Boki: Towards Data Consistency and Fault Tolerance with Shared Logs in Stateful Serverless Computing

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Boki is a new serverless runtime that exports a shared log API to serverless functions. Boki shared logs enable stateful serverless applications to manage their state with durability, consistency, and fault tolerance. Boki shared logs achieve high throughput and low latency. The key enabler is the *metalog*, a novel mechanism that allows Boki to address ordering, consistency and fault tolerance independently. The metalog orders shared log records with high throughput and it provides read consistency while allowing service providers to optimize the write and read path of the shared log in different ways. To demonstrate the value of shared logs for stateful serverless applications, we build Boki support libraries that implement fault-tolerant workflows, durable object storage, and message queues. Our evaluation shows that shared logs can speed up important serverless workloads by up to 4.2×.

CCS Concepts: • **Information systems** → **Distributed storage**; • **Computer systems organization** → **Dependable and fault-tolerant systems and networks**; **Cloud computing**.

Additional Key Words and Phrases: Serverless computing, function-as-a-service, shared log, consistency

1 Introduction

Serverless computing has become increasingly popular for building scalable cloud applications. Its function-as-a-service (FaaS) paradigm empowers diverse applications including video processing [23, 34], data analytics [42, 51], machine learning [29, 56], distributed compilation [33], transactional workflows [61], and interactive microservices [41].

One key challenge in the current serverless paradigm is the mismatch between the stateless nature of serverless functions and the stateful applications built with them [38, 52, 57, 64]. Serverless applications are often composed of multiple functions, where application state is shared. However, managing shared state using current options, e.g., cloud databases or object stores, struggles to achieve strong consistency and fault tolerance while maintaining high performance and scalability [54, 61].

The shared log [25, 32, 60] is a popular approach for building storage systems that can simultaneously achieve scalability, strong consistency, and fault tolerance [7, 24, 26, 28, 37, 45, 59, 60]. A shared log offers a simple abstraction: a totally ordered log that can be accessed and appended concurrently. While simple, a shared log can efficiently support state machine replication [53], the well-understood approach for building fault-tolerant stateful services [26, 60]. The shared log API also frees distributed applications from the burden of managing the details of fault-tolerant consensus, because the consensus protocol is hidden behind the API [24]. Providing shared logs to serverless functions can address the dual challenges of consistency and fault tolerance (§ 2.1).

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We present Boki (meaning bookkeeping in Japanese), a FaaS runtime that exports the shared log API to functions for storing shared state. Boki realizes the shared log API with a LogBook abstraction, where each function invocation is associated with a LogBook (§ 3). For a Boki application, its functions share a LogBook, allowing them to share and coordinate updates to state. In Boki, LogBooks enable stateful serverless applications to manage their state with durability, consistency, and fault tolerance.

The shared log API is simple to use and applicable to diverse applications [24, 26, 27, 60], so the challenge of Boki is to achieve high performance and strong consistency while conforming to the serverless environment (§ 2.2). Data locality is one challenge for serverless storage, because disaggregated storage is strongly preferred in the serverless environment [38, 52, 57]. Boki separates the read and write path so that read locality can be achieved at the same time as high-throughput writes. Boki optimizes read locality with a cache on function nodes. It scatters writes over a variable numbers of shards while providing consistency and fault tolerance (§ 4.4). In Boki, high write throughput, read consistency and fault tolerance are achieved by a single log-based mechanism, the *metalog*.

The metalog defines a total order of Boki's internal state that applications can use to enforce consistency when they need it. For example, monotonic reads are enforced by tracking metalog positions. The metalog contains metadata that totally orders a log's data records, meaning the durability and consistency of the metalog are vital. The data format is compact, so a single machine can handle the metalog's throughput. To achieve fault-tolerant consensus, Boki stores and updates metalogs using a simple primary-driven design.

Boki handles machine failures by reconfiguration, similar to previous shared log systems [24, 32, 60]. Because the metalog controls Boki's internal state transitions, sealing the metalog (making it no longer writable) pauses state transitions. Therefore, Boki implements reconfiguration by sealing the metalog, changing the system configuration, and starting a new metalog.

Boki's metalog allows easy adoption of state-of-the-art techniques from previous shared log designs because it makes log ordering, consistency, and fault tolerance into independent modules (§ 4.1). Boki adapts ordering from Scalog [32] and fault tolerance from Delos's [24] sealing protocol. Another benefit of the metalog is it decouples read consistency from data placement, enabling indices and caches for log records to be co-located with functions (Table 2). Without interfering with read consistency, cloud providers can build simple caches which optimize data locality when scheduling functions on nodes where their data is likely to be cached.

We implement Boki's shared log designs on top of Nightcore [41], a FaaS runtime optimized for microservices. Nightcore has no specialized mechanism for state management, Boki provides it; while Nightcore's design for I/O efficiency benefits Boki. Boki achieves append throughput of 1.2M Ops/s within a single LogBook, while maintaining a p99 latency of 6.3ms. With LogBook engines co-located with functions, Boki achieves a read latency of 86μs for best-case LogBook reads.

To make writing Boki applications easier, we build support libraries on top of the LogBook API aimed at three different serverless use cases: fault-tolerant workflows, durable object storage, and serverless message queues. Boki support libraries leverage techniques from Beldi [61], Tango [26], and vCorfu [60], while adapting them for the LogBook API. Boki and its support libraries are open source on GitHub `ut-osa/boki`.

This paper makes the following contributions.

- Boki is a FaaS runtime that exports a LogBook API for stateful serverless applications to manage their state with durability, consistency, and fault tolerance.
- Boki proposes a unified mechanism, the metalog, to address log ordering, read consistency, and fault tolerance. The metalog decouples the read and write path of LogBooks, letting Boki achieve high throughput and low latency.
- We build Boki support libraries that use the LogBook API to demonstrate the value of shared logs for stateful serverless applications. The libraries implement fault-tolerant workflows (BokiFlow), durable object storage (BokiStore), and serverless message queues (BokiQueue).

• Our evaluation shows: BokiFlow executes workflows 3.8–4.2× faster than Beldi [61]; BokiStore achieves 1.20–1.28× higher throughput than MongoDB, while executing transactions 2.0–2.5× faster; BokiQueue achieves 2.16× higher throughput and up to 17× lower latency than Amazon SQS [2], while achieving 1.26× higher throughput and up to 1.6× lower latency than Apache Pulsar [3].

2 Background and Motivation

Serverless functions, or function as a service (FaaS) [4, 6], allow developers to upload simple functions to the cloud provider which are invoked on demand. The cloud provider manages the execution environment of serverless functions.

State management remains a major challenge in the current FaaS paradigm [38, 52, 57, 64]. Because of the stateless nature of serverless functions, current serverless applications rely on cloud storage services (e.g., Amazon S3 and DynamoDB) to manage their state. However, current cloud storage cannot simultaneously provide low latency, low cost, and high throughput [46, 51]. For example, storing 1KB payloads takes 108ms for Amazon S3, and 11ms for DynamoDB [38]. Most function executions are short (for example, one large-scale study finds on average half of executed functions run for less than 1 second [55]), so these storage overheads represent a significant portion of execution time.

Even if we can improve cloud storage performance, data consistency remains challenging for stateful applications. One notable example is stateful workflows [61], as functions in a workflow can fail in the middle which leaves behind inconsistent workflow state. To provide exactly-once semantics for workflows, Beldi [61] uses a database for its state management—not a key-value store. A key-value store is insufficient because Beldi requires that its storage system, "[provides] strong consistency, tolerates faults, supports atomic updates on some atomicity scope (e.g., row, partition), and has a scan operation with the ability to filter results and create projections." [61]

Boki provides sequential consistency, fault tolerance, and atomic log append, which is sufficient to run the same workflow workloads as Beldi which model movie reviews and travel reservations. Beldi requires four logs for each stateful serverless function maintained within a database, and its performance suffers accordingly. Boki provides a more efficient solution for state management with exactly-once semantics as we quantify in Section 7.2.

2.1 Shared Log Approach for Stateful Serverless

In the current FaaS paradigm, stateful applications struggle to achieve fault tolerance and strong consistency of their critical state. For example, consider a travel reservation app built with serverless functions. This app has a function for booking hotels and another function for booking flights. When processing a travel reservation request, both functions are invoked, but both functions can fail during execution, leaving inconsistent state. Using current approaches for state management such as cloud object stores or even cloud databases, it is difficult to ensure the consistency of the reservation state given the failure model [61]. This consistency challenge is due to the current serverless programming model, where there is no mechanism for state updates that are transactional across function boundaries.

The success of log-based approaches for data consistency and fault tolerance motivates the use of shared logs for stateful FaaS. For example, Olive [54] proposes a client library interacting with cloud storage, where a write-ahead redo log is used to achieve exactly-once semantics in face of failures. Beldi [61] extends Olive's log-based techniques for transactional serverless workflows. State machine replication (SMR) [53] is another general approach for fault tolerance, where application state is replicated across servers by a command log. The command log is traditionally backed by consensus algorithms [49, 50, 58]. But recent studies demonstrate a shared log can provide efficient abstraction to support SMR-based data structures [26, 60] and protocols [24, 27]. Boki provides shared logs to serverless functions. Boki shared logs are totally ordered and can be shared among serverless

functions. Boki's runtime guarantees sequential consistency for reading and appending the shared log, both within one function and across function boundaries. Therefore, Boki's applications can leverage well-understood log-based mechanisms to efficiently achieve data consistency and fault tolerance.

By examining demands in serverless computing, we identify three important cases where shared logs provide a solution. Boki provides support libraries for these use cases (§ 5).

Fault-tolerant workflows. Workflows orchestrating stateful functions create new challenges for fault tolerance and transactional state updates. Beldi [61] addresses these challenges via logging workflow steps. Beldi builds an atomic logging layer on top of DynamoDB. We adapt Beldi's techniques to the LogBook API without building an extra logging layer.

Durable object storage. Previous studies like Tango [26] and vCorfu [60] demonstrate that shared logs can support high-level data structures (i.e., objects), that are consistent, durable, and scalable. Motivated by Cloudflare's Durable Objects [18], we build a library for stateful functions to create durable JSON objects. Our object library is more powerful than Cloudflare's because it supports transactions across objects, using techniques from Tango [26].

Serverless message queues. One constraint in the current FaaS paradigm is that functions cannot directly communicate with each other via traditional approaches [33], e.g., network sockets. Shared logs can naturally be used to build message queues [32] that offer indirect communication and coordination among functions. We build a queue library that provides shared queues among serverless functions.

2.2 Technical Challenges for Serverless Shared Logs

While prior shared log designs [24, 25, 32, 60] provide inspiration, the serverless environment creates new challenges.

Elasticity and data locality. Serverless computing strongly benefits from disaggregation [22, 36], which offers elasticity. However, current serverless platforms choose physical disaggregation, which reduces data locality [38, 57]. Boki achieves both elasticity and data locality, by decoupling the read and the write paths for log data and co-locating read components with functions.

