DELFT UNIVERSITY OF TECHNOLOGY

MASTERS THESIS

Incremental Snapshotting in Transactional Dataflow SFaaS Systems

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DELFT UNIVERSITY OF TECHNOLOGY

Abstract

Electrical Engineering, Mathematics and Computer Science
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Incremental Snapshotting in Transactional Dataflow SFaaS Systems

by Nikolaos GAVALAS

TODO

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Chapter 1

Introduction

Cloud Computing has seen a dramatic rise in its adoption the recent years, with an increasing number of enterprises migrating their software and hardware to the cloud, and this trend is only expected to continue [López et al., 2021]. Historically, this shift towards managed infrastructure has been arguably inevitable, because with cloud computing the cost per unit of computation is minimized [Castro et al., 2019]. The drive for increased efficiency in computation has culminated in the emergence of the *serverless* architecture [Rajan, 2018].

In the serverless cloud computing execution model, applications are being developed as collections of fine-grained event-driven and stateless units of computation called *cloud functions*. Cloud providers offer the execution of serverless functions as a paid service, known as *Function-as-a-Service* or *FaaS* [Shafiei, Khonsari, and Mousavi, 2019].

In order to be highly scalable, FaaS offerings are stateless. However, as most applications require some form of state-keeping, developers are often forced to manage their applications' state using external databases. Recently, there have been multiple works that aim to relieve the burden of state-management from the shoulders of application developers [Bykov et al., 2011; Burckhardt et al., 2021; Zhang et al., 2020], by handing application state to external databases and making their management transparent to the developers, providing them with *stateful functions*, or *SFaaS*.

SFaaS systems ease the development of stateful applications, but they are not a panacea per se. Any programmer that develops distributed applications will eventually have to deal with fundamental potential issues such as network partitioning, system failures and the Byzantine generals messaging problem [Lamport, Shostak, and Pease, 2019]. These problems become especially hard to deal with when the application level requires implementing *transactional* logic, as transactions require extra guarantees. Transactions are sets of operations that have to be ACID - Atomic, Consistent, Isolated, and Durable [Gray and Reuter, 1992].

The result is often the developers mixing business logic with consistency checks, rollbacks, snapshots and timeouts, leading to systems that are exceptionally hard to maintain and prone to failures. The need for an intermediary layer that abstracts the distributed fault-tolerance logic and provides the application developer with certain guarantees, at the state level or even at the transactional level if possible, becomes evident.

SFaaS systems build on top of *stateful streaming dataflow engines* such as Apache Flink StateFun [Carbone et al., 2015] make excellent candidates for implementing *transactional SFaaS* systems, primarily for two reasons [Heus et al., 2022]:

1. They offer *exactly-once* message delivery semantics, eliminating the need for identifying lost messages and resending them, and also guarantee the message delivery order - the communication channels between the distributed components are FIFO.

2. They fully manage the system's global distributed state by periodically creating consistent snapshots and recovering them upon failures. This is especially important for implementing transactions, since for failed transactions there needs to be a rollback mechanism to guarantee the atomicity property.

Dataflow SFaaS systems are comprised of multiple worker processes, with each of them keeping a partition of the global state locally [Carbone et al., 2015]. The state is represented as key-value pairs [TODO cite], making key-value stores an ideal choice as embedded databases for this task.

As the key-value store is a critical component of this architecture, it is essential to carefully evaluate the available options of suitable types of key-value stores and motivate our selection.

1.1 Problem Statement

In a (transactional) dataflow SFaaS system, the key-value stores need to have specific properties to be considered suitable. These properties are [Chandramouli et al., 2018]:

1. *Incremental snapshots* [TODO cite?]. When the dataflow engine requests a worker to create a snapshot of its state, the state backend (the key-value store) will dump the state and save it. As this process happens many times during the execution of a workflow, to ensure fault-tolerance and fast state recovery, it is imperative that it is done efficiently, building on previous snapshots.

   The naive solution is to save the whole state every time, but if there is a way to only save the updates on the state at each step, incrementally, it would definitely be more efficient. However, saving only the updates on each step, would make recovery very slow, as the state would need to be rebuilt from the very beginning in case of a system failure. In this work, we will present a way to have the best of both worlds: *both fast incremental snapshotting and low recovery times*.

2. *State recovery to a previous version from previous snapshots (rollback)* [TODO cite?]. Upon execution, the dataflow coordinator process may request the workers to restore some previous version of their state, so that the system can go back to some consistent global state and "replay" events to recover from some failure.

3. *Larger-than-memory data (spill-to-disk)*. When dealing with large volumes of data, it is expected that during execution the state will exceed in size the amount that can be stored in memory. Hence, it is essential that the key-value store employs persistent storage when necessary to handle states larger than the available memory.

4. *Update-intensity*. In dataflow systems, changes to the state are typically characterized by the volume of updates rather than inserts or deletes, especially for workflows that perform aggregations on data or analytics [TODO cite?]. Therefore, the state backend should be suitable for update-heavy workloads.

5. *Locality*. In real-world dataflow applications, access to data is rarely uniformly distributed. Keys that are "alive" at any moment may be of many orders of magnitude, but it's usually a subset of those that are "hot" at some given time, i.e. accessed or updated frequently. The hot set may drift as time passes but the strong temporal locality property is maintained [TODO cite].

6. *Point operations*. A key-value store for our use-case should be optimal for point operations, i.e. operations associated with a single key, as opposed to range operations. Since state updates rarely operate on ranges of keys, we can leverage this knowledge to our advantage.

