact this number. Assuming insert queries are uniformly distributed among the storage layer, and the aggregate number of insert and delete queries does not exceed the threshold upon which the rebuilding of the index layer will be triggered. The number of data nodes during key search process will become $\frac{(1+iR/N)(1+P)}{2P}$, where i is the number of queries that have been processed, and R is the ratio of insert queries among the processed i queries.

In our implementation, the probability of key elevation, P, is 0.25 as suggested in [32], and each entry contains 4 keys, each being a 32-bit float number. Therefore, the size of each entry, S_e, is 4*(4+8)=48 bytes, where the additional 8 bytes for each key is required by route table to determine the next entry to compare. Each data node occupies 20 bytes: 4 bytes are used for key, and the other 16 bytes compose two pointers, one pointing to the value, e.g., a tuple in a database

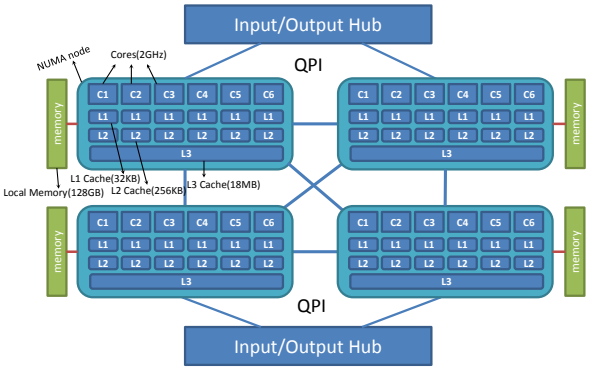


Figure 5: CPU architecture for the experiments

table, and the other for the next data node. Consider an instance of PI with 512K keys. Its size can be computed by $20 * 512K + 1/3 * 48 * 512K = 18M$, and the whole index can be kept in the last level cache of most servers (e.g. the one we use for the experiments). Therefore, the processing of each search/delete query fetches about 12 cache lines, 9 for the index layer and 3 for the storage layer. The total time cost is thus $12T_c$, where T_c is the time to read a cache line from the last level cache.

5.2 Rebuilding the Index Layer

For the sake of simplicity, we only focus on the indices with a lot of data nodes, in which case the data nodes are unlikely to be cached, and hence require to be read from memory during the rebuilding of the index layer. In addition, a data node occupies 48 bytes, as mentioned in last section, and hence can be fetched within a single memory access, which normally brings a 64-byte cache line into the cache. Therefore, for an index with N data nodes, scanning the storage layer costs a time of NL. In addition, there are $NP/(1-P)$ entries and routing tables that need to be written back into memory, which costs another $2NP/(1-P)$ memory accesses. Therefore, the total time of rebuilding the index layer can be approached by $(1+P)NL/(1-P)$. However, with more threads participating in the rebuilding process, this time can be reduced almost linearly before bounded by memory bandwidth.

6. PERFORMANCE EVALUATION

We evaluate the performance of PI on a platform with 512 GB of memory evenly distributed among four NUMA nodes. Each NUMA node is equipped with an Intel Xeon 7540 processor, which supports 128-bit wide SIMD processing, and has a L3 cache of 18MB and six on-chip cores, each running at 2 GHz. The CPU architecture is described in Figure 5, where QPI stands for Intel QuickPath Interconnect. The operating system installed in the experimental platform is Ubuntu 12.04 with kernel version 3.8.0-37.

The performance of PI is extensively evaluated from various perspectives. First, we show the adaptivity of PI's performance of query processing by varying the size of the dataset and batch, and then adjust the number of execution threads to investigate the scalability of PI. Afterwards, we study how PI performs in the presence of mixed and

Table 2: Parameter table for experiments

Parameter	Value
Dataset size(M)	2, 4, 8, <u>16</u>, 32, 64, 128, 256
Batch size	2048, 4096, <u>8192</u>, 16384, 32768
Number of Threads	1, 2, 4, <u>8</u>, 16, 32
Write Ratio(%)	0, 20, 40, 60, 80, 100
Zipfian parameter θ	<u>0</u>, 0.5, 0.9