Resource efficiency. Boki aims to support a high density of LogBooks efficiently, so it multiplexes many LogBooks on a single physical log. Multiplexing LogBooks can address performance problems that arise from a skewed distribution of LogBook sizes. But this approach creates a challenge for LogBook reads: how to locate the records of a LogBook. Boki proposes a log index to address this issue, with the metalog providing the mechanism for read consistency (§ 4.4).

The ephemeral nature of FaaS. Shared logs are used for building high-level data structures via state machine replication (SMR) [26, 60]. To allow fast reads, clients keep in-memory copies of the state machines, e.g., Tango [26] has local views for its SMR-based objects. However, serverless functions are ephemeral – their in-memory state is not guaranteed to be preserved between invocations. This limitation forces functions to replay the full log when accessing a SMR-based object. Boki introduces auxiliary data (§ 3) to enable optimizations like local views in Tango (§ 5.4). Auxiliary data are designed as cache storage on a per-log-record basis, while their relaxed durability and consistency guarantees allow a simple and efficient mechanism to manage their storage (§ 4.4).

3 Boki's LogBook API

Boki provides a LogBook abstraction for serverless functions to access shared logs. Boki maintains many independent LogBooks used by different serverless applications. In Boki, each function invocation is associated

```
struct LogRecord {
   uint64_t seqnum;     string data;
   vector<tag_t> tags;  string auxdata;
};

// Append a new log record.
status_t logAppend(vector<tag_t> tags, string data, uint64_t* seqnum);

// Read the next/previous record whose seqnum >= `min_seqnum`, or <= `max_seqnum`.
// Log reads guarantee "monotonic reads" and "read-your-writes" semantics.
status_t logReadNext(uint64_t min_seqnum, tag_t tag, LogRecord* record);
status_t logReadPrev(uint64_t max_seqnum, tag_t tag, LogRecord* record);

// Alias of logReadPrev(kMaxSeqNum, tag, record).
status_t logCheckTail(tag_t tag, LogRecord* record);

// Trim the LogBook until `trim_seqnum`, i.e., delete all log records
// whose seqnum < `trim_seqnum`.
status_t logTrim(uint64_t trim_seqnum);

// Set auxiliary data for the record of `seqnum`.
status_t logSetAuxData(uint64_t seqnum, string auxdata);
```

Fig. 1. Boki's LogBook API (§ 3).

with *one* LogBook, whose *book_id* is specified when invoking the function. A LogBook can be shared with multiple function invocations, so that applications can share state among their function instances.

Like previous shared log systems [24, 25, 32, 60], Boki exposes *append*, *read*, and *trim* APIs for writing, reading, and deleting log records. Figure 1 lists Boki's LogBook API.

Read consistency. LogBook guarantees *monotonic reads* and *read-your-writes* when reading records. These guarantees imply a function has a monotonically increasing view of the log tail, but different functions may have different views. Moreover, when a parent function invokes a child function, the child function inherits its parent's current view of the log tail, which ensures the child can read log records already seen by the parent. This property is important for serverless applications that compose multiple functions (§ 4.4).

Sequence numbers (seqnum). The `logAppend` API returns a unique seqnum for the newly appended log record. The seqnums determine the relative order of records within a LogBook. They are monotonically increasing but *not* guaranteed to be consecutive. Boki's `logReadNext` and `logReadPrev` APIs enable bidirectional log traversals, by providing lower and upper bounds for seqnums (§ 4.2).

Log tags. Every log record has a set of tags, that is specified in `logAppend`. Log tags enable selective reads, where only records with the given tag are considered (see the `tag` parameter in `logReadNext` and `logReadPrev` APIs). Records with same tags form abstract streams within a single LogBook. Having sub-streams in a shared log for selective reads is important for reducing log replay overheads, that is used in Tango [26] and vCorfu [60] (§ 4.4).

Auxiliary data. LogBook's auxiliary data is designed as per-log-record cache storage, which is set by the `logSetAuxData` API. Log reads may return auxiliary data along with normal data if found. Auxiliary data can cache object views in a shared-log-based object storage. These object views can significantly reduce log replay overheads (§ 5.4).

As auxiliary data is designed to be used only as a cache, Boki does not guarantee its durability, but provides best effort support. Moreover, Boki does not maintain the consistency of auxiliary data, i.e., Boki trusts applications to

provide consistent auxiliary data for the same log record. Relaxing durability and consistency allows Boki to have a simple yet efficient backend for storing auxiliary data (§ 4.4).

Usage pattern of LogBook API. There are two different LogBook usage patterns that address the consistency and fault tolerance challenges for serverless applications.

The first usage pattern is write-ahead logging (WAL). Though serverless functions are supposed to be stateless, they often perform operations having external visible effects (e.g., writing to a database). If the function logs every write operations using a LogBook, when the function fails, the re-executed function can use the write-ahead log to recover its progress. One of Boki's support libraries, BokiFlow (§ 5.1), is an example of using LogBooks for WAL.

The second usage pattern is state machine replication (SMR). For a Boki application, its different functions can use a shared LogBook to store state machine commands. The total order provided by the LogBook enables functions to replay the state machine correctly. Though different functions are not guaranteed to see the same log tail, Boki allows client code to linearize state machine commands. Section 5.1.1 provides the details as part of explaining BokiFlow's lock design. In this usage pattern, auxiliary data stores materialized state machines. Log tags enable selective replay (like in Tango [26]) and composable state machine replication (like in vCorfu [60]). Two Boki support libraries, BokiStore (§ 5.2) and BokiQueue (§ 5.3), use LogBooks for SMR.

4 Boki Design

Boki's design combines a FaaS system with shared log storage. Boki internally stores multiple independent, totally ordered logs. User-facing LogBooks are multiplexed onto internal physical logs for better resource efficiency (§ 2.2). A Boki physical log has an associated *metalog*, playing the central role in ordering, consistency, and fault tolerance.

4.1 Metalog is "the Answer to Everything" in Boki

Every shared log system must answer three questions because they store log records across a group of machines. The first is how to determine the global total order of log records. The second is how to ensure read consistency as the data are physically distributed. The third is how to tolerate machine failures. Table 1 shows different mechanisms used by previous shared log systems to address these three issues, whereas in Boki, the *metalog* provides the single solution to all of them.

In Boki, every physical log has a single associated *metalog*, to record its internal state transitions. Boki sequencers append to the metalog, while all other components subscribe to it (Figure 2 and § 4.3). In particular, appending, reading, and sealing the metalog provide mechanisms for log ordering, read consistency, and fault tolerance:

- *Log ordering.* The primary sequencer appends metalog entries to decide the total order for new records, using Scalog [32]'s high-throughput ordering protocol. (§ 4.3)
- *Read consistency.* Different LogBook engines update their log indices independently, however, read consistency is enforced by comparing metalog positions. (§ 4.4)
- *Fault tolerance.* Boki is reconfigured by sealing metalogs, because a sealed metalog pauses state transitions for the associated log. When all current metalogs are sealed, a new configuration can be safely installed. (§ 4.5)

Metalog: economy of mechanism. Table 1 shows how the metalog is a single mechanism that plays the role of different mechanisms from previous distributed, fault-tolerant logs. All of the listed systems provide a log for applications, but Boki is the only system that also uses a log for its own metadata management. By using a log to manage its own metadata, Boki accrues the benefits available to its clients—problems of fault-tolerance and consistency are handled by the log.

Table 1. Comparison between vCorfu [60], Scalog [32], and Boki. Boki's metalog provides a unified approach for log ordering, read consistency, and fault tolerance (§ 4.1).

	Ordering log records	**Read consistency**	**Failure handling**
vCorfu	A dedicated sequencer	Stream replicas	Hole-filling protocol
Scalog	Paxos and aggregators	Sharding policy	Paxos
Boki	Appending *metalog* entries	Tracking *metalog* positions	Sealing the *metalog*

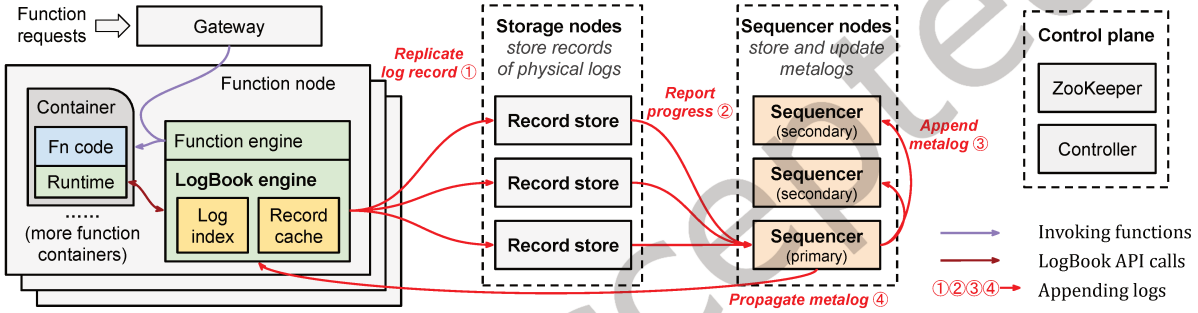


Fig. 2. Architecture of Boki (§ 4.2), where red arrows show the workflow of log appends (§ 4.3). Function nodes, storage nodes, sequencer nodes, and control plane run on different physical hosts or VMs.

Boki still requires the same building blocks as previous systems–for example, it needs sequencer nodes that impose a global total order on log appends. But instead of using a custom API to the sequencer to order its own metadata, Boki puts all metadata in the metalog, whose entries are ordered by the sequencer nodes. Fault tolerance of the metalog is achieved by a simple primary-driven protocol, but consensus algorithms like Paxos or Raft can be used as well. The metalog design lets Boki achieve an economy of mechanism in the management of its own metadata, simplifying the system. Additionally, future improvements to fault-tolerant logs can also apply to metalogs thus benefit Boki's metadata management.

4.2 Architecture

Figure 2 depicts Boki's architecture, which is based on Nightcore [41], a state-of-the-art FaaS system for microservices. In Nightcore's design, there is a gateway for receiving function requests and multiple function nodes for running serverless functions. On each function node, an engine process communicates with the Nightcore runtime within function containers via low-latency message channels.

Boki extends Nightcore's architecture by adding components for storing, ordering, and reading logs. As shown in Figure 2, Boki extends Nightcore's function engines to support the LogBook API. Boki adds storage nodes which manage persistent log records, and sequencer nodes which order log records. Boki also has a control plane for storing configuration metadata and handling component failures.

Table 2. Boki includes LogBook engines running on function nodes. LogBook engines augment Nightcore's function runtime to efficiently support LogBook operations for serverless functions.

Goal	Mechanism
Fast dispatch of LogBook API calls	User's function code is linked with LogBook library.
Low-latency reads of log records	LogBook engines cache log records using unique sequence numbers as keys and LRU for replacement.
Selective log reads using tags (§ 3)	LogBook engines maintain log indices (§ 4.4).
Efficient index updates	LogBook engines subscribe to the metalog, which drives incremental index updates and supports read consistency from unsynchronized index replicas.