1.2 Research Questions

At this point we can form our research questions:

1. Which types of key-value stores are more fitting as embedded state stores in the worker processes of transactional dataflow SFaaS systems?
2. How do changes in the parameters of each selected type of key-value store affect its performance?
3. In the selected types of key-value stores, which are the trade-offs that determine their operation? In which general use-cases does each of them perform better?
4. How does the performance of a key-value store that offers incremental snapshotting functionality compare to that of a "naive" in-memory key-value store that snapshots its entire state at each step, in terms snapshot creation time?
5. Is there a key-value store that is absolutely superior for state management?

1.3 Contributions

We summarize this work's contributions in the following points:

1. We have implemented four different key-value stores, as it is crucial to ensure that comparisons are made on a level playing field. This means that all key-value stores have been implemented using the same language and with similar design choices for mutual functionality, such as data encoding and data structures. This approach ensures that only the key-value store logic differs, allowing for fair comparisons.
2. We conduct a series of experiments to answer our research questions we posed in section 1.2. Specifically, we analyze the parameters of each implemented key-value store and examine the trade-offs in their designs with respect to resource utilization. We perform a comprehensive comparison among them, evaluate the effectiveness of incremental snapshotting, and ultimately determine whether a key-value store stands out as the best option for our use-case.

1.4 Outline

The rest of this thesis is structured as follows. In Chapter 2 we go through the related work. [...TODO] Chapter 3 contains extensive explanations of the internals of each type of key-value store and the implementation details and design decisions of each of them. [...TODO] In Chapter 4, we evaluate our implementations, performing benchmarks and comparisons between the key-value stores. We discuss the results and answer our reseach questions. Finally, in Chapter 5 we conclude by recapitulating the current work and proposing some directions for future reseach.

Chapter 2

Related Work

2.1 TODO

Chapter 3

Implementation

In this chapter, we will present some high-level design decisions that are common in all our implementations, then we will go through the internals and the implementation details of each of the key-value (KV) stores and finally present we leveraged log-structuring to fullfil the incremental snapshotting property we want our key-value store to have.

3.1 Common design decisions

Firstly, we designed our implementations to expose a common interface (API) to the user. This allows for easy benchmarking, testing, and ultimately a fair comparison between the engines. The API programmatically is defined in a parent class that the classes corresponding to each engines inherit and extend. Firstly, all the engines have a common API. This can be found in appendix A.

1. empty value == delet 2. binary keys and values because allows us to encode the length first for the encoding 3. disk binary encoding 4. data under a single directory 5. engine will rebuild from local files if found. if given remote replica, will restore the latest version by default. should be able to rollback

3.2 Log-Structured Merge-Tree

The Log-Structured Merge-Tree (LSM-Tree) is a disk-based data structure [O'Neil et al., 1996], and one of the most prominent, battle-tested, and well-researched key-value store backend engines. It was invented by Patrick O'Neil in 1996 and has since been used in multiple databases, such as Google's LevelDB [*LevelDB*], Meta's RocksDB [*RocksDB*] and Apache's Cassandra [*Cassandra*].

The LSM-Tree makes extensive use of the *log-structuring* technique, which first appeared in the LFS file system [Rosenblum and Ousterhout, 1992] and has since been used not only in LSM-Tree-based database management systems, but also in other types of storage engines, even B-Tree-based ones [Levandoski, Lomet, and Sengupta, 2013].

Log-structuring offers significant speedups by significantly reducing the number of writes per page and transforming them into a "sequential" format. In other words, it consolidates numerous random writes into a single large multi-page write [Levandoski, Lomet, and Sengupta, 2013].

In this work, we use log-structuring extensively, because, besides its advantages in I/O operations, it also provides a straightforward way to create incremental snapshots of the database's state. We analyze the way we leveraged log-structuring for incremental snapshotting later, in section 3.5.

Given the close relationship between log-structuring and the LSM-Tree (which makes extensive use of it), we will introduce the concept in tandem with the LSM-Tree.

3.2.1 Design

The power of the LSM-Tree can be partially attributed to the fact that it uses lightweight indices, when compared to B-trees which effectively double the cost of every I/O operation to maintain their indices [O'Neil et al., 1996]. This enables the LSM-Tree to scale to very high write and read rates.

However, one other important factor for the LSM-Tree's fast I/O is the use of an in-memory buffer, which aggregates the updates and when it's full, it flushes them to disk sequentially. As it is well known, disks perform much faster sequential operations that operations than require random-access, especially in the cloud, where inexpensive disks have limited I/O rates [Levandoski, Lomet, and Sengupta, 2013].

This buffer flushes the aggregated data into *sorted* chunks of data that are commonly referred to as SSTs for "Sorted String Tables", but we will just call them "runs". Sorting is essential for indexing, as it enables us to lookup keys in logarithmic time.

So, initially, as we are writing data, we keep them in our buffer, and when this buffer is full, we flush it into a file that we call a run.

3.3 AppendLog

3.4 HybridLog

3.5 Incremental Snapshots

Chapter 4

Evaluation

4.1 Parameters

Each of our implemented key-value stores is instantiated with a set of parameters. In Chapter 3 we explained what each parameter represents, but to be able to understand the trade-offs among them, and how various settings of them influence the behaviour of the respective engine, it is important to explore them visually.

In this section, the experiments performed aim to highlight qualitatively the effect of each parameter and do not constitute stress tests.

For the following demonstrations, we use by default - unless explicitly stated otherwise - the following settings: The randombly generated keys and values have length 4 bytes, the sets of available keys and values have cardinality 10^3 each, the distribution of picking keys and values from the sets is uniform, the input write and read throughput are 10^3 writes and 10^3 reads per second respectively, and for latency measurements that are sampled (to calculate the 50th and the 95th percentile), the number of samples is 10. Also, for the LSM-Tree we use `max_runs_per_level`=3, `memtable_bytes_limit`=10^3, `density_factor`=10, and for the parameters of HybridLog we use `mem_segment_len`=10^4, `ro_lag_interval`=10^3, `flush_interval`=10^3, and `compaction_enabled=False`.