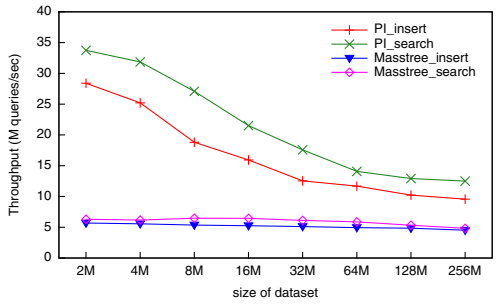


Figure 6: Query throughput vs dataset size

skewed query workloads, and finally examine PI's performance with respect to range query. For comparison, the result of Masstree [29] under the same experiment setting is also given, whenever possible. We choose Masstree as our baseline mainly due to its high performance and maturity which is evidenced by its adoption in a widely recognized system, namely SILO [37]. The Masstree code we use is retrieved from github [1], and its returned results are consistent with (or even better than) those presented in the original paper [29], as shown in the following sections.

If not otherwise specified, we use the following default settings for the experiments. The key length is four bytes. There are eight execution threads running on the four NUMA nodes, and the number of threads running on each node is proportional to the query workload for this node, as mentioned in Section 4.1. Three datasets, each with a different number of keys, are used. The small and medium datasets have 2M and 16M keys, respectively, and the large dataset has 128M keys. The index built from the dataset are evenly distributed among the four NUMA nodes. Each NUMA node holds a separate index accounting for approximately 1/4 of the keys in the dataset. All the parameters for the experiments are summarized in Table 2, where the default value is underlined when applicable.

The query workload is generated from *Yahoo! Cloud Serving Benchmark* (YCSB) [13], and the keys queried in the workload follow a zipfian distribution with parameter $\theta = 0$, i.e., a uniform distribution. A query batch, i.e., the set of queries allocated to a thread after partitioning in Algorithm 1, contains 8192 queries, and a discussion on how to tune this parameter is given in Section 6.2. The whole index layer is asynchronously rebuilt after a fixed number (15% of the original dataset size) of data nodes have been inserted/deleted into/from the index.

6.1 Dataset Size

Figure 6 shows the processing throughput of PI and Masstree for search and insert queries. For this experiment, we vary the number of keys in the dataset from 2M to 256M, and ex-

amine the query throughput for each dataset size. The whole index and query workload is evenly distributed among the four NUMA nodes, and there are two threads running over each NUMA node to process queries.

From Figure 6, one can see that the throughput for both search and insert experiences a moderate decrease as the dataset size increases from 2M to 64M, and then becomes relatively stable for larger dataset sizes. This variation trend in the throughput is natural. For the dataset with 2M keys, as we have explained in Section 5, the entire index can be accommodated in the last level caches of the four NUMA nodes, and the throughput is hence mainly determined by the latency to fetch the entries and data nodes from the cache. As the dataset size increases, more and more entries and data nodes are no longer able to reside in the cache and hence can only be accessed from memory, resulting in higher latency and lower query throughput.

The throughput of insert queries of PI is not as high as that of search queries. The reason is two-fold. First, as insert queries are processed, more and more data nodes are inserted into the storage layer of the index, resulting in an increase in the time to iterate over the storage layer. Second, the creation of data nodes leads to the eviction of entries and data nodes from the cache, and a reduced cache hit rate. This also explains why the performance gap between insert and search queries gradually shrinks with the size of dataset.

As can be observed from Figure 6, the throughput of both search and insert queries in Masstree is much less than that of PI. In particular, PI is able to perform 34M search queries or 29M insert queries in one second when the index can be accommodated in the cache, which are respectively five and four times more than the corresponding throughput Masstree achieves for the same dataset size. For larger datasets, PI can still consistently perform at least 1.5x and 1x better than Masstree in terms of the search throughput and insert throughout, respectively.

6.2 Batch Size

We now examine the effect of the size of query batches, on the throughput of PI. For this experiment, the three default datasets, i.e., the small, medium and large datasets with 2M, 16M and 128M keys, respectively, are used.

Figure 7 shows the result of query throughput with respect to query batch size for the three datasets. It can be seen that the size of query batches indeed affects query throughput. In particular, as the size of query batch increases, the throughput first undergoes a moderate increase. This is due to the fact that the queries contained in a batch are sorted based on the key value, and a larger batch size implies a better utilization of CPU caches. In addition, there is an interception adjustment stage between key search and query execution in the processing of each query batch, whose cost only depends on the number of running threads, and thus is similar across different batch sizes. Consequently, with more queries in a single batch, the number of interception adjustments can be reduced, which in turn translates into an increase in query throughput.