Storage nodes. Boki stores log records on dedicated storage nodes. Boki's physical logs are sharded. Each function node has a log shard, i.e., the sharding is based on which function node produces the record because that maximizes locality.

Sharding configuration, i.e., mapping between log shards and storage nodes, is flexible in Boki. Individual storage nodes contain different shards from the same log, and/or shards from different logs. Log shards must be replicated for fault-tolerance. They are replicated on n_{data} different storage nodes (n_{data} equals 3 in the prototype).

Sequencer nodes. Fault-tolerant distributed logs support high throughput log appends while maintaining a total order for appended records. A collection of sequencer nodes execute a fault-tolerant protocol for ordering log records.

Boki sequencers generate ordering information in the form of progress vectors, similar to Scalog [32]'s protocol (§ 4.3). Boki stores these vectors, as well as log trim commands (§ 4.4) in the metalog. The total order of the metalog defines the global order of Boki's distributed log. Scalog's protocol orders log records in batches with progress vectors, so that high throughput log ordering can be achieved with low append rate to the metalog (e.g., a few thousands appends per second to the metalog can order more than one million records per second). The low append rate and the small size of metadata ordering information (tens of bytes per entry) means that a single node is fully capable of maintaining the metalog.

To achieve fault tolerance, every metalog is replicated on n_{meta} sequencer nodes (which is 3 in the prototype). One of the n_{meta} sequencers is configured as primary, and only the primary sequencer can append the metalog. To append a new metalog entry, the primary sequencer sends the entry to all secondary sequencers for replication. Once acknowledged by a quorum, the new metalog entry is successfully appended. The primary sequencer always waits for the previous entry to be acknowledged by a quorum before issuing the next one. Sequencers propagate appended metalog entries to other Boki components that subscribe to the metalog.

Configuration of sequencer nodes in Boki is flexible, just as storage node configuration is flexible. For example, sequencer nodes can be dedicated to different metalogs; sequencers can execute on dedicated nodes or they can be colocated with storage nodes.

LogBook engines. Boki's persistence model is that all serverless functions use LogBooks for persisting data. Therefore, it must be efficient for Boki to service LogBook API calls from functions. In Nightcore, the engine processes running on function nodes are responsible for dispatching function requests. Boki extends Nightcore's engine functionality by adding a new component serving LogBook calls. We refer to the new part as the LogBook engine to distinguish it from the part of engine process that serves function requests.

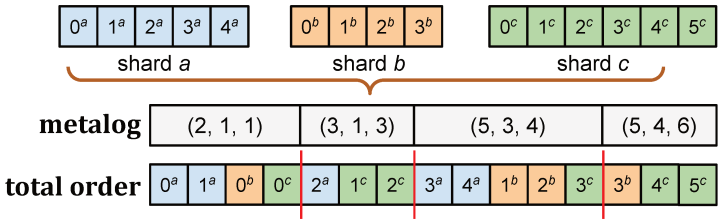


Fig. 3. An example showing how the metalog determines the total order of records across shards. Each metalog entry is a vector, whose elements correspond to shards. In the figure, log records between two red lines form a delta set, which is defined by two consecutive vectors in the metalog (§ 4.3).

Table 2 summarizes how the LogBook engine uses different mechanisms to achieve high performance for log operations. Co-locating LogBook engines with functions means that, in the best case, LogBook reads can be served without leaving the function node.

Control plane. Boki's control plane uses ZooKeeper [39] for storing its configuration. Boki's configuration includes (1) addresses of gateway, function, storage, and sequencer nodes; (2) the set of storage and sequencer nodes backing each physical log; (3) the sharding and index configuration of each physical log; (4) parameters of consistent hashing [43] used for the mapping between LogBooks and physical logs. Every Boki node maintains a ZooKeeper session to keep synchronized with the current configuration. ZooKeeper sessions are also used to detect failures of Boki nodes.

Boki's controller (see the control plane in Figure 2) is responsible for global reconfiguration. Reconfiguration happens when node failures are detected, or when instructed by the administrator to scale the system, e.g., by changing the number of physical logs (see §7.1 for reconfiguration latency measurements). We define the duration between consecutive reconfigurations as a *term*. Terms have a monotonically increasing *term_id*.

4.3 Workflow of Log Appends

When appending a LogBook (shown by the red arrows in Figure 2), the new record is appended to the associated physical log. For simplicity, in this section, the term *log* always refers to physical logs.

Records in a Boki log are sharded, and each shard is replicated on n_{data} storage nodes. Within a Boki log, each function node corresponds to a shard, i.e. the number of shards simply equals to the number of function nodes. For a function node, its LogBook engine maintains a counter for numbering records from its own shard. On receiving a `logAppend` call, the LogBook engine assigns the counter's current value as the *local_id* of the new record.

The LogBook engine replicates a new record to all storage nodes backing its shard (① in Figure 2). Storage nodes then need to update the sequencers with the information of what records they have stored. The monotonic nature of *local_id* enables a compact progress vector, v. Suppose the log has M shards. We use a vector v of length M to represent a set of log records. The set consists of, for all shards j, records with *local_id* $< v^j$. If shard j is not assigned to this node, we set the j-th element of its progress vector as ∞. Every storage node maintains their progress vectors, and periodically communicates them to the primary sequencer (② in Figure 2).

By taking the element-wise minimum of progress vectors from all storage nodes, the primary sequencer computes the global progress vector. Based on the definition of progress vectors, we can see the global progress vector represents the set of log records that are fully replicated. Finally, the primary sequencer periodically appends the latest global progress vector to the metalog (③ in Figure 2), which effectively orders log records across shards.

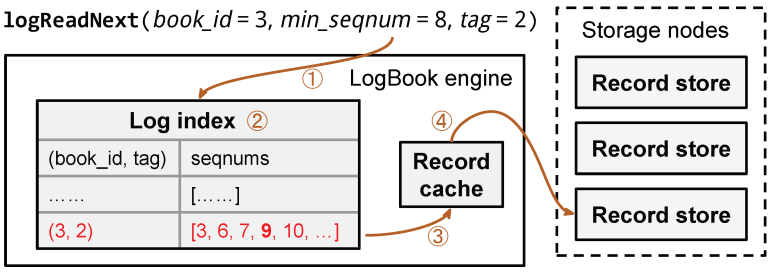


Fig. 4. Workflow of LogBook reads (§ 4.4): ① Locate a LogBook engine stores the index for the physical log backing *book_id* = 3; ② Query the index row (*book_id*, *tag*) = (3, 2) to find the metadata of the result record (seqnum = 9 in this case); ③ Check if the record is cached; ④ If not cached, read it from storage nodes.

We now explain how the total order is determined by the metalog. Consider a newly appended global progress vector, denoted by v_i. By comparing it with the previous vector in the metalog (denoted by v_{i-1}), we can define the delta set of log records between these two vectors: for all shards j, records satisfying $v_{i-1}^j \leq local\_id < v_i^j$. This delta set exactly covers log records that are added to the total order by the new metalog entry v_i. Records within a delta set are ordered by (*shard*, *local_id*). Figure 3 shows an example of metalog and its corresponding total order. In this figure, between two consecutive red lines is a delta set.

The LogBook engine initiating the append operation learns about its completion by its subscription to the metalog (④ in Figure 2). The metalog allows the LogBook engine to compute the final position of the new record in the log, used to construct the sequence number returned by `logAppend`.

4.4 From Physical Logs to LogBooks

Boki virtualizes LogBooks by multiplexing them on physical logs. LogBooks have unique identifiers, *book_id*. Recall that in Boki, each function invocation is associated with a LogBook (*book_id* is specified when invoking the function), while multiple function invocations can share a *book_id* (§ 3). Current design of Boki allows each function to only associate with exactly one LogBook, so that all LogBook API calls operate on only one LogBook.

Structure of sequence numbers (seqnum). As shown in the LogBook APIs (Figure 1), every log record has a unique seqnum. The seqnum, from higher to lower bits, is (*term_id*, *log_id*, *pos*). *term_id* identifies the current configuration. *log_id* identifies the physical log and *pos* is the record's position in the physical log. Seqnums in this structure determine a total order within a LogBook, which is in accordance with the chronological order of terms and the total order of the underlying physical log. But note that this structure cannot guarantee seqnums within a LogBook to be consecutive, whose records can be physically interspersed with other LogBooks.

Building indices for LogBooks. Multiplexing LogBooks on physical logs creates one challenge for efficient reads – how to avoid consulting every log shard to find the desired log record. Previous systems [60] have used fixed sharding, where a LogBook maps to some fixed log shard. The fixed-sharding approach limits a LogBook's read and write throughput to a single log shard's throughput. For performance and operational advantages, Boki does not place records from a LogBook using a fixed policy. Boki will store LogBook records in any shard, so that a LogBook can achieve the full read and write throughput of the underlying physical log if needed. Boki builds a log index for locating records when reading LogBooks.

Boki's log index is compact, only including necessary metadata of log records (i.e., seqnum and tags, but not data), so that a single machine can store the entire index. Log indices are stored and maintained by LogBook engines, leading to locality benefits because LogBook engines reside on function nodes. Every physical log has

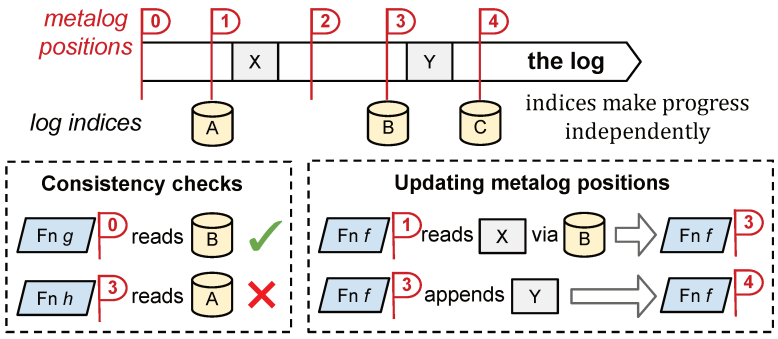


Fig. 5. Consistency checks by comparing metalog positions (§ 4.4). For a function, if reading from a log index whose progress is behind its metalog position, it could see stale states. For example, function h have already seen record X, so that it cannot perform future log reads through index A.

multiple copies of the log index maintained by different LogBook engines, for higher read throughput and better read locality.

The structure of the log index is designed to fit the semantic of LogBook read APIs. First, the log index groups records by their *book_id*, because a read can only target a single LogBook. The API semantics for `logReadNext` and `logReadPrev` (see Figure 1) allow selective reads by log tags (tags are specified by users in `logAppend`). Both APIs seek for records sequentially by providing bounds for seqnums, e.g., `logReadNext` finds the first record whose seqnum $\geq$ *min_seqnum*. Putting them together, Boki's log index groups records by (*book_id*,*tag*). For each (*book_id*,*tag*), it builds an index row as an array of records, sorted by their seqnums. Figure 4 depicts the workflow of LogBook reads using the index.