4.1.1 LSM-Tree

Max Runs per Level

The first parameter of the LSM-Tree is `max_runs_per_level`. This controls the maximum amount of runs allowed in a level. As explained in Chapter 3, as the number of runs per level increases, a log-structured database becomes write-optimized, and when it is kept close to 1, the database is optimized for reads. In figure 4.1 we demonstrate this behaviour:

Clearly, the write latency drops, when `max_runs_per_level` increases, and the read latency is low when the parameter is relatively small.

The LSM-Tree behaves as expected due to the following reasons: when the number of runs per level increases, the log-structuring scheme degrades into a large fragmented log spread over several smaller logs with infrequent merges. This essentially becomes a large log, enabling the maximum writing speed. However, at the same time, accessing a key requires searching through multiple runs per level, leading to slower reads.

This parameter is central, and relevant not only to the LSM-Tree but to the other two log-structured engines, HybridLog and AppendLog. More specifically, the effect on the write latency on these two is the same, but not quite so for the read

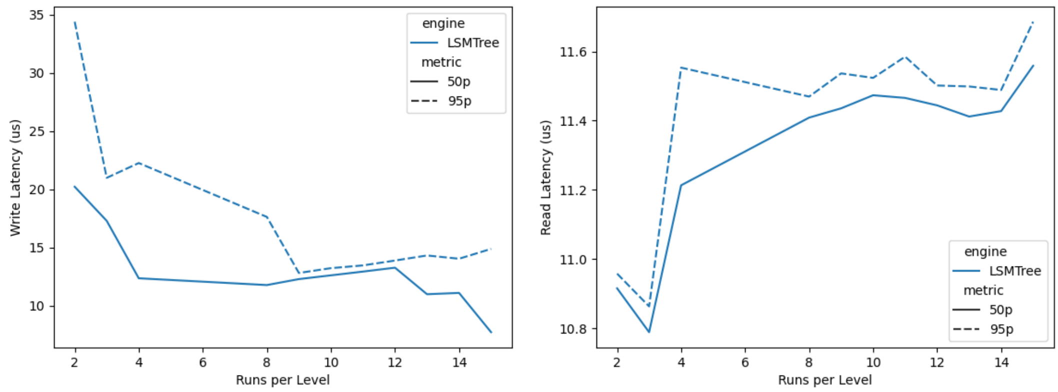


FIGURE 4.1: Latency vs Max Runs per Level.

latency. Because of the fundamental difference in indexing (the latter two use in-memory hash-based indices that point directly to files and offsets), the read latencies are not affected. One needs to just keep the parameter "balanced" enough so that then merges are not very large and infrequent, which would impact the overall performance of the stores.

Density Factor

The `density_factor`, as explained in section 3.2.1, controls the width of gaps between the fence pointers of the LSM-Tree.

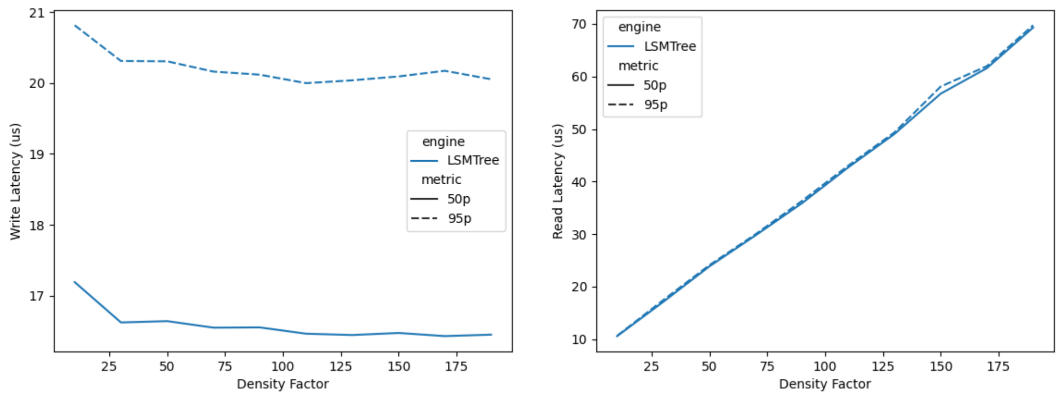


FIGURE 4.2: Latency vs Density Factor.

In figure 4.2 we observe the following: as the density factor increases, the writes remain virtually unaffected, and reads become drastically slower. This is because the LSM-Tree, when the density factor is high and therefore the gaps within the offsets are large, has to go through more bytes in the file to find the requested key, which slows down the reads.

However, there is an obvious tension here: we cannot keep the density factor too small, because that would result in higher memory and disk usage, as demonstrated in figure 4.3.

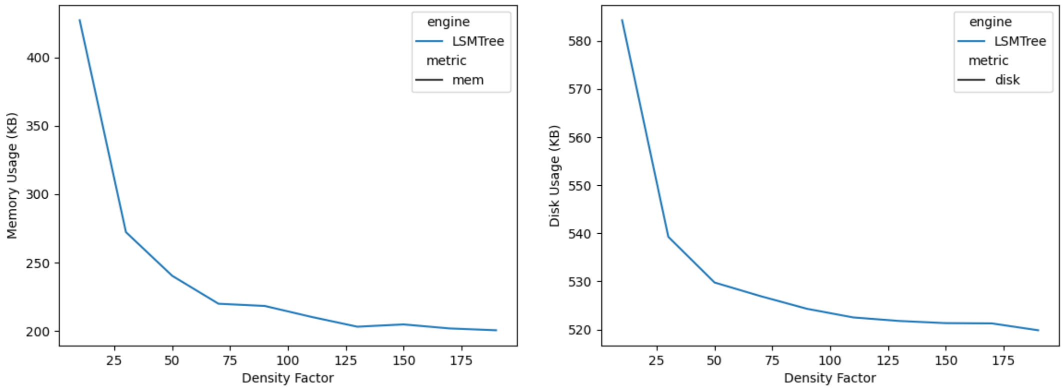


FIGURE 4.3: Memory and Disk Usage vs Density Factor.

