HotSpots: Reducing Contention on Hot Leaves in B-trees

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Abstract

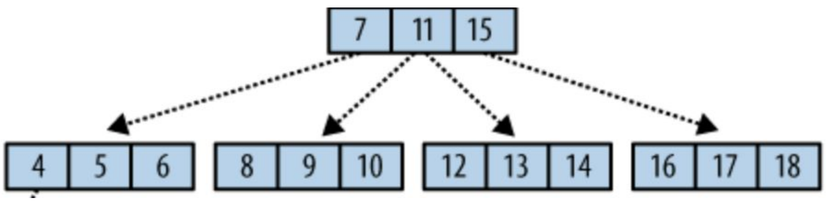
B-Tree indices are heavily used in modern transactional database systems for efficient search and range queries. Concurrency in these systems is maximized by locking at fine granularity. Lock contention among writers can be a severe performance bottleneck. In particular, when insertions are on a sequential key, all threads will contend for the rightmost leaf of the B-tree. We propose an Auxiliary Structure to augment concurrent B-trees and reduce contention. We evaluate our design against a concurrent B-tree using Optimistic Lock Coupling (OLC) [3] and an implementation we call *byte-reordering* that solves contention but does not support range queries. We find that in the OLC implementation, lookups scale well with number of threads but insertions do not. We find that byte-reordering is very effective at reducing contention and is a viable solution if the use case does not require range scans. Due to implementation difficulties, we were not able to optimize our Auxiliary Structure's performance, so it's performance lags significantly behind that of the other implementations; however, we believe more engineering effort is required to evaluate the full potential of this idea. Finally, we summarize some lessons learned regarding the design and implementation of concurrent data structures.

Introduction

The B-tree has become a standard access method for database systems owing to its efficient search, versatility, easy-to-maintain structure, and good performance on hard drives. Minimal locking strategies for B-trees are also well known [6].

Our paper focuses on the case of a B-tree index on a *sequential* attribute (that is, an attribute for which consecutive elements are sequential in the key-space). If the workload has heavy concurrent record insertions on such a sequential attribute, then all threads will contend on the same rightmost leaf node of the B-tree index. We call such a leaf node with contention, a *hot spot*.

For example, suppose that the following B-Tree represents an index on a Sales table of database, which is keyed by an auto-incremented order ID. Note that insertions for orders 19, 20, and 21 will all lock the same page. Additionally, in order to split the rightmost leaf, we will need to lock the entire path up to the root of the B-Tree. The contention on rightmost leaf, the hot-spot, is what we aim to solve in this work.



To mitigate contention on hot spots, we propose a modification to B-trees with Optimistic Lock Coupling (OLC) [3]: maintaining an auxiliary structure to keep a track of hot pages. The pages are identified to be hot through maintained statistics. An insertion to a hot page would update the auxiliary structure with this information, rather than the B-tree. Searches for a given key first look in the auxiliary structure. The auxiliary structure uses traditional locking and concurrent data structures, rather than OLC, to tolerate contention while attempting to maintain reasonable performance.

A user-defined policy determines which pages are stored in the auxiliary structure, based on statistics. When a page is evicted from the auxiliary structure, it is inserted back to the B-tree. This amortizes the cost of locking the hot area of the B-Tree over many operations.

Our B-tree design can efficiently support all major common index operations, including insertions, deletions, range scans, and point lookups, though our prototype implements only insertions and point lookups.

We evaluate our technique's performance against B-Trees with OLC and against a solution that reduces contention at the expense of range scans called byte-reordering. We find that in the OLC implementation, lookups scale well with number of threads but insertions do not. We find that byte-reordering is very effective at reducing contention and is a viable solution if the use case does not require range scans. Due to implementation difficulties, we were not able to optimize our Auxiliary Structure's performance, so it's performance lags significantly behind that of the other implementations; however, we believe more engineering effort is required to evaluate the full potential of this idea. Finally, we summarize some lessons learned regarding the design and implementation of concurrent data structures.