Figure 7 also demonstrates that the effect of batch size exerting on query throughput is more significant for smaller datasets than for larger datasets. The reasons are as follows. For query batches of the same size, the processing time increases with the size of dataset, as we have already shown in

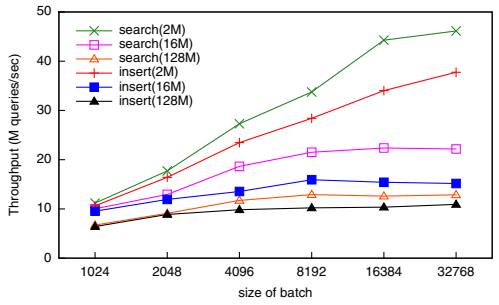


Figure 7: Query throughput vs batch size

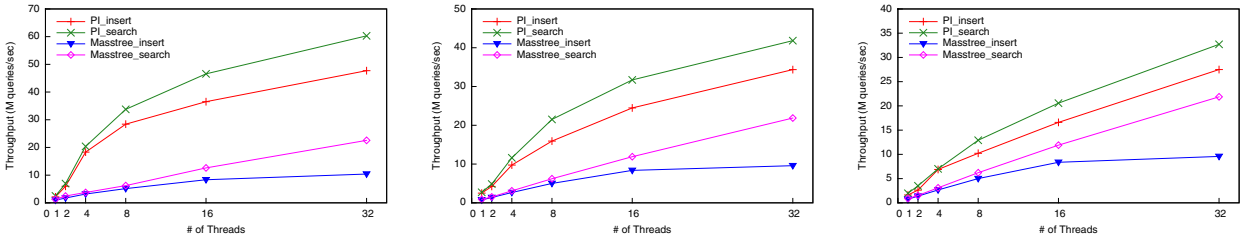
Figure 6. Therefore, for smaller datasets, the additional time spent in interception adjustment and warming up the cache, which is similar across the three datasets, plays a more important role than for larger datasets. As a result, smaller datasets benefit more from the increase in query batch size than larger datasets do. It can be seen from Figure 7 that PI performs reasonably well under the default setting of 8192 for batch size, but there still remains space of performance improvement for small datasets. Hence, there is no one-size-fits-all optimal setting for batch size, and we leave behind the automatic determination of optimal batch size as future work.

6.3 Scalability

Figure 8 shows how the query throughput of PI and of Masstree varies with the number of execution threads. The threads and the index are both evenly distributed among the four NUMA nodes. For the case in which there are $n < 4$ execution threads, threads and the whole index are evenly distributed among the same number of NUMA nodes which are randomly selected from the available four. We use the three datasets, i.e., 2M, 16M and 256M respectively, for this experiment.

It can be seen from Figure 8 that apparently, both PI and Masstree can get their query throughput to increase significantly with more computing resources, but there exists a substantial gap in the rate of improvement between PI and Masstree, especially in the cases with a small number of threads. In PI, when the number of threads changes from 1 to 4, the throughput undergoes a super-linear increase. This is because when the number of threads is no larger than 4, the whole index is evenly distributed among the same number of NUMA nodes. Consequently, the index size, i.e., the number of entries and data nodes, halves when the number of threads doubles. With a smaller index size, cache can be more effectively utilized, leading to an increased single-thread throughout, and hence a super-linear increase in aggregate throughout. Since smaller indices are more cache sensitive than larger ones, they benefit more from the increase of the number of threads in terms of the throughput of query processing, as can be observed from Figure 8.

When the number of threads continues to increase, the increase rate in query throughput of PI gradually slows down, but is still always better than or equal to that of Masstree. This flattening can be attributed to the adjustment of interceptions which take place when there are more than one thread servicing the queries in a NUMA node. And since the cost of interception adjustment only depends on the number



(a) dataset size = 2M (b) dataset size = 16M (c) dataset size = 128M

Figure 8: Query throughput vs thread number

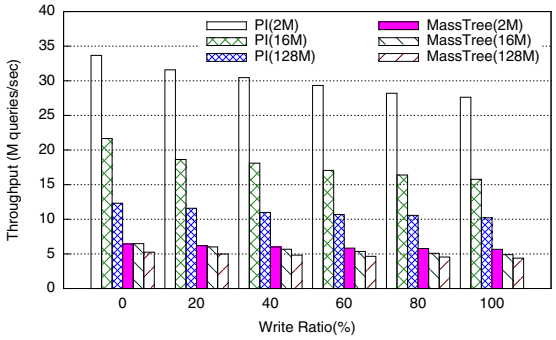


Figure 9: Query throughput of mixed workloads

of threads, it is same across the indices with different sizes, and hence accounts for a larger fraction of query processing time for smaller indices. This also explains why query throughput of smaller indices drops faster than that of larger ones.