Memtable Size

The size of the LSM-Tree's memtable, controlled by the `memtable_bytes_limit`, is the amount of bytes the in-memory structure can hold before it flushes to disk.

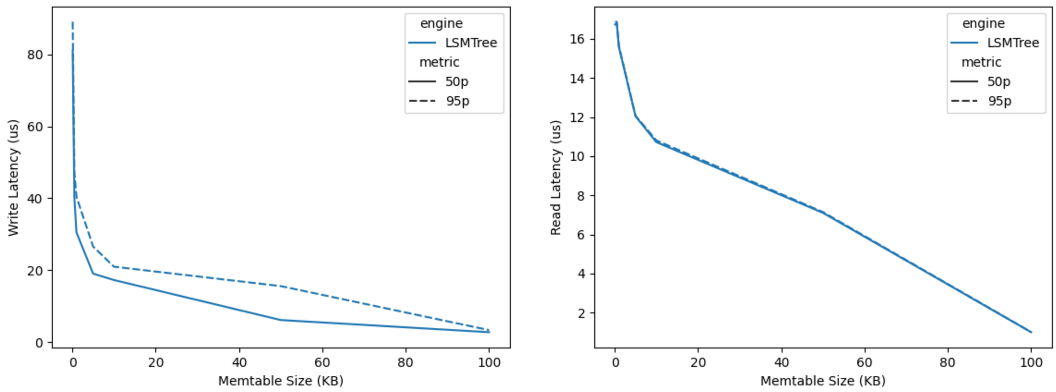


FIGURE 4.4: Latency vs Memtable Size.

In figure 4.4 we notice that as the size of the memtable increases, the latency of both the writes and reads drops. This is expected, as with bigger memtables, the probability of accessing a key without the need to reach to the disk is higher. However, the memory usage obviously goes up, as seen in figure 4.5, and thus we cannot keep this parameter too large.

4.1.2 HybridLog

Memory Segment Size

Besides the indices, HybridLog also keeps a memory segment in memory, which is essentially a ring buffer. The parameter `mem_segment_len` controls the size of this segment. In figure 4.6 we see its influence in the latencies of the writes and the reads, and in figure 4.7 we see the memory usage.

As expected, the size of the in-memory segment is irrelevant to the speed of both writes and reads, while it directly affects the memory used by the engine. It

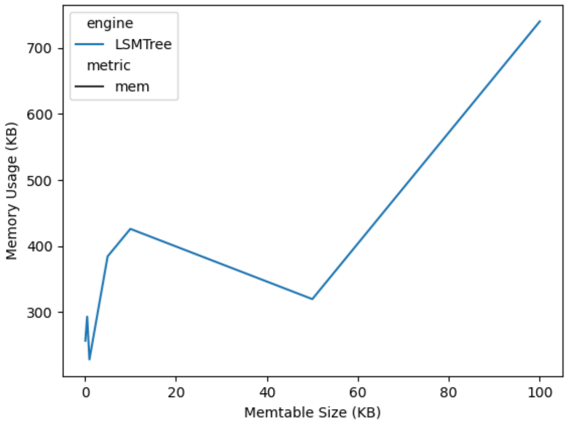


FIGURE 4.5: Memory Usage vs Memtable Size

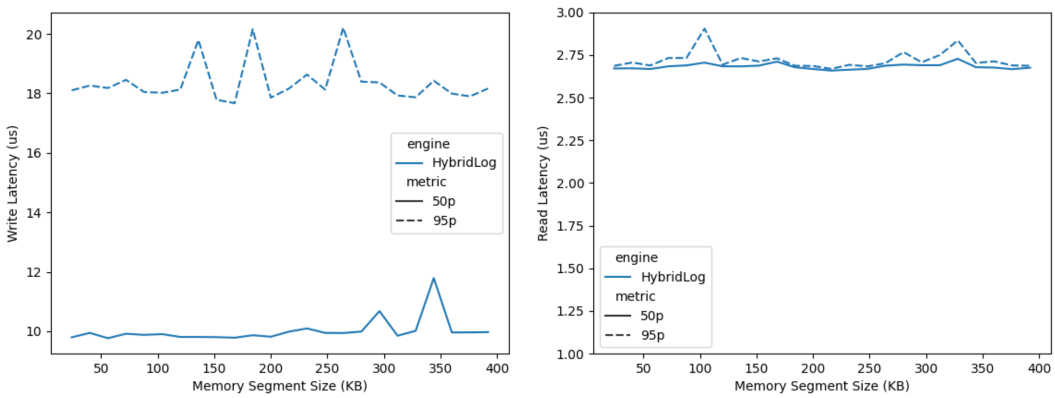


FIGURE 4.6: Latency vs Memory Segment Length.

is irrelevant to the latencies because, as we will see later, it is the `ro_lag_interval` which actually matters.

Hence, it is important that we keep this parameter as low as possible. Since it must always hold that the size of the memory segment is larger than the sum of the sizes of the sub-segments defined by `ro_lag_interval` and `flush_interval`, this parameter should ideally be set a value slightly larger than the sum of these two intervals.

Read-only Segment Size

The read-only segment size is controlled via the value of `ro_lag_interval`. Contrary to the memory segment size, this is the parameter which actually influences directly the probability of an in-memory hit of a key lookup, and thus the cache-like behaviour of the whole memory segment.

If this value is big, we expect many in-memory hits, therefore better performance for both writes and reads. This is exactly what we observe in figure 4.8.