Background

Our design is a modification of B-trees with Optimistic Lock Coupling (OLC) [3]. In this section, we give a brief summary of OLC.

OLC is a locking technique in which writers acquire a traditional lock on nodes they need to update, while readers optimistically attempt to access data without acquiring a lock, restarting if there is a conflict with a writer. Moreover, as in normal Lock Coupling, at any given time, a writer holds at most two locks, while a reader never waits for locks.

Each node in the B-tree has an associated optimistic lock, which consists of a version counter and a traditional mutex lock. Each writer must acquire the mutex on nodes they wish to modify, possibly blocking until another writer releases the mutex. When a writer releases the mutex, it updates the version counter associated with the optimistic lock. When a reader wishes to read a node's contents, it will first read the version counter (but not acquire the mutex). When the reader is done, it must check if the version has changed during its read, indicating a conflict with a writer. If the version has changed, the reader must restart; otherwise, the reader is done. Care must be taken to handle deletions properly since a thread might be using a node when it is deleted. Many concurrent B-tree implementations use epoch-based techniques to handle deletion safely [3, 4].

Like other optimistic techniques, optimistic lock coupling has higher performance when conflicts are rare, since this decreases the probability that a thread must restart. In contrast, traditional locking techniques may have higher performance when conflicts are frequent, such as when there is a lot of contention on a hot node [5]. Our work aims to improve the performance of OLC under cases where there is contention on a few hot B-tree nodes.

Design

To reduce contention on pages in the B-tree, we propose a modification to B-trees with OLC. The key idea is to collect writes to hot pages efficiently in an auxiliary structure and then amortize the cost of locking the hot area of B-Tree over many operations when evicting the range from the auxiliary structure. Since B-Tree indices are secondary data stores, they can be slightly out of date from the primary store in the case of a crash. We suggest that during recovery, the lost updates can be rebuilt, though we do not explore crash recovery further in our work. Our approach attempts to achieve higher performance by designing the auxiliary structure with contention in mind while allowing the rest of data to use OLC.

Our design separates policy and mechanism:

Mechanism Our design augments the B-tree with an auxiliary structure that aims to allow higher-performance concurrent access to data with high contention. The auxiliary structure keeps track of ranges of the key-space. For each range, key-value pairs inserted into the ranges are diverted from the B-tree to the auxiliary structure, rather than being inserted into the B-tree. The auxiliary structure uses traditional fine-grain locking to handle concurrency with high contention.

Policy The auxiliary structure adds and evicts ranges of keys based on the policy in use. For our prototype, we use an LRU policy to enforce a maximum size on the auxiliary data structure.

Auxiliary Structure

The auxiliary structure (AS) is conceptually a concurrent map. It keeps track of ranges of the key-space as directed by policy. For each range, the AS stores all key-value pairs inserted into the range. Writes to a single range are insertions on a concurrent hashmap structure.

Updates to the set of tracked ranges are directed by the policy. Insertions and deletions of new ranges are serialized using a mutex. We expect these to be uncommon, so the impact of serialization should be low. When a range is chosen to be evicted from the AS, it is inserted into the B-tree.

Policy

The policy must be able to handle two possible queries:

1. “Is a key in a hot range?” This is used to determine if an insertion should be redirected to the AS.
2. “Mark range [low, high) as touched.“ This is used to update stats used by the policy to make decisions. This query may also return a range to evict from the AS.

The policy is completely decoupled from the AS, so different policies can be plugged in. In principle, it may be possible for the user to supply an arbitrary policy; however, we do not explore this idea further in our work.

B-tree Search and Insertion

Insertions and searches in the B-tree operate largely as described in prior work [2, 3]. In this section we describe briefly our modifications to insertion and search to use the AS and policy.

Search first checks if the key is present in the AS. If the key being searched for is not present in the AS, a normal B-Tree lookup is performed. The policy is not informed of access because reads do not contend with each other.