Log indices are built incrementally by subscribing to the metalog. When a new progress vector is appended to the metalog, it means a new batch of records is appended to the physical log (§ 4.3). Individual index replicas update their data structures to include the new record batch. Metadata of log records (i.e., log tags) are read directly from storage nodes to update log indices. Different index replicas will not synchronize with each other, but data consistency is achieved by different replicas comparing their positions in the metalog (explained in the next section).

Read consistency. The consistency of Boki's log reads are determined by the log index. The log index is used to find the seqnum of the result record. The seqnum uniquely identifies a log record, while both data and metadata (i.e., tags) of a log record are immutable after they are appended.

The challenge of enforcing read consistency comes from multiple copies of the log index, which are maintained by different LogBook engines. Keeping these copies consistent makes the system vulnerable to "slowdown cascades" [21, 48], i.e., the slowdown of a single node can prevent the whole system from making progress.

Boki uses *observable consistency* [30, 48], where consistency checks are delayed to the time of data reads. The metalog position defines the version of the log index a function reads. A log index whose version is determined by metalog position l means the log index includes all records ordered by the l-prefix of the metalog.

When a user function reads a LogBook at an index with metalog position l, it can never read an index at $< l$, because that would violate *monotonic reads*. Similarly, if a function appends a log record that is ordered by the l-th metalog entry, subsequent reads from the same function cannot be served by an index whose position $< l$ or *read-your-writes* could be violated.

Therefore, Boki maintains a metalog position for each function and that position provides consistent LogBook reads. LogBook engines subscribe to the metalog to periodically update their indices. Consistency checks are

performed by comparing a function's metalog position with the index version. Figure 5 depicts the mechanism. If a consistency check fails, the read is suspended by the engine until its index has caught up. Successful reads and appends from a function update the function's metalog position, ensuring the consistency of future reads. A child function inherits the metalog position from its parent function, so that consistency guarantees hold across function boundaries.

Trim operations. Because the log index plays an important role in read consistency, trimming records in log indices effectively makes trim operations observable. Storage space for trimmed records can be reclaimed independently in the background by storage nodes. Therefore, Boki implements `logTrim` API calls by simply appending a trim command to the metalog. For a trim command in the metalog, the LogBook engine executes it by trimming related index rows in their log indices, while storage nodes gradually reclaim space for trimmed records.

Auxiliary data. Described in the LogBook API (§ 3), the auxiliary data of log records have relaxed requirements of durability and consistency. This allows a very simple store of auxiliary data that reuses the record cache within LogBook engines. The relaxed consistency of auxiliary data does not even require Boki to exchange them between nodes. Therefore, for `logSetAuxData` calls, Boki simply caches the provided auxiliary data on the same function node. To serve reads from the user function Boki checks if there is auxiliary data in the local cache. If found, it is returned along with the result record.

4.5 Reconfiguration Protocol

Boki's controller can initiate a reconfiguration if node failures (including failures of primary sequencers) are detected or when instructed by a system administrator.

The main part of Boki's reconfiguration protocol is to seal all current metalogs. A sealed metalog cannot have any more entries appended, so the corresponding physical log is sealed as well. Boki employs Delos [24]'s log sealing protocol, that is surprisingly simple but fault-tolerant. To seal a metalog, the controller sends the seal command to all relevant sequencers. On receiving the seal command, the primary sequencer stops issuing new metalog entries, while secondary sequencers commit to reject future metalog entries from the primary sequencer. The sealing is completed when a quorum of sequencers have acknowledged the seal command (see the Delos paper [24] for details).

After all metalogs are successfully sealed, Boki can install a new configuration to start the next term. In the new term, all physical logs start with new, empty metalogs. To ensure read consistency across terms, we include the *term_id* in the consistency check, which is compared before metalog positions. If the number of physical logs changes, the consistent hashing parameters are updated accordingly.

To tolerate failures of the controller, Boki runs a group of controller processes. The reconfiguration protocol is executed by a leader, elected via ZooKeeper.

4.6 Takeaways for Future Shared Log Systems

Serverless has been very successful for (mostly) stateless computing, but struggles to accommodate stateful programs [52]. Boki enables stateful serverless programs by adding a shared log to address consistency and fault tolerance. Independent of that goal, we believe that two of Boki's design choices, the metalog and log index, will also benefit other shared log designs.

As explained in Section 4.1, the metalog plays a central role in Boki's design. The metalog simultaneously provides log ordering (Figure 3), read consistency (Figure 5), and fault tolerance (§ 4.5). The metalog incorporates Delos' [24] VirtualLog design with Scalog [32]'s high-throughput log ordering protocol, but in Boki, the metalog does more than a simple mixture of these two existing techniques. The metalog maintains a replicated state

machine for Boki's meta state. Thanks to Scalog's ordering protocol, the append rate to the metalog is relatively low, allowing all Boki components running on different nodes to subscribe to the metalog and replay the meta state machine. With proper design (like in Boki's log index), different nodes can even replay the meta state machine without synchronization, but still maintain the required consistency property (monotonic reads and read-my-writes).

The log index is the key mechanism in Boki to support LogBook multiplexing and log tags within a LogBook. The log index design fully decouples two properties of a shared log: (1) how the log is logically partitioned (log tags in Boki); and (2) where log records are physically stored (log shards in Boki). In previous shared log designs such as vCorfu [60], logical partitioning of the log directly determines storing locations. When logical partitioning is associated with physical sharding, the append throughput to a particular log partition is constrained by the number of nodes backing corresponding shards. Boki's design fully overcomes this constraint. Boki's log index design also provides maximum flexibility regarding how the log is logically partitioned. There are two levels of logical partitioning in a Boki shared log: the first level is different LogBooks, and the second level is log tags within a LogBook. A log record can have multiple log tags also results from the flexibility of Boki's log index design.

5 Boki Support Libraries

In this section, we present Boki support libraries, designed for three different stateful FaaS paradigms that benefit from the LogBook API: fault-tolerant workflows (§ 5.1), durable object storage (§ 5.2), and queues for message passing (§ 5.3).

5.1 BokiFlow: Fault-Tolerant Workflows

We build a support library called BokiFlow for fault-tolerant workflows. BokiFlow adapts Beldi [61]'s techniques to ensure exactly-once semantics and support transactions for serverless workflows. BokiFlow provides the same user-facing APIs as Beldi.

Beldi's techniques for exactly-once semantics closely resemble write-ahead logging in storage systems. In a Beldi workflow, every operation that has externally visible effects (e.g., a database write) is logged with monotonically increasing *step* numbers. To assign *step* numbers, Beldi maintains a STEP variable within each workflow (Figure 6), which also means Beldi requires workflow steps to have a deterministic order. When a workflow fails, Beldi re-executes it using the workflow log. To ensure the exactly-once semantic, Beldi recovers the internal state of the failed workflow step-by-step, while skipping operations with externally visible effects. Beldi builds a logging abstraction on top of DynamoDB, a cloud database from AWS. Beldi applications store user data in the same DynamoDB database with workflow logs.

In Beldi, the workflow log is the source of truth which ensures exactly-once workflow execution. Boki's LogBook API can naturally provide this logging layer due to its being totally ordered. Our evaluation shows Boki's LogBook is more performant than Beldi's logging abstraction (§ 7.2). Note that BokiFlow only stores workflow logs in LogBooks. Application data tables are still stored in DynamoDB, allowing BokiFlow to achieve feature parity with Beldi.

5.1.1 Distinctions between BokiFlow and Beldi. Because the LogBook API is very different from a cloud database API, BokiFlow needs new techniques to address issues caused by these differences. There are three ways BokiFlow distinguishes itself from Beldi.

Atomic "test-and-append". Beldi requires an atomic operation to check if the current step is previously logged and it logs the step only if the check fails. Beldi relies on conditional updates provided by a cloud database for this operation. Unfortunately, the LogBook API does not support conditional log appends. Shown in Figure 6,

```
1  def write(table, key, val):
2      # Append write-ahead log for this DB update
3      tag = hashLogTag([ID, STEP])
4      logAppend(tags: [tag], data: [table, key, val])
5      # Always consider the first log record for this step,
6      # so that during workflow re-execution the original log record is used
7      record = logReadNext(tag: tag, minSeqnum: 0)
8      # The write-ahead log also determines a total order for DB writes, where
9      # sequence numbers of log records are used as "version numbers"
10     rawDBWrite(table, key,
11         cond: "Version < {record.seqnum}",
12         update: "Value = {val}; Version = {record.seqnum}")
13     STEP = STEP + 1

14 def invoke(callee, input):
15     # Generate UUID for child function and store it in pre-invoke log record
16     tagPre = hashLogTag([ID, STEP, "pre"])
17     logAppend(tags: [tagPre], data: {"calleeId": UUID()})
18     # Read calleeId from log record for child function,
19     # so that during workflow re-execution we use the original UUID
20     record = logReadNext(tag: tagPre, minSeqnum: 0)
21     calleeId = record.data["calleeId"]
22     # Invoke child function with the given input
23     retVal = rawInvoke(callee, [calleeId, input])
24     # Post-invoke log record stores return value of child function
25     tagPost = hashLogTag([ID, STEP, "post"])
26     logAppend(tags: [tagPost], data: {"retVal": retVal})
27     record = logReadNext(tag: tagPost, minSeqnum: 0)
28     STEP = STEP + 1
29     return record.data["retVal"]
```

Fig. 6. Pseudocode demonstrating BokiFlow's write and invoke functions (§ 5.1.3). `hashLogTag` computes a hashing-based log tag for the provided tuple. Variable `ID` stores the unique ID of the current workflow. Variable `STEP` stores the step number, which is increased by 1 for each operation within the workflow.

BokiFlow uses a different mechanism based on log tags provided by LogBooks. The pseudocode shows how BokiFlow uses log tags to distinguish the log records of workflow steps. BokiFlow always reads log records immediately after appends, and only honors the first record of a step (line 7, 20, and 26). This allows BokiFlow to recognize completed steps during workflow re-execution, by checking if the appended record is the first one (§ 5.1.3 explains in more details).

Idempotent database update. For a workflow step that updates the database, Beldi requires the database update and logging of this step to be a single atomic operation. Because Beldi stores its logs along with user data in the same database, it can use the atomic scope provided by the database (e.g., a row in DynamoDB) for this requirement. However, BokiFlow's LogBook is not in the same atomic scope as user data, so no mechanism exists to update both in a single atomic operation. Instead, BokiFlow makes data updates *idempotent*. Pseudocode in Figure 6 demonstrates the approach, where the `rawDBWrite` statement uses the sequence number of the step

log as the "version" of the database update (line 10). During workflow re-execution, re-executing this database update will fail the update condition.