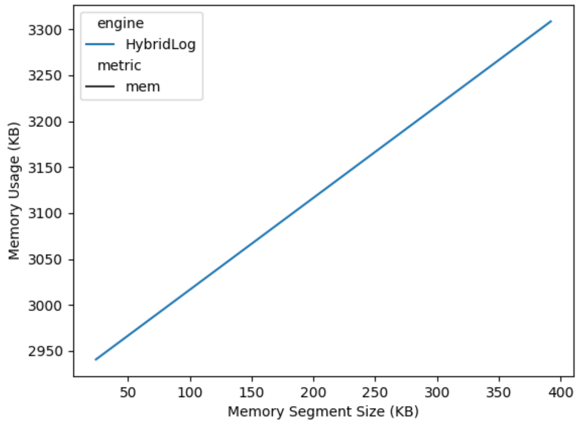


FIGURE 4.7: Memory Usage vs Memory Segment Size

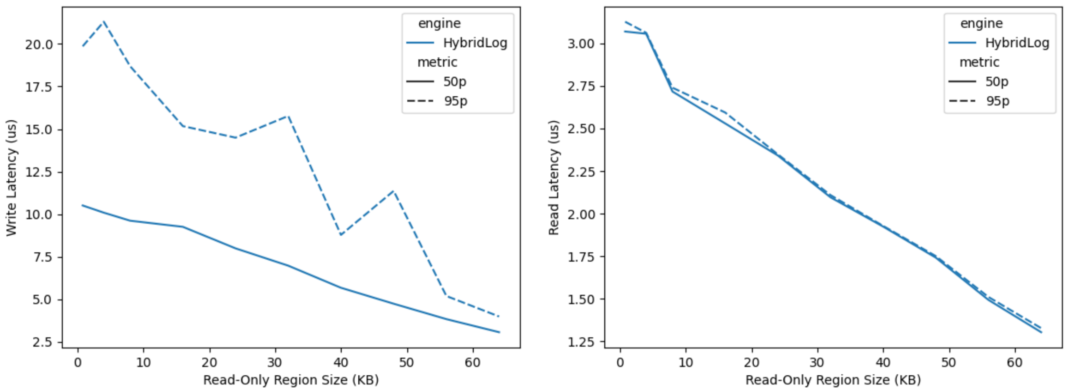


FIGURE 4.8: Latency vs Read-only Segment Size.

Flush Segment Size

The flush segment, whose size is adjusted via the `flush_interval` parameter, contains read-only entries that are ready to be flushed to disk. The bigger the segment, the less the probability for disk access and therefore the higher the performance of the key-value store. This is evident in figure 4.9. The obvious trade-off present here, is that if this value is set to be large, we require a larger memory segment size, which will use more memory.

Additionally, it is crucial to ensure that the value is not set too low. If it is set too low, it may impede the speedup of performance from large flushes to disk, which occur sequentially and are therefore fast. Furthermore, setting the value too low may result in numerous small logs that require frequent merges, thus adversely impacting performance. This phenomenon is also illustrated in the same figure 4.9.

Compaction

Regarding compaction, one may wonder if it could offer some speedup in practice, since it could be the case that its potential benefit is implicitly provided during merging already, and the system is just wasting time doing extra unnecessary work.

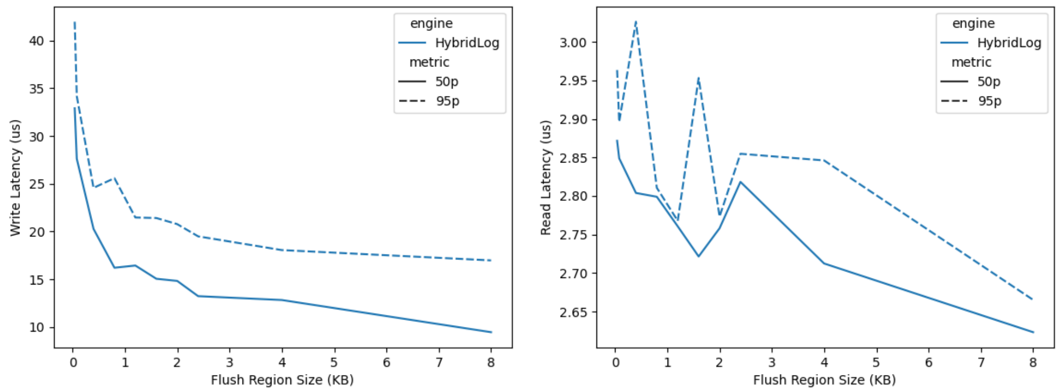


FIGURE 4.9: Latency vs Flush Segment Size.

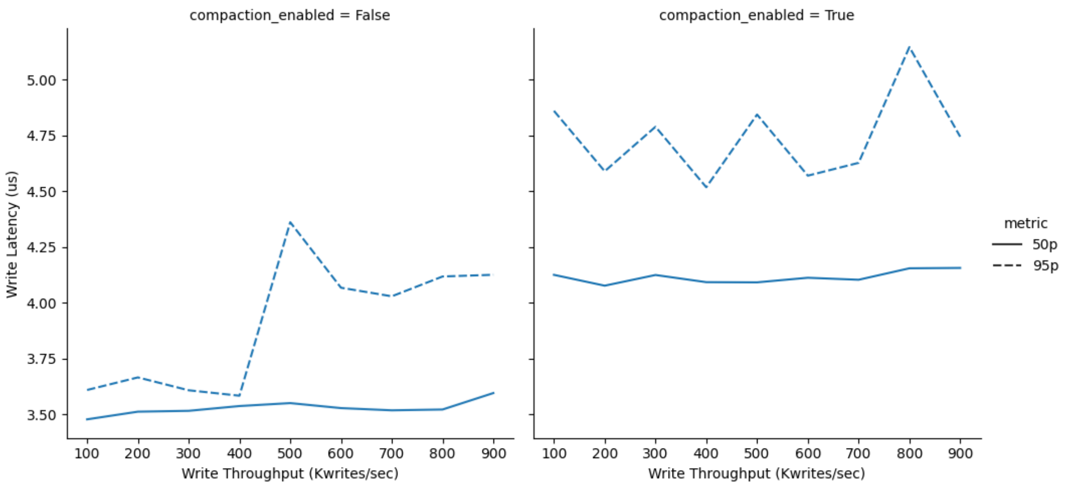


FIGURE 4.10: Write Latency vs Throughput, with Compaction disabled (left) and enabled (right).