On an insertion, if the policy indicates that the key is in a hot range, the new pair is inserted into the AS. This may require traversing the B-tree once to find out the maximum and minimum values that can land on the key’s B-tree leaf node. This is the range inserted into the AS. Otherwise, if the key is not in a hot range, it is inserted into the B-tree using the traditional algorithm. Ranges from the AS are evicted to the B-Tree based on policy as mentioned above. We use a special bulk-insertion operation to amortize locking over many keys.

Byte-Reordering

We also evaluate a solution that reorders the bytes of a key in a specific way to mitigate contention at the expense of range queries. In this solution, we swap the greatest and least bytes of keys before using them for B-tree operations. We call this solution *byte-reordering*. Byte reordering redistributes consecutive keys to different leaves. This means that threads inserting sequential values no longer contend on the rightmost leaf. Unfortunately, it also means that range queries are inefficient.

Implementation

Our implementation is available at https://github.com/mark-i-m/hot-spots. We borrow the B-tree OLC implementation directly from https://github.com/wangziqi2016/index-microbench [3]. Our other implementations are modifications of this implementation.

All implementations are written in C++. Byte-reordering consists of a 73 line change from the OLC implementation. The hybrid implementation with our auxiliary structure consists of 757 lines changed. In addition, we use the concurrent hash map found at https://github.com/efficient/libcuckoo.

Experimental Evaluation

Methodology

We evaluate our design by comparing read and sequential write performance to B-trees with OLC and byte-reordering.

For each implementation, we evaluate throughput and scalability of lookups and insertions. We run a series of experiments in which we measure the number of operations per second for a given number of reader threads (threads that only do lookups) and writer threads (threads that only do insertions). To measure performance of lookups, we hold the number of writer threads constant and vary the number of reader threads. Likewise, to measure performance of insertions, we hold the number of reader threads constant and vary the number of writer threads. All read operations are point lookups on a random key. All write operations are sequential, leading to high lock contention.

For our experiments measuring insertion performance we fix the number of reader threads at 20 and vary the number of writer threads from 1 to 20, and vice versa for our experiments measuring lookup performance. Each thread performs 100 million operations on the tree. For each experiment, the B-tree under test is initialized with 1 billion key/value pairs before any measurements are taken.

Though they are possible to implement, range searches and deletions have not been implemented or evaluated in this project due to time constraints. We leave this to future contributions and research.

All experiments were run on CloudLab c220g2 instances with 40 logical cores (Intel Xeon E5-2660 v3) and 160GB RAM. All B-trees are in-memory. Before each experiment, we set scaling governors to “performance” on all cores. Each thread is pinned to its own core. We use `rdtsc` for acquiring timing information.

Results

OLC

Figure [1] shows the lookup performance of the OLC implementation. As the figure shows, the reader throughput scales nearly linearly with the number of threads, achieving a maximum throughput of 17.5 million operations per second with 20 threads.