Locks. Beldi provides locks for mutual exclusion; locks also serve as building blocks for Beldi's transactions (§ 5.1.2). Implementing locks requires an atomic "test-and-set" operation, where Beldi uses conditional updates provided by the database. BokiFlow implements locks as registers backed by replicated state machines using the LogBook API. For a BokiFlow lock, its register stores the lock holder (unique identifiers such as UUID), or a special `EMPTY` value. The most natural way to "test" a lock is to execute a predicate on the current state machine. The most natural "set" is to append an update. When we try to combine these operations into a "test-and-set", the LogBook API cannot linearize the result because other BokiFlow clients may also append updates to the same state machine. BokiFlow's solution is to include the log position of the current state machine in the log record of the proposed update. On log replay, choose only the first of any updates that were concurrently proposed. In this way, the total order provided by the LogBook API becomes a mechanism for linearizability.

Pseudocode in Figure 7a demonstrates BokiFlow locks. The lock uses the *prev* field to store the log position, as shown in Figure 7b. The "prev" pointers form a linearizable chain of state machine updates. This technique provides a general approach for building linearizable replicated state machines with the LogBook API.

5.1.2 Transactions in BokiFlow. Same as Beldi, BokiFlow supports transactions that can span across function boundaries with a workflow. Transactions provide stronger guarantees than the workflow's exactly-once semantic: (1) transactions guarantee isolation so that they will not observe data writes from other concurrently running workflows; (2) transactions can be aborted and data writes made within an aborted transaction will never be observed by another workflow.

When initiating a transaction, BokiFlow assigns a unique *txn_id* for it and creates a log for recording operations made within this transaction. Records of transaction logs are appended to the same LogBook used by workflow logs, but use *txn_id* as log tags. These transaction identifiers are passed between functions if the transaction spans across function boundaries.

On committing a transaction, BokiFlow follows the transaction log to commit data writes to DynamoDB. Similar to Beldi, BokiFlow uses locks to guarantee consistency and isolation. BokiFlow maintains per-key locks for tables in DynamoDB. Within a transaction, locks are acquired for database read and write operations. To prevent deadlock, acquiring a lock is a non-blocking operation.

5.1.3 Walk-through of BokiFlow operations. BokiFlow inherits Beldi's log-based techniques for exactly-once execution semantics [54, 61]. In § 5.1.1, we discussed the distinctions between Beldi and BokiFlow. To make it easier to understand BokiFlow's techniques without prior knowledge of Beldi, we will walk through BokiFlow's write and invoke operations in detail, based on pseudocode in Figure 6.

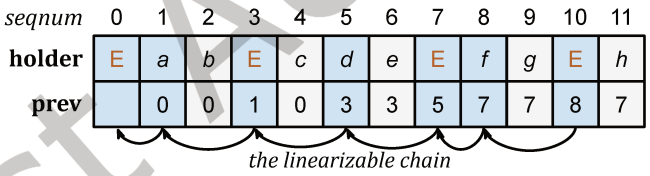
We first explain the write operation. `write`(*table*, *key*, *val*) updates a key-value pair in a DynamoDB table. Same as in Beldi, database writes are logged before execution for fault tolerance. Line 4 in Figure 6 shows the write-ahead logging, where the log record is tagged by the workflow ID and the current step number. The log tag allows BokiFlow to uniquely distinguish this write operation. When failure happens and the workflow is re-executed, `logAppend` (line 4) will be executed again, appending a new and different log record. But the next `logReadNext` (line 7) will read the original record because it looks for the *smallest* sequence number. This append-then-read approach can even guarantee consistency under an extreme condition where concurrent instances of the same workflow are executing, caused by, e.g., unreliable detections of workflow failures. Finally, `rawDBWrite` (line 10) performs the real DynamoDB write. We previously explain BokiFlow uses sequence numbers to version writes, making them idempotent. Because sequence numbers are critical for achieving idempotence, during workflow re-execution the same log record must be used for each write operation.

```
1  def checkLockState(key):
2      tail = None              # Tail of the "linearizable chain"
3      nextSeqnum = 0
4      while True:
5          record = logReadNext(tag: key, minSeqnum: nextSeqnum)
6          if record == None:
7              break            # No more log record for this lock
8          if tail == None or record.data["prev"] == tail.seqnum:
9              tail = record    # This record is part of the linearizable chain
10         nextSeqnum = record.seqnum + 1
11     return tail

12 def tryLock(key, holderId):
13     record = checkLockState(key)
14     if record.data["holder"] == EMPTY:
15         # Presume the lock is not held, and append log record to acquire
16         logAppend(tags: [key], data: {"holder": holderId,
17                                       "prev":   record.seqnum})
18         record = checkLockState(key)
19     if record.data["holder"] == holderId:
20         # Lock succeeded, and the acquire record will be used for unlock
21         return record
22     return None    # Lock failed

23 def unlock(key, acquireRecord):
24     logAppend(tags: [key], data: {"holder": EMPTY,
25                                   "prev":   acquireRecord.seqnum})
```

(a) Pseudocode of BokiFlow's lock operations.



(b) An example log behind a BokiFlow lock. Holders $\{a, d, f\}$ acquire the lock. *prev* pointers in the log form an implicit linearizable chain, which alternates successful acquire and release attempts. Holders share the same *prev* pointers, e.g., holders $\{a, b, c\}$, mean they try to acquire the lock concurrently. Also note holder c's tryLock record is after holder a's lock release record, which is a valid outcome from interleaving.

Fig. 7. Locks in BokiFlow (§ 5.1).

We then look at the invoke operation that calls child functions in a workflow. Unlike the write operation, the invoke operation needs two log records: one before invoking the child function, and the other after invoking. Same as Beldi, BokiFlow generates a unique ID for each function within a workflow, and function IDs must be preserved during workflow re-executions to ensure deterministic recovery. The pre-invoke log record (line 17 in Figure 6) stores the unique ID for the child function, so that the previous function ID can be retrieved during workflow re-execution (line 21). The post-invoke log record (line 26) stores the return value of the child function call. Pseudocode in Figure 6 shows that *invoke* always calls into the child function even during workflow re-execution,

```
# Get the object with name "x"
x = getObject("x")
# Suppose object x is {"a":{}, "b":"foo"}
print(x.Get("b")) # => "foo"
x.Set("a.c", "bar")
# x => {"a":{"c":"bar"},"b":"foo"}
x.MakeArray("a.d");  x.PushArray("a.d", 1)
# x => {"a":{"c":"bar", "d":[1]}, "b":"foo"}

txn = createTransaction(readonly: False)
alice = txn.GetObject("alice")
bob = txn.GetObject("bob")
if alice.Get("balance") >= 10:
    alice.Inc("balance", -10)
    bob.Inc("balance", 10)
txn.Commit()
```

Fig. 8. Demonstration of BokiStore API (§ 5.2).

which can be redundant. BokiFlow's implementation optimizes this redundancy by checking the post-invoke log record before calling into the child function. If the post-invoke log record exists, we can immediately return with the *retVal* in the log record.

5.2 BokiStore: Durable Object Storage

The second support library we built is BokiStore, providing durable object storage for stateful functions. BokiStore employs Tango's [26] techniques for building replicated data structures over a shared log. BokiStore's objects are represented as JSON objects. Objects are identified by unique string names. Figure 8 shows the BokiStore APIs for reading and modifying fields of JSON objects. BokiStore stores all object updates within a LogBook. Reading object fields requires replaying the log to re-construct the object's state. Log records containing object updates are tagged with object names, so that objects can be re-constructed by reading only relevant records.

Transactions. BokiStore supports transactions for reading and modifying multiple objects. BokiStore's log-based transaction protocol largely follows Tango. To start a transaction, BokiStore first appends a *txn_start* record with its *txn_id*. For all subsequent object reads within the transaction, BokiStore replays the log only up to the position of its *txn_start* record. This essentially takes a snapshot of the entire object storage at the *txn_start* position, which achieves *snapshot isolation*.

When committing the transaction, BokiStore appends a *txn_commit* record, including its *txn_id* and all object writes made within the transaction. The *txn_commit* record is *speculative* – by itself, it does not indicate the success of this transaction. To determine the commit outcome of a transaction, BokiStore replays the log up to the *txn_commit* record. A transaction succeeds in committing if and only if there is no conflicting write made between its *txn_start* and *txn_commit* records (i.e., within the conflict window). Figure 9 depicts a transaction log. In this example, *TxnB* is a failed transaction and it is ignored when determining the commit outcome of *TxnC*. BokiStore transactions require frequent log replays, but auxiliary data (§ 5.4) reduces the log replay overhead.

Transactions in BokiStore can be marked as read-only when they are created (see Figure 8). This feature makes read-only transactions simpler to implement: they do not need to append actual *txn_start* and *txn_commit* records, because there is no need for conflict detection. To achieve isolation, when starting the transaction, BokiStore simply caches the current tail position of the log, instead of appending a real *txn_start* record. For object reads within the transaction, BokiStore replays log records only until the cached position.

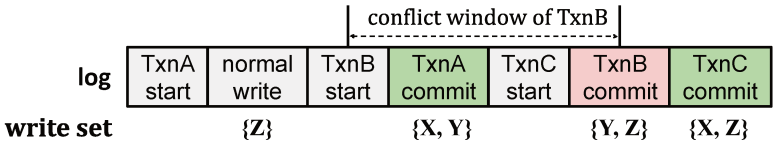


Fig. 9. Transactions in BokiStore (§ 5.2). *TxnB* fails due to conflict with *TxnA*. For *TxnC*, despite its write set overlaps with *TxnB*'s, *TxnC* still succeeds due to the failure of *TxnB*.

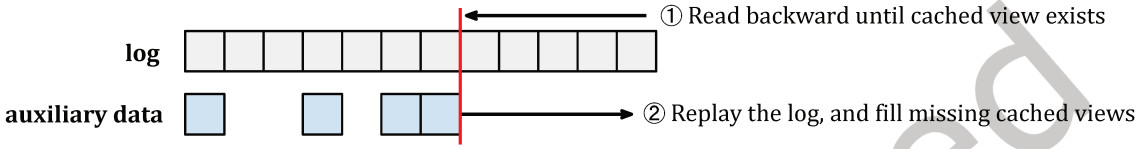


Fig. 10. Use auxiliary data to cache object views in BokiStore, which can avoid a full log replay (§ 5.4).

5.3 BokiQueue: Message Queues

Queues are the most common data structure for message passing. The final support library we build is BokiQueue which provides serverless queues. BokiQueue provides a push and pop API for sending and receiving messages. Like BokiStore, BokiQueue uses the log to store all writes, i.e., push and pop operations. The outcome of a pop is determined by replaying the log. To improve the scalability of BokiQueue, we use vCorfu [60]'s composable state machine replication (CSMR) technique, that divides a single queue into multiple SMR-backed queue shards. Each queue shard is consumed by a single consumer, which reduces contention. A queue producer can choose an arbitrary queue shard to push. In our implementation, we simply use round-robin.