6.4 Mixed Query Workload

In order to thoroughly profile the performance of PI, we study how it behaves in the presence of query workload consisting of various types of queries. As before, we conduct this experiment over three default datasets (2M, 16M and 128M). The query workload consists of keys following a uniform distribution, and the entire index layer is rebuilt once a specified number (15% of dataset size) of data nodes have been inserted into the index.

Figure 9 shows the result when the ratio of insert queries increases from 0% to 100%. For each ratio, the number of queries issued to the index is such that the index layer is rebuilt for the same number as for other ratios. As shown in Figure 9, with the increase of updates in the query workload, the throughput of PI undergoes a slight decrease as a result of more data nodes in storage layer being traversed, demonstrating PI's capability in processing uniform query workload. Masstree also experiences a similar variance trend in the query throughput.

6.5 Resistance to Skewness

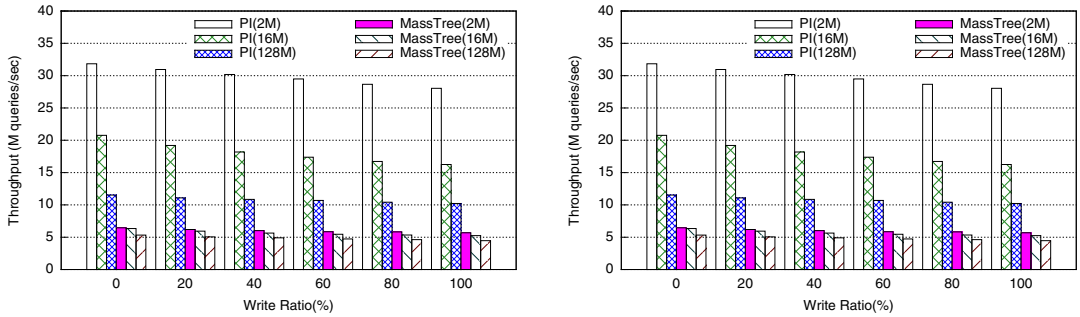
In this section, PI's performance of query processing is explored in the presence of query skewness. As before, there are eight threads running over the four NUMA nodes, and three datasets with default sizes (2M, 16M and 128M) are used. The skewness in query workload is realized via varying the probability parameter, θ, of zipfian distribution for workload generation. An intuitive impression on the skewness of the query workloads used in this section is given in Appendix 6.6 .

Figure 10 exhibits the variation in the throughput query processing with respect to query skewness and update ratio in query workloads. By comparing this figure with Figure 9, we can observe that query skewness has only a little impact on the performance of PI in terms of query processing. We attribute this resistance to query skewness of PI to the self-adjusted threading mechanism presented in Section 4.3.2, which dynamically allocates computing resources among NUMA nodes based on the query load on each node. In fact, for the query workload with zipfian probability parameter $\theta = 0.5$, the numbers of threads spawned at four NUMA nodes are 3, 2, 2 and 1, respectively, and for the other query workload with $\theta = 0.9$, these numbers become 4, 2, 1 and 1, respectively. For comparison purposes, the corresponding result measured with the threading mechanism disabled is shown in Figure 11, from which one can see that the threading mechanism does significantly enhance the throughput.

It should also be noted that the skewness in query workload does not always exert a negative impact on the throughput. When fed with a workload consisting of pure search queries against keys following a zipfian distribution with $\theta = 0.5$, PI is able to achieve a throughput that is even higher than what is achieved in the case of no query skewness, as shown in Figure 9 and 10(a). This is probably because in the NUMA node with the most amount of query load, each of the three spawned thread accesses only an even restricted portion of the index, and hence can utilize the cache more efficiently.