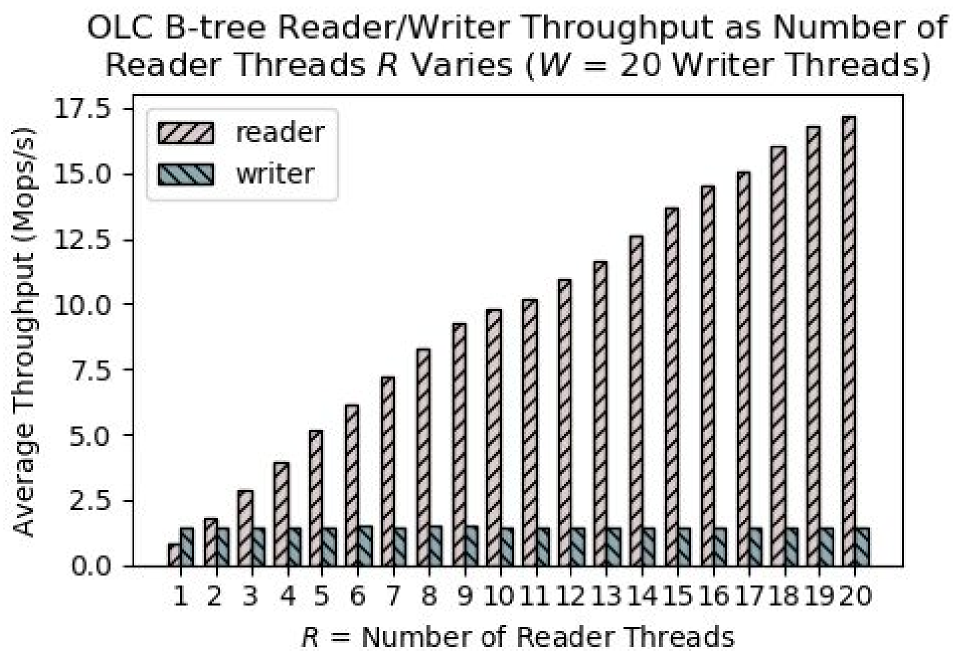


Figure 1

Figure [2] shows the insertion performance of the OLC implementation. As the figure shows, the writer throughput scales linearly up to 4 threads, reaching a peak throughput of 11 million operations per second. After that, performance drops to about 2.5 million operations per second. This experiment demonstrates that insertions under contention do not scale in the OLC implementation.

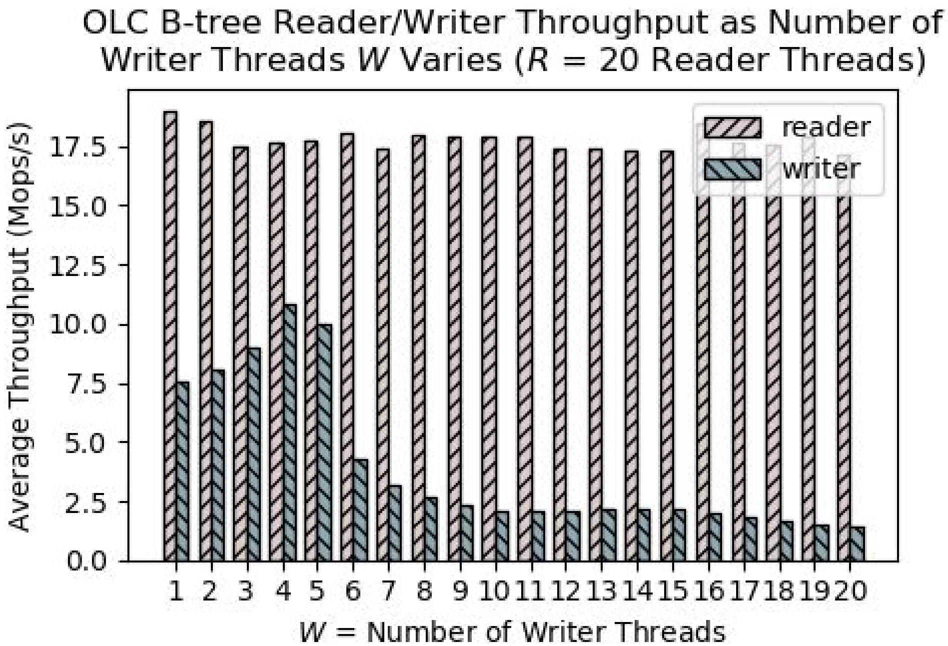


Figure 2

Byte-reordering

Figure [3] shows the insertion performance of the byte-reordering implementation. As the figure shows, reader throughput matches that of the OLC implementation.