From the experiment results in figures 4.10 and 4.11 it seems that this is exactly the case. Compaction offers no advantage for reads (which was expected, since file access is still the same), but also neither for writes, which are in fact impaired, as compaction introduces a significant overhead. Therefore, compaction should be avoided in log-structuring.

4.1.3 AppendLog

In AppendLog we only have one tunable parameter, the threshold value, which is the maximum amount of bytes we can write to a runfile before closing it and starting the next one.

This parameter is similar to the `flush_interval` parameter of the HybridLog. When it is too low, frequent merges hinder the write performance, and as it increases, writes on average become faster (because the runfile becomes essentially a large append-only log). However, if the threshold is too high, the files become large and the merges infrequent and cumbersome, which explains the widening of the gap between the 50p and 95p lines in the write latencies in figure 4.12. As for the reads, they are not significantly affected, as expected.

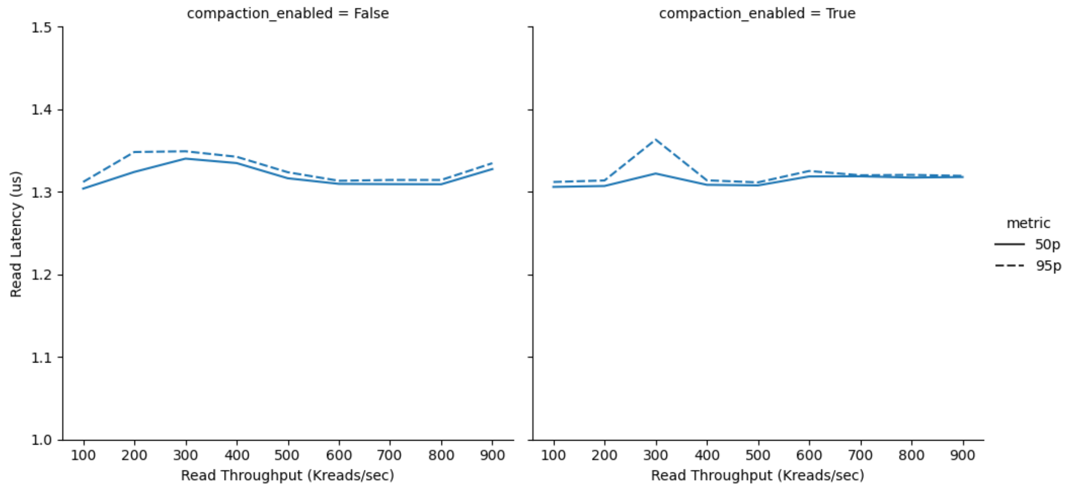


FIGURE 4.11: Read Latency vs Throughput, with Compaction disabled (left) and enabled (right).

Threshold

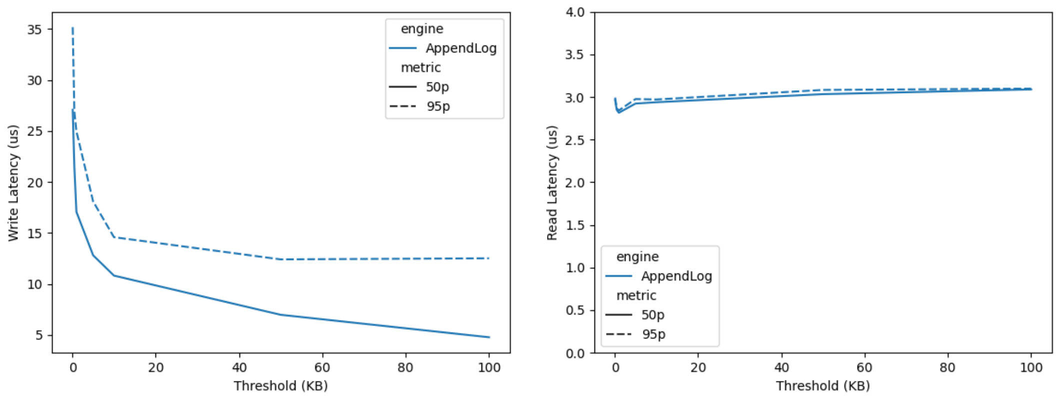


FIGURE 4.12: Latency vs Threshold.