5.4 Optimizing Log Replay with Auxiliary Data

Reads in BokiStore are served by replaying the log to re-construct object state. This naive approach makes read latency proportional to the number of relevant log records, i.e., the number of object writes. Tango optimizes log replay by caching local object views, such that only new records from the shared log are replayed. However, in the FaaS setting, in-memory state is not guaranteed to be preserved between invocations, so a simple memory cache for objects is not a viable solution.

Boki's auxiliary data (§ 3) is motivated by the need to provide per-log-record cache storage. In BokiStore, for every object write that generates a log record, the auxiliary data of the record stores a snapshot view of the object. When reading an object, BokiStore seeks from the log tail to find the first relevant record having a cached object view in its auxiliary data. Then BokiStore replays the log from this position to re-construct the target object state. During replay, for records missing cached object views, their auxiliary data are filled with object views. Figure 10 demonstrates this accelerated replay process.

One important special case for accelerating log replay is commit records. For *txn_commit* records, their auxiliary data stores the decided commit outcome and if the commit succeeds, the auxiliary data also caches a view of modified objects.

In BokiFlow's log-based locks (shown in Figure 7a), auxiliary data of a record is used for caching the current tail of the linearizable chain. This allows the `checkLockState` function to optimize its log replay as illustrated in Figure 10.

5.5 Garbage Collector Functions

The FaaS paradigm simplifies garbage collection (GC) in shared-log-based storage systems. Boki support libraries use garbage collector functions to trim useless log records, in order to prevent unlimited growth of LogBooks. These functions are periodically invoked and they reclaim space via LogBook's `logTrim` API (Figure 1). The `logTrim` API trims a prefix of the log: it takes a single parameter *trim_seqnum* and deletes all log records with sequence numbers less than *trim_seqnum*. Given the API semantic, garbage collector functions have to efficiently figure out the safe trim position. We then describe specific mechanisms used by different Boki support libraries.

BokiFlow. BokiFlow follows Beldi's GC strategy [61]: the garbage collector function scans for completed workflows whose completion timestamp is old enough, and marks these workflows as recyclable. When a prefix of the log contains only records from recyclable workflows, `logTrim` can be called to reclaim space.

BokiStore. In BokiStore, the log stores a history of writes for individual objects. The garbage collector function periodically materializes object states in the log, so that log records corresponding to the old history can be safely deleted.

To scale this strategy with more objects, BokiStore uses multiple GC functions for materializing object states in parallel. Each GC function is responsible for a shard of objects, and the shard numbers are determined by hashing object names.

One of the GC functions is designated as *master*, who is responsible for actually calling `logTrim`. Other GC functions periodically store safe trim positions for their shards in the log (with some special tag), so that the *master* can determine the global trim position. The *master* GC function also takes extra care to ensure the trim position is not within any ongoing transactions.

BokiQueue. In BokiQueue, each queue shard is consumed in FIFO order, where log records of popped elements become useless. For each queue shard, its consumer can determine the safe trim position, and periodically stores the position in the log with some special tag. A dedicated GC function reads trim positions from all shards, and calls `logTrim` accordingly.

6 Implementation

The Boki prototype is based on Nightcore [17], where we add 13,133 lines of code, mostly in C++. Boki's support libraries are implemented in Go, consisting of 3,569 lines of code. One of the support libraries, BokiFlow, derives from the Beldi codebase [11]. The LogBook API makes Beldi's techniques easier to implement, so that BokiFlow shrinks the Beldi library from 1,823 lines to 1,137 lines, or a 38% reduction.

Boki uses 64-bit integers as the tag type for LogBook records. In Boki support libraries, when we need other types (e.g., strings) as the log tag, we use their hash values instead and store the original string in the record data. Boki employs Dynamo [31]'s variant of consistent hashing (strategy 3 in their paper) to uniformly map between LogBooks and physical logs.

In the current implementation, metalogs are replicated in the DRAM of sequencer nodes. This is viable in our failure assumption that requires a quorum of sequencers for a metalog to always be alive.

6.1 Storage Backend

Boki provides two different options as its storage backend for log records.

The first option is to use a third-party key-value store (KVS) library. LogBook records are stored with their unique sequence numbers (seqnum) as keys, and log data and other metadata are serialized as values. The current implementation supports RocksDB [13] and Tkrzw [15]'s TreeDBM. RocksDB is a key-value store based on a log-structured merge-tree (LSM), and Tkrzw is based on a B-tree.

The second option is Boki's JournalStore, which implements an on-disk journal for storing log records. Boki's journal is implemented by append-only files. Every I/O thread [1] has its own private journal file to which it appends data records. Having private journal files for individual I/O threads means no locking is required when appending to the journal.

Although records within one journal file are implicitly ordered by their offset within the file, Boki records are explicitly ordered by the sequencer, which assigns unique sequence numbers to individual log records. These two orders may not match due to multiple journal files. To read a log record by its seqnum, Boki maintains a separate hash table to locate log records within journal files.

To facilitate log trims (record deletes), for each journal file, Boki maintains a bitmap indicating trimmed log records. Boki gradually reads trim commands stored in the metalog and updates the trimmed record bitmap of the relevant journal files. Boki removes a journal file when its bitmap is fully set, indicating that all of its data has been trimmed, the journal file can be deleted, and its space reclaimed. Note that the bitmap is only used for determining when a journal file can be deleted. To bound the size of bitmaps and journal files, Boki imposes two size limits: one limits the maximum number of records in a file, and the other limits the file byte size. When an I/O thread's current journal file reaches either limits, it closes the old file and creates a new one. The current implementation sets the record limit to 1,048,576 (2^{20}), and the file size limit to 256MB.

When using the JournalStore, Boki persists data records earlier in the workflow than when it uses a third-party KVS. In Figure 2, when Boki uses JournalStore to append to the log, it flushes new log records to their journal files before storage nodes report progress to sequencers (②). In contrast, when using a third-party KVS as a storage backend, log records are only written to the KVS after the metalog is propagated (④ in Figure 2). Boki must wait until ④ because the KVS backend uses sequence numbers as keys, which are only available after ④.

Boki also provides the option to use its on-disk journal along with a third-party KVS. In this setup, the on-disk journal acts as a write-ahead log, which can combine the benefits of earlier persistency with the flexibility of using third-party KVS libraries. Our evaluation (Table 4) shows using KVS with Boki's journal has moderate performance penalty.

JournalStore provides some performance advantages over a third-party KVS. Our microbenchmark (Table 4) shows JournalStore achieves 4.7–9.8x lower p99 tail latency (under similar throughput) than using KVS backends. We attribute the latency improvement to JournalStore's tight integration with Boki's design. Boki has to pay some integration overheads when using third-party KVS libraries. For example, RocksDB creates extra background threads to flush its internal memtables, and Tkrzw's B-tree implementation shards the data structure and uses mutexes to protect each shard. In contrast, JournalStore does not need extra threads for background work, and has no lock contention on the journal append path.

In our previous presentation of Boki [40], only the first option (using a key-value store library) is described and evaluated. Boki's on-disk journal is a new storage option added in this work.

6.2 Validating Correctness

We have used software engineering best practices to validate the prototype's correctness regarding the consistency semantics of the shared log abstraction, the durability of log record data, and fault tolerance.

- *Invariant checks.* Throughout the Boki code base there are many checks for basic invariants, in particular invariants related to metalogs. The serialized metalog entry not only includes its own cut vector, but also the cut vector from its predecessor entry. Such redundancy allows checking invariants when replaying the metalog.
- *Data integrity.* To validate that Boki's storage layer persists the user's payload data in log records, we implement checksums for log payloads. The checksum mode is disabled for some evaluations due to its performance

[1] Boki inherits Nightcore [41]'s I/O design, where I/O threads handle socket and file I/O with event-driven syscalls. I/O threads also execute callback functions for incoming messages from other Boki nodes.

penalty. There is also a testing mode to validate the correctness of the cache layer (recall that Boki has a record cache on its read path, depicted in Figure 4). The testing mode always reads from storage nodes even when cache hits, and log record data read from the cache is compared against the storage node to check that they are equal.

• *Unit testing with Boki support libraries.* We have unit tests to validate Boki support libraries which also validate the properties of Boki's shared logs. Some examples of tests we have implemented: (1) We test BokiStore transactions with counters which are concurrently updated;(2) We test the FIFO property of BokiQueue; (3) We test if BokiFlow's locks properly linearize lock commands. All these tests validate LogBook's total order property, and the correctness of log-based protocols used in Boki support libraries.

• *Relying on production-grade third-party libraries.* For some parts of the prototype, we use existing libraries such as ZooKeeper, RocksDB, and Tkrzw. We rely on these production-grade libraries to provide important properties including durability and fault tolerance.

7 Evaluation

In this section, we first evaluate Boki with microbenchmarks to explore its performance characteristics (§ 7.1). We then evaluate Boki's support libraries using realistic workloads (§ 7.2, § 7.3, and § 7.4). Finally, we analyze how Boki's techniques benefit its use cases (§ 7.5).

Experimental setup. We conduct all our experiments on Amazon EC2 instances in the us-east-2 region. Boki's function, storage, and sequencer nodes use c5d.2xlarge instances, each of which has 8 vCPUs, 16GiB of DRAM, and 1 × 200GiB NVMe SSD. Boki's gateway and control plane use c5d.4xlarge instances. Experimental VMs run Ubuntu 20.04 with Linux kernel 5.10.17, with hyper-threading enabled. We measure that the round trip time between VMs is 107μs ±15μs, and the network bandwidth is 9,681 Mbps.

Unless otherwise noted, the following Boki settings are fixed in our experiments: (1) the ZooKeeper cluster in the control plane has 3 nodes; (2) the replication factors of both physical logs (n_{data}) and metalogs (n_{meta}) is three; (3) one single physical log configured for all LogBooks; (4) for each physical log, there are 4 LogBook engines that store its index (though functions can read their LogBooks via remote engines); (5) the record cache per LogBook engine is 1GB (for both record data and auxiliary data §3).

Table 3. Boki's throughput in append-only microbenchmark. Boki is configured to use JournalStore backend for storing LogBook records (§ 7.1).

	Concurrent functions / Storage (S) nodes			
	320/4S	640/8S	1280/16S	2560/32S
$n_{\text{meta}} = 3$	156.1	314.5	654.8	1142.7
$n_{\text{meta}} = 5$	155.9	323.1	639.4	1153.8

(a) Append throughput (in KOp/s) of a single LogBook, where n_{meta} denotes the replication factor of Boki's metalog. Boki can scale append throughput of a totally ordered log to 1.2M Ops/s.

	1 PhyLog	**2 PhyLogs**	**4 PhyLogs**
100 LogBooks	161.8	324.5	696.9
100K LogBooks	162.8	310.3	665.9

(b) Aggregate throughput (in KOp/s) when using multiple physical logs (PhyLogs) to virtualize LogBooks. Boki scales with more physical logs, and can efficiently virtualize 100K LogBooks.