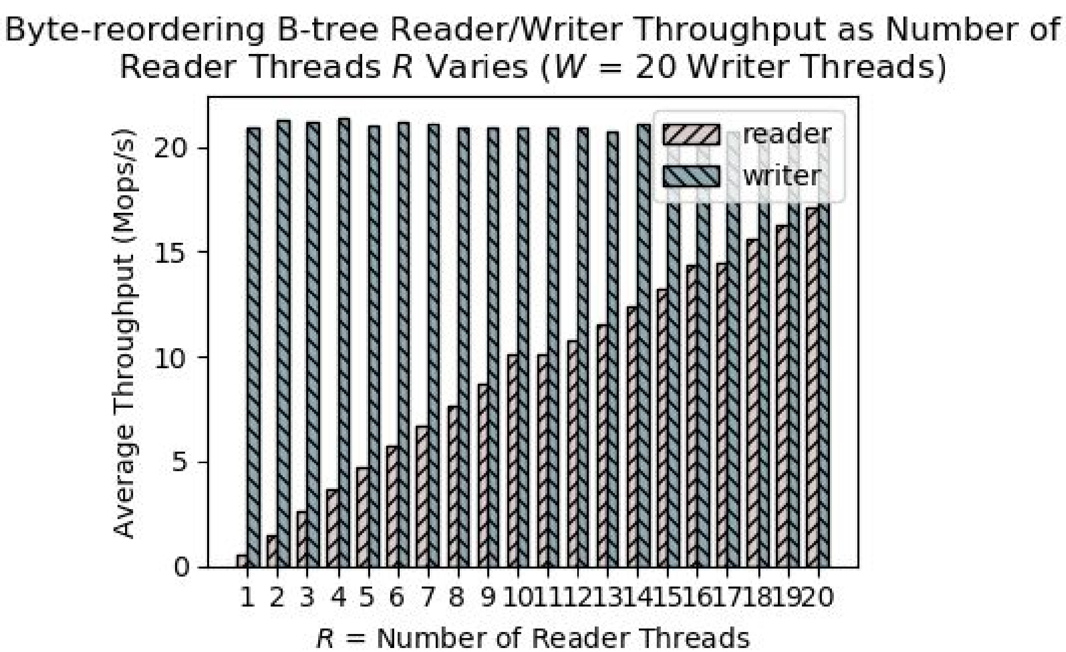


Figure 3

Figure [4] shows the insertion performance of the byte-reordering implementation. Unlike the OLC implementation, the byte-reordering implementation demonstrates linear scalability with number of threads, reaching a peak throughput of over 20 million operations per second. This demonstrates that byte-reordering is effective at mitigating hot spots. If range queries are not needed, byte-reordering is a viable solution.