4.2 Comparison

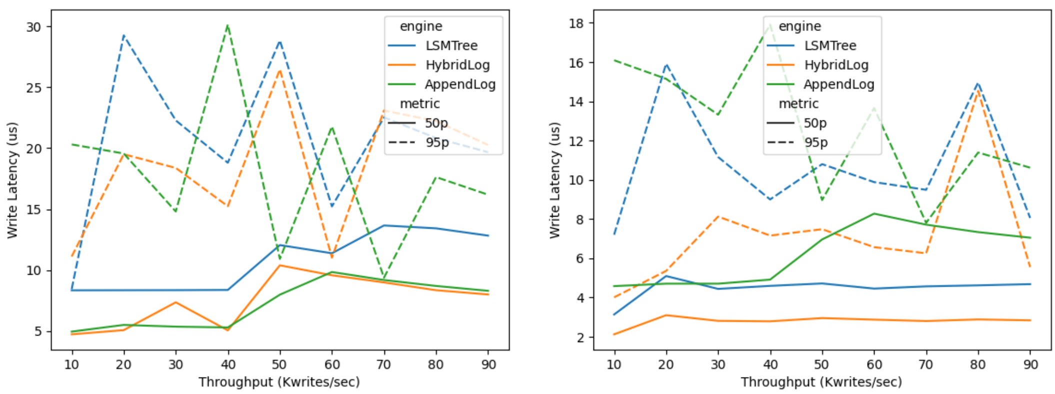
In this section we proceed to compare the engines on their performances when executing the same task with similar parameters. For the following experiments, we use the following parameters: Key and value lengths of 5 bytes each (so 10-byte key-value pairs), 10^5 unique keys and values, and 10 samples per average latency measurement for the percentiles. Also, for all engines we use `max_runs_per_level`=10, for the LSM-Tree `density_factor`=10 and `memtable_bytes_limit`=100K, for the HybridLog `mem_segment_len`=210K, `ro_lag_interval`=10K, `flush_interval`=10K, and for the AppendLog `threshold`=100K.

The above settings lead to almost equally sized files on disk, and use the same configurable memory, so the comparison is fair.

4.2.1 Write Latencies

In figure 4.13 we observe the write latencies of each engine as we increase the input throughput. When choosing keys uniformly, HybridLog and AppendLog are significantly faster than the LSM-Tree. This can be attributed to the fast (amortized $O(1)$) hash-based indexing of those engines, versus the LSM-Tree's memtable's data structure, which has an insert complexity of $O(log(n))$. This is also the reason that when we use a state with a size that fits the in-memory structures and therefore does not need to "spill" to disk, the HybridLog still performs faster, as can be seen in figure 4.14.

When we choose keys using a Zipfian distribution instead, some keys are accessed compared to the Uniform distribution, the LSM-Tree and the HybridLog become faster than earlier, because the Zipfian distribution allows them to better leverage their in-memory buffering structures before flushing, thus reducing I/O operations, and the AppendLog becomes slower, because it lacks any similar buffering method to take advantage of the Zipfian distribution. Among them, the HybridLog is clearly the fastest, precisely because its memory segment with its fast in-place updates of recently written records exploits the Zipfian distribution best.



(A) Uniform distribution (B) Zipfian distribution

FIGURE 4.13: Latency vs Max Runs per Level.

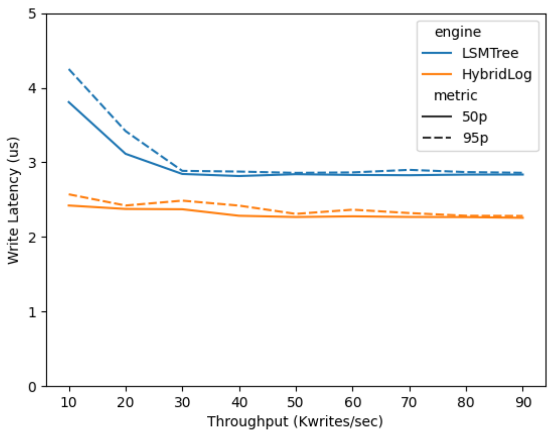


FIGURE 4.14: Write Throughtput when data fits the memory

4.2.2 Read Latencies

Upon examining the latencies for the reads in figure 4.15, it becomes clear that the HybridLog and AppendLog outperform the LSM-Tree by a large margin. This is because of their fast hash-based in-memory indices and minimal I/O.

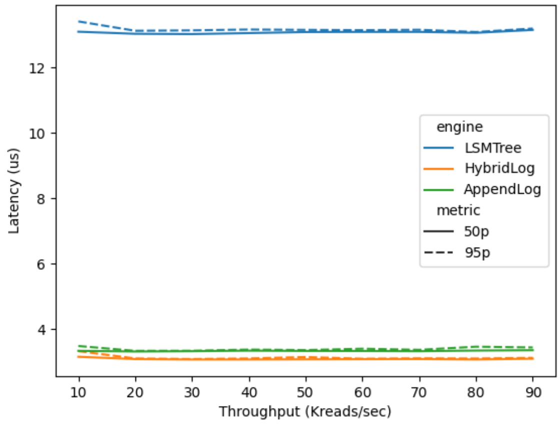


FIGURE 4.15: Read Latencies

4.2.3 Memory

HybridLog's superiority as the fastest key-value store comes at the cost of high memory usage, as can be seen in figure 4.16. Indeed, it is the store with the most in-memory structures, including its main index. After that comes the AppendLog, which also keeps its index in memory. Finally, the LSM-Tree uses the least memory of all, making it ideal for low-memory environments (and also the cheaper option). The components requiring memory in the LSM-Tree are the Bloom filters and the fence pointers, which we keep in memory for fast access.