Table 4. Comparison of Boki's different storage backends, using append-only microbenchmark (§ 7.1). Using Boki's on-disk journal provides quicker persistency 6.1, though results in slightly lower throughput. Also note JournalStore achieves the lowest tail latency among all options.

	Throughput (KOp/s)	**Latency (ms)** *median*	*99% tail*
RocksDB (LSM)	764.2	1.39	53.2
Tkrzw (B-tree)	651.1	1.58	25.7
Storage options using on-disk journal			
JournalStore	654.8	1.66	5.42
RocksDB with journal	655.4	1.47	79.3
Tkrzw with journal	448.6	1.98	45.6

Table 5. Boki's read latencies under different scenarios (§ 7.1).

	Local LogBook (LB) engine *cache hit*	*cache miss*	**Remote LB engine**
median	0.09ms	0.29ms	0.43ms
99% tail	0.40ms	0.75ms	0.99ms

7.1 Microbenchmarks

We start the evaluation of Boki using microbenchmarks, where we answer the following questions.

• *What is the append throughput of a single LogBook?* We use an append-only workload to measure the throughput, and how the throughput scales with more resources. In this workload, each function is a loop of appending 1KB log records. Boki is configured to use JournalStore (the second option mentioned in § 6) as the storage backend. Results are shown in Table 3a. From the table, we see that when Boki is configured with 64 nodes, the append throughput scales to 1.2M Ops/s under 2,560 concurrent appending functions. At this point, the median latency is 1.94ms, and the p99 tail latency is 6.33ms. We also increase the replication factor of metalogs (n_{meta}) to 5, that provides higher durability for a metalog but potentially affects the metalog's append latency. However, it demonstrates similar LogBook throughput and scalability as $n_{\text{meta}} = 3$.

• *Can Boki efficiently virtualize LogBooks?* We use the same append-only workload, but log appends are uniformly distributed over many LogBooks. We use 1, 2, and 4 physical logs to virtualize 100 and 100K LogBooks. Boki is configured with 4 function and 4 storage nodes when using one physical log, and resources are added linearly with more physical logs. Table 3b shows the results. From the table, we can see Boki is capable of virtualizing LogBooks with high density.

• *How do Boki's log storage options compare to each other?* As described in § 6.1, Boki supports multiple options for storing log records. We use the append-only workload to compare throughput and latencies of different options. In the evaluation, Boki is configured with 16 storage nodes, and we use 1,280 concurrent appending functions. Table 4 shows the result. From the result, we see using Boki's on-disk journal provides better persistency property but with the cost of slightly lower append throughput and higher p50 latency. Notably, Boki's JournalStore can achieve very low 99% tail latency (5.42ms) compared with other options, because its tight integration with Boki design 6.1.

• *How fast can Boki functions read LogBook records?* We use an append-and-read workload to measure read latencies, where each function loops a procedure that first appends a log record, then reads the appended record 4

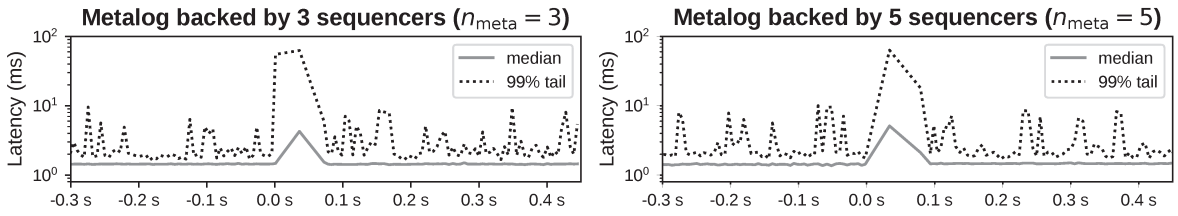


Fig. 11. Log append latencies during reconfiguration. The x-axis shows the timeline (in seconds). The reconfiguration starts at $t = 0$.

times. We configure Boki with 8 function and 8 storage nodes. Table 5 shows the results when using JournalStore for log storage. For other storage options, we observe similar latency numbers. For *remote engine* case, we enforce Boki to use remote LogBook engines for log reads. Cache hits take 86μs and never leave the local LogBook engine, retrieving the result from the record cache (§ 4.4).

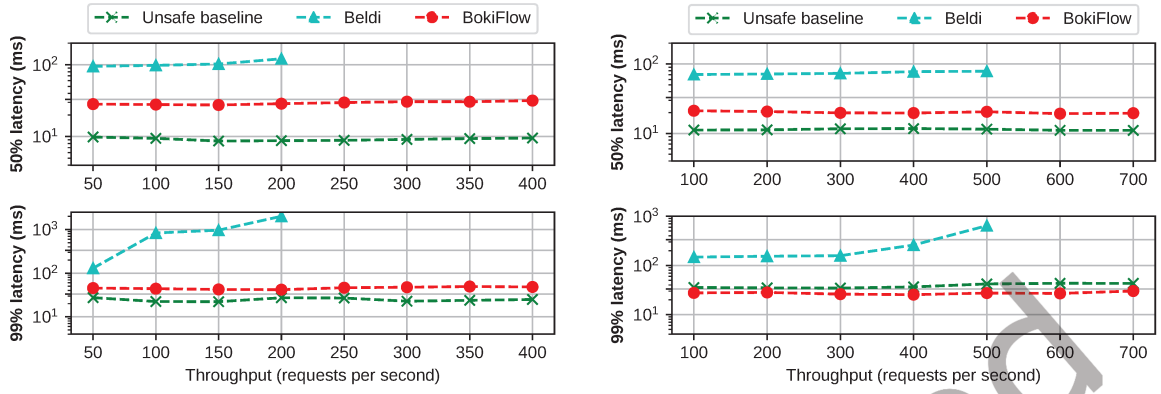
- *What is the impact of reconfiguration?* We use the append-only workload to evaluate the impact of reconfiguration. In the experiment, Boki is reconfigured to a new set of sequencer nodes. New sequencer nodes are provisioned before the reconfiguration, to factor out provisioning delays from the experiment. Figure 11 shows the results. We see that Boki recovers to normal append latency after reconfiguration within 100ms. The actual reconfiguration protocol, executed by the controller, takes 15.7ms and 18.1ms, in experiments of $n_{meta} = 3$ and $n_{meta} = 5$, respectively.

7.2 BokiFlow: Fault-Tolerant Workflows

We evaluate BokiFlow by comparing it with Beldi [61]. We use Beldi's workflow workloads, which model movie reviews and travel reservations. Both of them are adapted from DeathStarBench [8, 35] microservices. For a fair comparison, we port Beldi and its workloads to Nightcore, the underlying FaaS runtime of Boki. Both BokiFlow and Beldi store user data in DynamoDB [1]. BokiFlow stores workflow logs in a LogBook, while Beldi uses its linked DAAL technique to store logs in DynamoDB. For both systems, they are configured with 8 function nodes and Boki is configured with 3 storage nodes. Boki uses JournalStore as the storage backend.

Figure 12 shows the results. In both workloads, BokiFlow achieves much lower latencies than Beldi for all throughput values. In the movie workload, when running at 200 requests per second (RPS), BokiFlow's median latency is 28.7ms, 4.2× lower than Beldi (121ms). In the travel workload, BokiFlow's median latency is 20.5ms at 500 RPS, 3.8× lower than Beldi (78ms). In this experiment, we also run a baseline without Beldi's techniques, where it cannot guarantee exactly-once semantics or support transactions for workflows. When comparing BokiFlow with this baseline, we see that exactly-once semantics and transactions increase median latency by 3.3× in the movie workload, and by 1.8× in the travel workload.

We then run the microbenchmark that evaluates Beldi's primitive operations (Figure 13 in the Beldi paper [61]). Results are shown in Figure 13. The *Invoke* operation shows the largest differences among the three implementations and *Invoke* operations are very frequent in microservice-based workflows. In the baseline without workflow logs, the *Invoke* operation is very fast (well below 1ms). The underlying FaaS runtime, Nightcore, is heavily optimized to reduce invocation latencies. In BokiFlow, the *Invoke* operation needs needs 5 LogBook appends, thus it has a median latency of 4.0ms. Two of the five log appends are demonstrated in Figure 6 and the other three appends are made within the child function. For comparison, *Invoke* operation in Beldi also need 5 log appends, but has a median latency of 19ms, because of multiple DynamoDB updates for each log append. These



(a) Movie review workload. (b) Travel reservation workload.

Fig. 12. Comparison of BokiFlow with Beldi [61]. BokiFlow takes advantage of the LogBook API. "Unsafe baseline" refers to running workflows without Beldi's techniques, where it cannot guarantee exactly-once semantics or support transactions (§ 7.2).

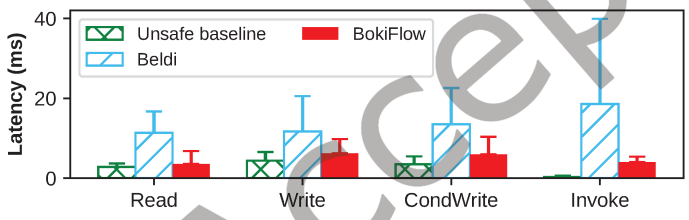


Fig. 13. Microbenchmarks of Beldi primitive operations (§ 7.2). Main bars show median latencies, while error bars show 99% latencies.

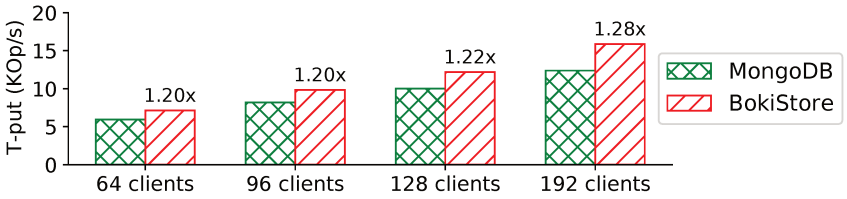
results justify the value of shared logs for the serverless environment, where building logging layers using a cloud database is difficult to make performant.

7.3 BokiStore: Durable Object Storage

Retwis workload. To evaluate BokiStore, we build a transaction workload inspired by Retwis, a simplified Twitter clone [16]. The Retwis workload has been used as a transaction benchmark in previous work [62, 63]. We re-implement the Retwis workload in Go, requiring 1,458 lines of code. Our implementation uses BokiStore objects to store users, tweets, and timelines. For comparison, we also implement a version that uses MongoDB [14] to store objects, because MongoDB also employs a JSON-derived data model.

The evaluation workload first initializes 10,000 users, and then runs a mixture of four functions: UserLogin (15%), UserProfile (30%), GetTimeline (50%), and NewTweet (5%). UserLogin are UserProfile are normal single object reads. GetTimeline is a read-only transaction that reads the timeline and multiple tweets. NewTweet is a transaction that writes multiple user, tweet, and timeline objects.