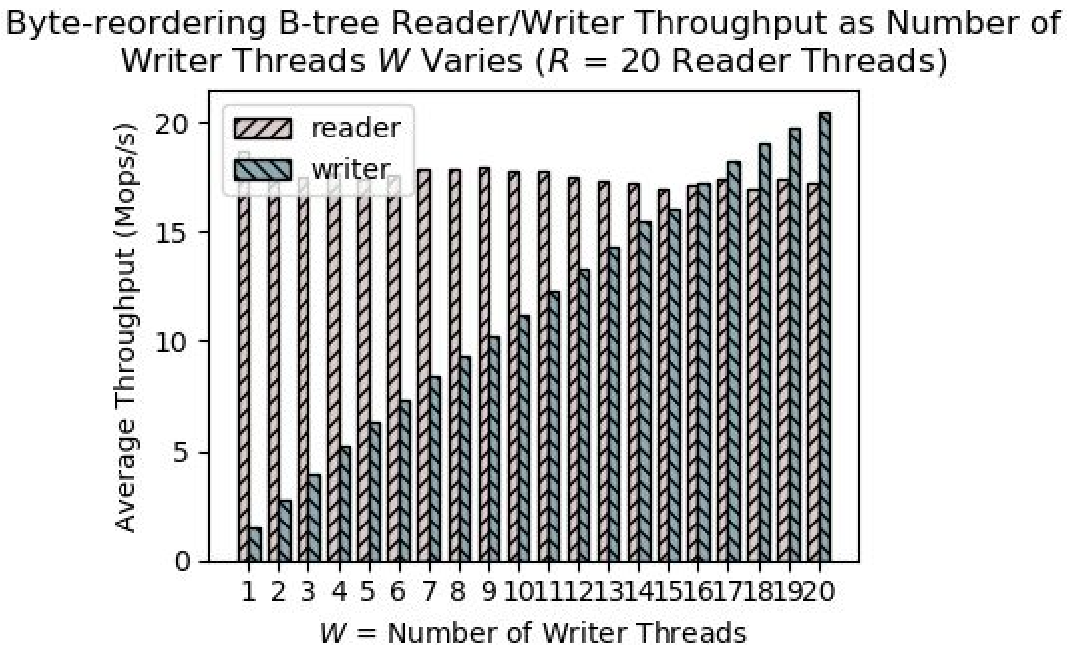


Figure 4

Hybrid B-tree with Auxiliary Structure

Figures [5] and [6] show the lookup and insertion performance respectively. As the figures show, our design has significantly poorer performance than either of the other designs. Peak throughput for lookups was around 2 million operations per second, while peak insertion throughput was around 0.5 million operations per second. We do observe, however, that lookups scale with number of threads, suggesting that there may be promise to our technique.

We believe the poor performance of the hybrid design is largely due to our implementation. Due to time constraints and the challenges of implementing concurrent data structures, our implementation had more exclusive locks than we intended originally. Moreover, we discovered late during implementation that the concurrent hash map implementation we borrowed does not support any efficient filtering operation [7]. Thus, evictions from the caching layer are extremely inefficient. We believe using a custom-designed caching layer would significantly improve throughput.