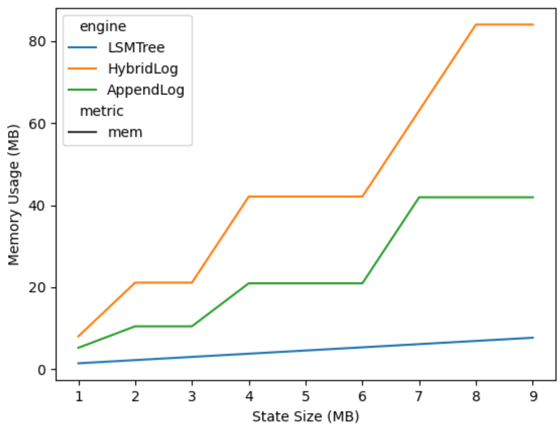


FIGURE 4.16: Memory Usage

4.3 Incremental Snapshotting

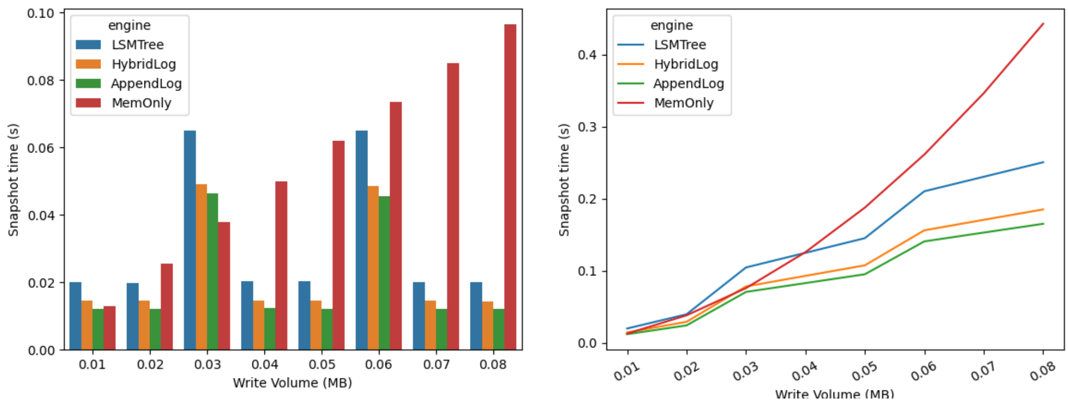
This section focuses on evaluating the incremental snapshotting capabilities of the three log-structured engines. Towards this goal, to demonstrate the advantage of having incremental snapshots, we compare the LSM-Tree, HybridLog and Append-Log to "MemOnly", which is a naive implementation of a key-value store based on an entirely in-memory hosted HashMap that dumps its whole state to disk every time we want to take a snapshot of it.

We do two experiments. In the first, we iterate and write new key-value pairs, taking also a snapshot at the end of each iteration. In the second experiment, we first perform a large write-volume of 1GB, and then we write data in small increments on 1KB, taking a snapshot after each increment.

For both experiments, we use keys and values of 2 and 8 bytes respectively so that the available keys are no more than 2^{16} and therefore we will not need too much memory for the indices of HybridLog, AppendLog and MemOnly. Also, to simulate a snapshot over the network, we add an overhead of 1μs per byte (as if we had a network channel of 1MB/s). The settings for all engines are similar so that the comparison is as fair as possible.

The results of the first experiment are shown in figure 4.17. As expected, the naive MemOnly database dumps the whole state at every step, leading to a quadratic increase of the total time taken to take n snapshots, while the other log-structured stores increase linearly. During each snapshotting step, they only dump the new inserts, except from a few cases when some merging takes place and have to push some larger files as well, but still, they perform better than MemOnly.

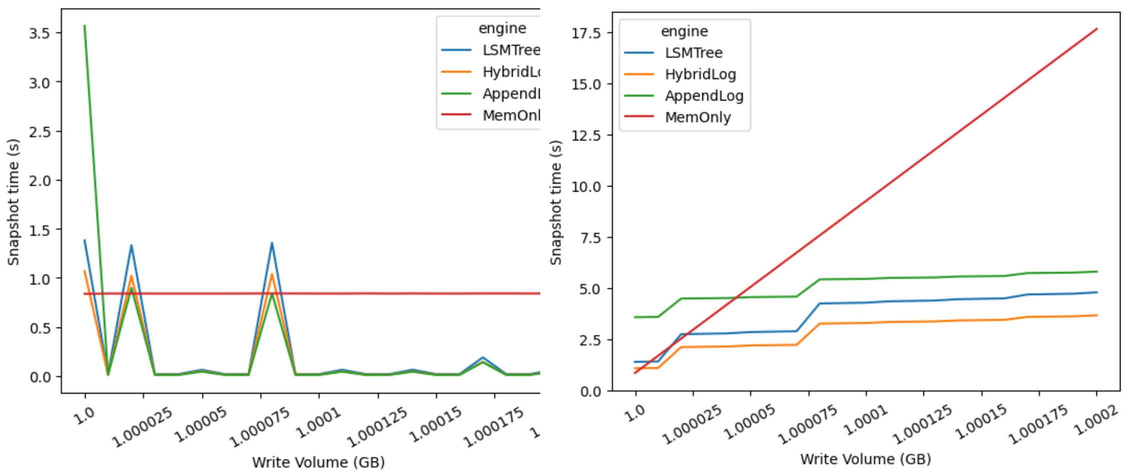
For the second experiment, where only updates take place, the results can be seen in figure 4.18. Again, as expected, the LSM-Tree, HybridLog and AppendLog only push the updates, while the MemOnly store pushes the whole state every time. By observing the cumulative graph, it is evident that the log-structured stores take snapshots more efficiently than the naive method.



(A) Discrete (B) Cumulative

FIGURE 4.17: Snapshotting Time vs Write Volume, when we increase the state by inserting new records.

The important takeaway from these two experiments is that while the cumulative time of the naive snapshotting method increases quadratically at the worst case, the log-structured incremental methods increase linearly. This distinction can have significant ramifications in the performance of systems that keep large states.



(A) Discrete (B) Cumulative

FIGURE 4.18: Snapshotting Time vs Write Volume, when state stays the same and we only update it.

Chapter 5

Conclusion

5.1 Summary

5.2 Future Work

Appendix A

Code

A.1 Key-value store API

```python
def get(key: bytes) -> bytes:
    # retrieves a value associated with the given key.
    # if empty

def set(key: bytes, value: bytes):

def __sizeof__(self):

def close(self):

def snapshot(self):

def restore(version: Optional[int] = None):
```

LISTING A.1: API function signatures.

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