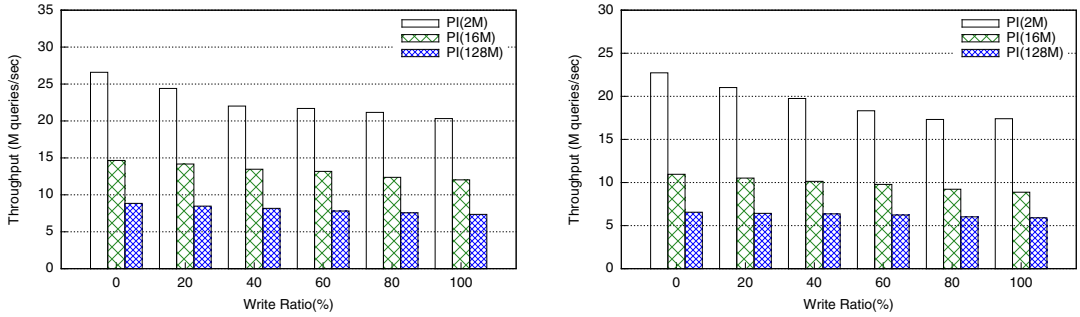
6.6 Details on YCSB Workload

Figure 12 shows the variance of skewness in the key distribution of the three YCSB workloads for the experiment of Section 6.5. In this figure, each circle consists of 100 sectors separating the whole key space into 100 disjoint ranges with equal coverage, and the color of a sector represents how frequently the keys within the relative range are queried. Since the keys in each YCSB workload follow a zipfian distribution, the workload becomes more skewed with the increase of probability parameter θ. However, as shown in Figure 10, the skewness in the query workload rarely affects the performance of PI (as well as Masstree) , which is also validated in Figure 13, where the zipfian parameter in three YCSB query workloads, each with a different update ratio (0.5, 0.05 and 0, respectively), are varied from 0 to 0.9 to investigate how PI can adapt to query skewness.



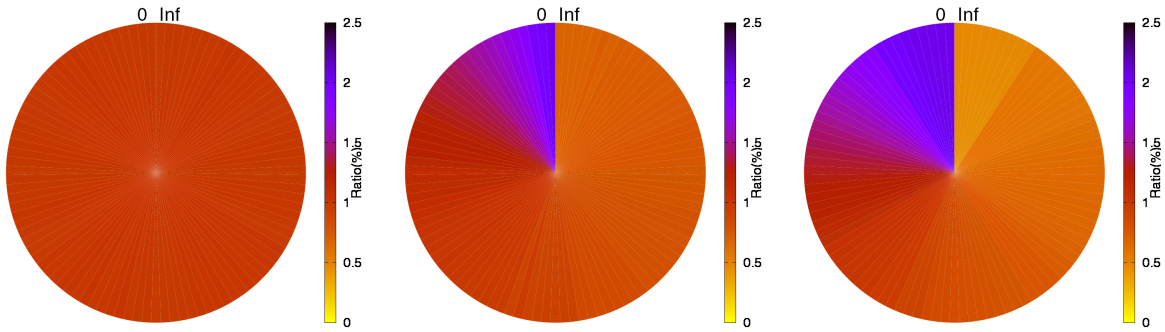
(a) $\theta = 0.5$ (b) $\theta = 0.9$

Figure 10: Query throughput vs query skewness (with self-adjusted threading)



(a) $\theta = 0.5$ (b) $\theta = 0.9$

Figure 11: Query throughput vs query skewness (without self-adjusted threading)



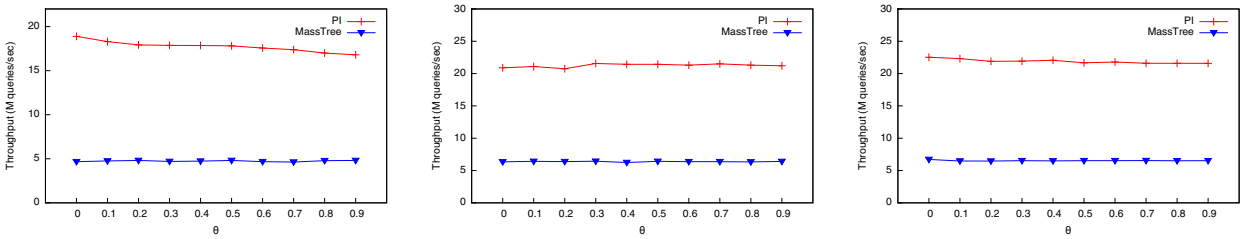
(a) $\theta = 0$ (b) $\theta = 0.5$ (c) $\theta = 0.9$

Figure 12: Key distribution in three YCSB query workloads

6.7 Range Queries

Figure 14 describes how the performance of range queries varies with granularity, by which we mean the average number of results (data nodes) returned for a given range query. In this experiment, only the performance of search queries is explored, and the same number of query batches, each with 8192 range queries, are issued for each dataset. For comparison, the result for point query (granularity = 1) is also shown in this figure.