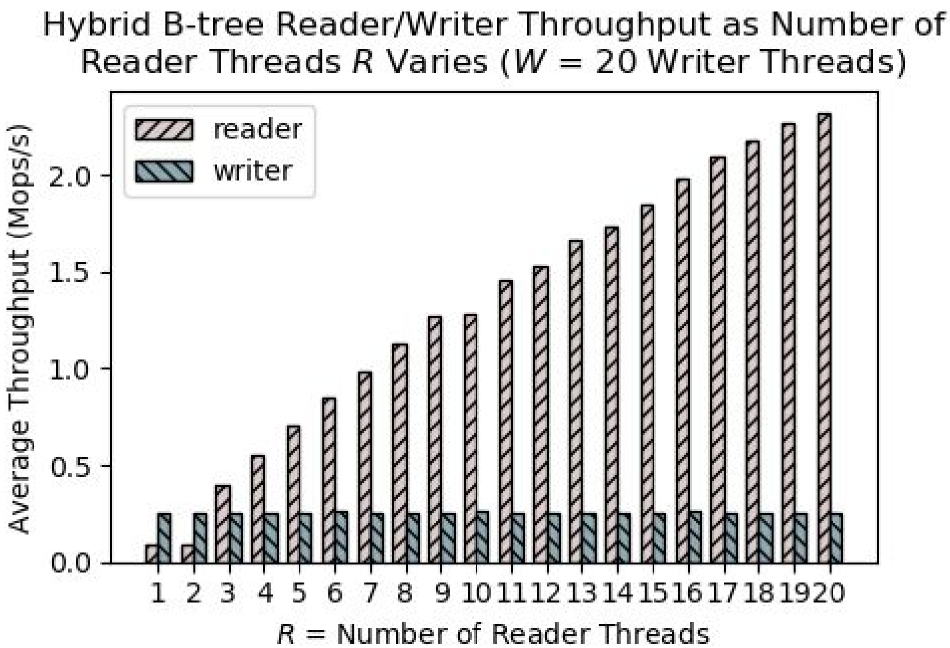


Figure 5

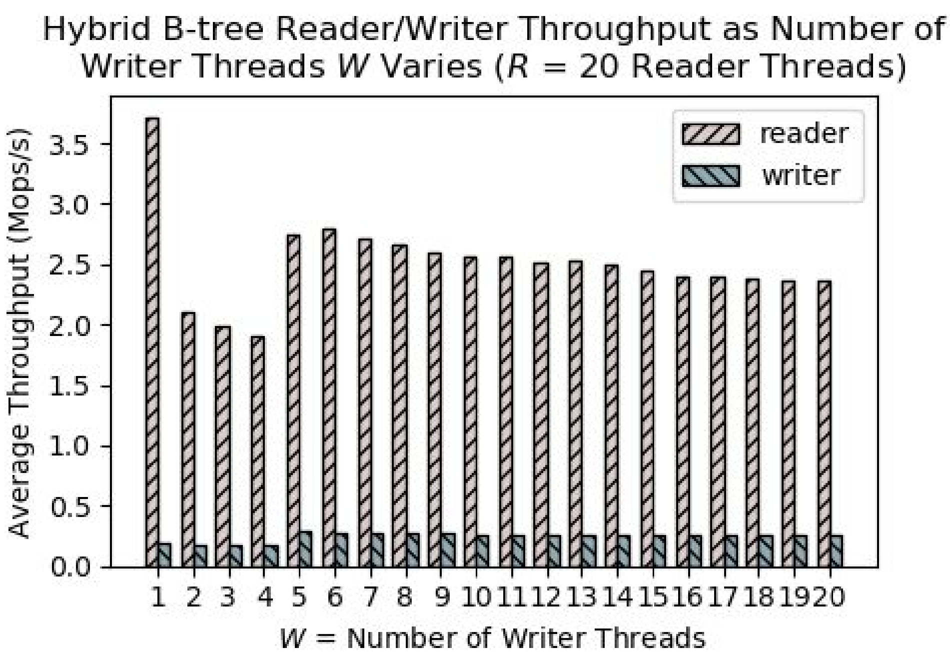


Figure 6

Lessons Learned

The implementation of the hybrid B-tree with our auxiliary structure was challenging. This section summarizes lessons we learned in the process.

We began our implementation by designing the policy and caching layers as independent thread-safe data structures. However, when we tried to “glue” these data structures together, we found that we had to insert extra locking to make sure that each data structure stayed synchronized with others.

Also, we found that integrating conventional locking with optimistic methods and lock-free methods is challenging. For example, a conventional critical section is nested inside an optimistic critical section, then restarts of the optimistic critical section may need to release and re-acquire locks. Worse yet, many operations need to become idempotent to tolerate restarts.

These factors significantly delayed our progress on implementation and evaluation. In retrospect, we would make the following recommendations:

1. Design concurrency control first. It is part of the design; it is *not* an implementation detail.
2. Design short, incremental critical sections between valid states. This reduces the size and critical sections and increases concurrency.
3. Replace complex atomic operations by smaller atomic operations, even at a slight cost in performance.
4. Use formal reasoning, proofs, or other systematic mathematical techniques. Determine the invariants of your system and enforce them. Then use them to simplify your thinking about the system. Tests are helpful, but insufficient.

Related Work

Bw-Tree is a latch-free B-tree implementation. It makes use of delta nodes to avoid changing data in place and atomic compare and swap instructions to transition between consistent B-tree states, eliminating the need for locks [4]. Since locks aren’t used at all in a Bw-Tree, there is no contention due to locks in the rightmost leaves. However, follow-up work has suggested that the extra indirection layer and delta nodes used by Bw-tree outweigh the benefits of lock-freedom [2]. In our work, we use a locking-based approach but aim to be conscientious about lock contention.

B-trees with OLC, as mentioned above, attempt to achieve higher performance by doing optimistic reads and pessimistic writes [1, 3]. However, we hypothesize that this approach will have poor performance for workloads with sequential writes due to reader/writer conflicts. We attempt to modify the B-Tree with OLC to make it behave efficiently in face of the hotspot problem.

Conclusion

In this paper, we explore two different techniques for mitigating lock contention on the rightmost leaf of a B-tree under sequential insertions. We demonstrate experimentally that such contention is indeed a concern for a B-tree implementation using OLC. We then demonstrate that byte-reordering is an effective way of mitigating the concern if one is willing to give up efficient range scans. We also propose a design for reducing contention using a caching layer that handles contention well. Our implementation was not highly-performant, though we did identify some implementation choices that may be limiting performance. We believe more engineering effort is required to fully evaluate the approach. Finally, we summarize some lessons we learned regarding the design and implementation of concurrent data structures.

Acknowledgements

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