It can be observed from Figure 14 that query throughput decreases with the granularity of range query at a constant rate for each dataset. Due to the better cache utilization of the index built from smaller datasets, the query throughput decreases a little more slowly for smaller datasets than for larger datasets. For the granularity of 1000, the processing of each query batch accesses almost 8M of data nodes, which means there are many data nodes being accessed multiple times for the small and medium datasets with 2M and 16M keys, respectively. Hence, the number of slow memory accesses incurred by reading entries and data nodes is further reduced by a larger amount for these two datasets than for



(a) workload A (b) workload B (c) workload C

Figure 13: Query throughput vs skewness

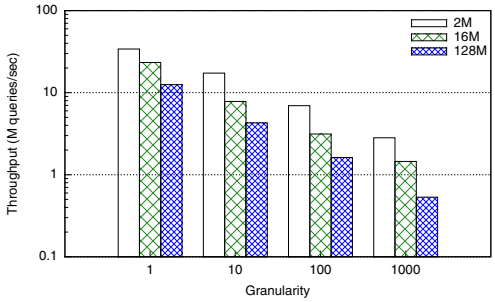


Figure 14: Query throughput of range query

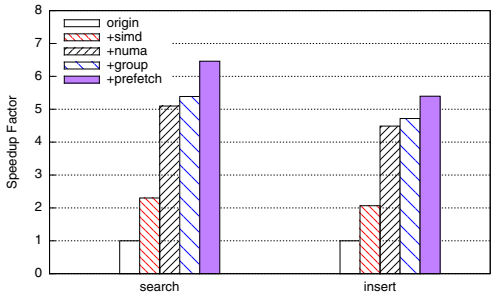


Figure 15: Effects of optimizations

the large dataset, and this is the reason to that the search throughput for the large dataset drops much faster than that for the other two datasets when the granularity varies from 100 to 1000.

6.8 Effects of Optimizations

We now explore how the optimization techniques such as SIMD processing, NUMA-aware index partitioning, prefetching and group query processing, affect the performance of PI. The impact of organizing queries into batches has already been studied in Section 6.2, and hence is not discussed here. The dataset used for this experiment contains 16M keys, and the other parameters are set to the default sizes.

Figure 15 shows the breakdown of the gap between the query performance of PI and a typical skip list with none of the optimizations enabled. By grouping the keys appearing at higher layers into entries, and leveraging SIMD to significantly reduce the number of key comparisons and hence memory/cache accesses, the throughput of PI can be improved by 1.3x and 1x for search and insert queries, respectively. NUMA-aware operation leads to another huge performance gain, improving the query throughput by 1.2x for both kinds of queries. This performance gain is because our NUMA-aware optimization largely eliminates accessing the memory of remote NUMA nodes, which is several times slower than accessing local memory. Group query processing brings in a slight improvement of 0.05x in query throughput, and prefetching contributes to the final performance gain of 0.2x and 0.14x in the throughput of search and insert queries, respectively.

7. CONCLUSION AND FUTURE WORK

In this paper, we argue that skip list, due to its high parallezability, is a better candidate for in-memory index than B^+-tree in concurrent environment. Based on this argument, we propose PI, a cache-friendly, latch-free index that supports both point query and range query. PI consists of an index layer, which is in charge of key search, and a storage layer responsible for data retrieval, and the layout of the index layer is carefully designed such that SIMD processing can be applied to accelerate key search. The experimental results show that PI is three times faster than Masstree in terms of query throughput.

For future work, we seek to implement a finer-grained mechanism for the rebuilding of the index layer, which is currently conducted against the whole index layer and thus not necessary in the presence of skewed queries which only update a small portion of the index layer. In addition, we are also exploring applying several other optimizations to PI. For instance, cache locality can be further enhanced by pinning the high levels of the index layer in the cache to prevent them from being evicted in the case of insufficient cache space, and a large memory page size can reduce the number of TLB misses incurred by memory accesses.

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