In the experiment, we configure Boki with 8 function nodes and 3 storage nodes using JournalStore. MongoDB is configured with 3 replicas. To ensure snapshot isolation in MongoDB transactions, we use a write concern of "majority" [20] and a read concern of "snapshot" [12]. For BokiStore, we configure LogBook engines on all



(a) Throughput of BokiStore compared with MongoDB.

Request types	50% latency		99% latency	
	Mongo	Boki	Mongo	Boki
`UserLogin` (non-txn read)	**0.86**	1.41	**3.32**	5.47
`UserProfile` (non-txn read)	**0.86**	0.99	**3.57**	4.93
`GetTimeline` (read-only txn)	7.57	**3.24**	25.01	**10.09**
`NewTweet` (read-write txn)	7.72	**5.42**	21.39	**10.56**

(b) Latencies (in ms) under 192 clients. Although non-transactional reads in BokiStore are slower than MongoDB, transactions in BokiStore are up to 2.5× faster. Best performing result is in bold.

Fig. 14. Evaluating BokiStore on Retwis workload (§ 7.3). Boki uses JournalStore as storage backend.

8 function nodes to have log index for the target LogBook, which achieves best data locality. We analyze the performance impact of using remote LogBook engines in § 7.5.

Figure 14 shows the results. From the figure, we see BokiStore achieves 1.20–1.28× higher throughput than MongoDB. When breaking down latency details by request types, we see BokiStore has considerable advantages over MongoDB in transactions (up to 2.5× faster). On the other hand, BokiStore is slower than MongoDB for non-transactional reads. This is caused by the log-structure nature of BokiStore, where log replay incurs overheads for data reads.

Comparison with Cloudburst. Cloudburst [57] is a recently proposed stateful FaaS runtime, which exports a put/get interface (i.e., key-value store) for functions to store state. BokiStore can also be used as a key-value store, by using keys as object names and storing values in the corresponding BokiStore object. However, BokiStore provides stronger consistency guarantees (sequential) than Cloudburst (causal). BokiStore also supports transactions reading and modifying multiple keys, which are not supported by Cloudburst.

We use a microbenchmark to compare Cloudburst's performance with BokiStore. Both systems use 8 storage nodes and 8 function nodes in the experiment. Figure 15 shows the result. BokiStore can achieve up to 2.16× higher throughput than Cloudburst on get operations. For put operations, BokiStore achieves 1.33× higher throughput when the concurrency is high. BokiStore provides higher throughput and lower median latency at 192 clients than Cloudburst, but it does have higher tail latency.

7.4 BokiQueue: Message Queues

We evaluate BokiQueue by comparing it with Amazon Simple Queue Service (SQS) [2] and Apache Pulsar [3]. Amazon SQS is a fully managed message queue service from AWS, while Pulsar is a popular open source distributed message queue. Similar to BokiQueue, both SQS and Pulsar use sharding to improve the data throughput of their message queues. In the experiment, we configure Boki with 8 function nodes and 3 storage nodes. Boki is configured with Tkrzw as storage backend for best performance. For Pulsar, we run its broker services on function nodes for better locality, and use the 3 storage nodes for queue data.

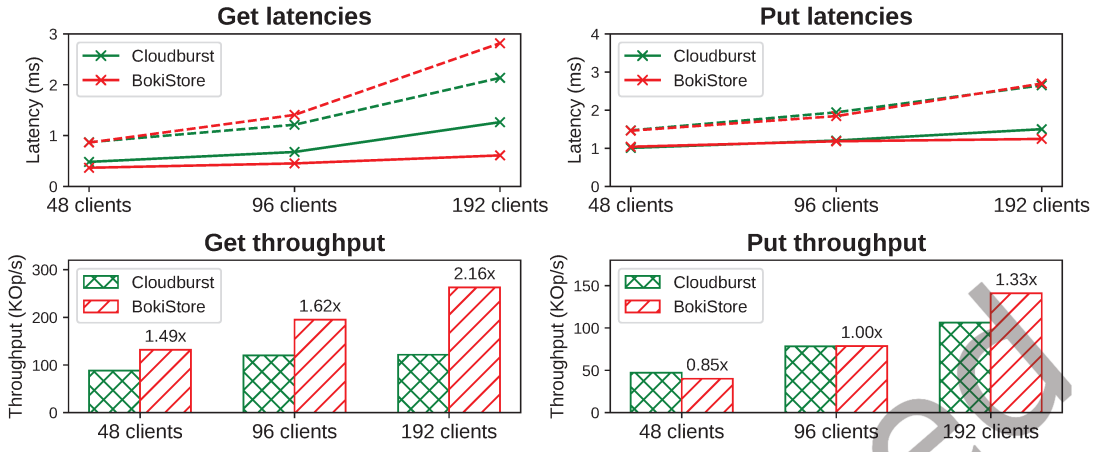


Fig. 15. Comparison of BokiStore with Cloudburst [57]. We measure the latencies and throughput for put and get operations, using different numbers of concurrent clients. In the latency charts, solid lines show median latencies, and dashed lines show 99% tail latencies. BokiStore not only provides stronger consistency guarantees, but also achieves higher performance than Cloudburst (§ 7.3).

Table 6. Comparison of BokiQueue with Amazon SQS [2] and Pulsar [3] (§ 7.4). Boki is configured with Tkrzw as storage backend, which achieves best performance for BokiQueue. Throughput is measured in 10^3 message/s. Delivery latency is the duration that a message stays in the queue. Latencies are shown in the form of "median (99% tail)". For each row in the table, best performing result is in bold.

Producer/ Consumer	Throughput			Delivery latency (ms)		
	SQS	Pulsar	Boki	SQS	Pulsar	Boki
16P/64C	2.25	5.05	**5.21**	6.27 (52.5)	4.01 (12.3)	**2.97 (5.05)**
32P/128C	4.03	9.67	**10.4**	6.01 (51.3)	6.70 (12.8)	**3.18 (6.12)**
64P/256C	7.62	14.1	**15.5**	6.08 (56.5)	7.39 (13.7)	**4.67 (14.8)**
64P/16C	2.34	**8.71**	7.92	33.9 (228)	6.20 (12.7)	**5.10 (14.9)**
128P/32C	5.35	**14.6**	14.1	53.9 (370)	7.38 (14.0)	**5.48 (19.2)**
256P/64C	9.77	19.1	**21.1**	99.8 (764)	7.81 (33.7)	**5.75 (20.2)**
64P/64C	6.37	10.0	**10.5**	7.22 (76.0)	6.77 (12.9)	**3.15 (6.64)**
128P/128C	10.1	17.8	**21.0**	7.24 (79.6)	7.74 (21.4)	**3.81 (9.53)**
256P/256C	18.5	25.0	**31.5**	12.1 (84.5)	8.21 (39.5)	**5.64 (17.5)**

We use a fixed number of producer and consumer functions for the evaluation, where each producer keeps pushing 1KB messages to the queue. We experiment with three ratios of producers to consumers (P:C ratio), which are 1:4, 4:1, and 1:1. In the evaluation, we measure the message throughput of the queue, and the median and p99 latency of message deliveries.

Table 6 shows the results. When the P:C ratio is 1:4, the queue is lightly loaded. We see both BokiQueue and Pulsar achieve double the throughput of Amazon SQS. BokiQueue achieves up to 1.6× lower latencies than Pulsar. When the P:C ratio is 4:1, the queue is saturated. Amazon SQS suffers significant queueing delays, limiting its

Table 7. The importance of log replay optimization using auxiliary data (§ 7.5). The table shows Retwis throughput (in Op/s).

Workload duration	1min	3min	10min	30min
Optimization disabled	1,565	939	–	–
AuxData w/ Redis	11,014	10,046	9,548	9,344
AuxData w/ Boki	11,388	11,078	10,923	10,891

throughput. BokiQueue and Pulsar have very similar throughput, while BokiQueue achieves 1.36× lower latency than Pulsar in the case of 256 producers. Finally, when the P:C ratio is 1:1, the queue is balanced. BokiQueue consistently achieves higher throughput and lower latency than both Amazon SQS and Pulsar.

Combining these three cases, BokiQueue achieves 1.70–2.16× higher throughput than Amazon SQS, and up to 17× lower latency. Compared with Pulsar, BokiQueue achieves 1.10–1.26× higher throughput, and up to 1.6× lower latency.

7.5 Analysis

The importance of auxiliary data. We describe in § 5.4 the log replay optimization using LogBook's auxiliary data. We use Retwis workload to demonstrate its importance for BokiStore. We run an experiment that disables this optimization. Furthermore, to demonstrate the efficiency of Boki's storage mechanism for auxiliary data, we modify Boki to store auxiliary data in a dedicated Redis instance.

Table 7 shows the results. From the table, we see that the log replay optimization is crucial for BokiStore to achieve an acceptable performance. The results also show the optimization is robust even for long executions, where more object writes are logged. Compared to the Redis-backed implementation, Boki achieves 1.17× higher throughput. Boki's approach is more efficient because it maintains data locality by reusing the record cache within LogBook engines.

Locality impact from LogBook engines. In the previous evaluation of BokiStore, we configure Boki so all LogBook reads are served by local LogBook engines. In a large-scale deployment, having all LogBook engines maintain an index for a particular physical log is not viable. Boki relies on the function scheduler to optimize for the locality of LogBook engines.

To experiment with the impact from using remote LogBook engines we limit the ratio of log reads that are locally processed, with the remainder processed remotely. Table 8 shows the results. We see even under a poor locality of LogBook engines, the performance drop is moderate (e.g., 77% of maximum throughput at 25% local reads).

Read locality also comes from the record cache included in LogBook engines. The cache stores both record data and auxiliary data for LogBook records. We experiment with different cache sizes to analyze its impact on BokiStore performance. Results are shown in Table 9. We observe a sharp dorp in throughput when the cache size is decreased to 16MB. The cause of this drop is insufficient cache storage for auxiliary data. Auxiliary data is important for BokiStore performance, and a small record cache decreases the effectiveness of the log replay optimization. We modify Boki to backup auxiliary data on storage nodes, so that under a cache miss, storage nodes can also return auxiliary data. With this mechanism, small cache sizes no longer cause a sharp dorp in performance.

Log index versus fixed sharding. In § 4.4, we motivate the log index design because it allows records from a LogBook to be placed in arbitrary log shards. An alternative approach is fixed sharding used in previous systems such as vCorfu [60]. We use the append-only microbenchmark to demonstrate the advantage of Boki's approach.

Table 8. Locality impact from LogBook engines (§ 7.5). The table shows Retwis throughput (in Op/s), when adjusting the percentage of reads processed by local LogBook engines.

Local reads	25%	50%	75%	100%
Throughput	8,548	9,319	10,262	11,078
Normalized tput	0.77x	0.84x	0.93x	1.00x

Table 9. LogBook engines maintain local cache for log records, and the cache size has performance impact for Boki's applications (§ 7.5). The table shows Retwis throughput (in Op/s).

LRU cache size	16MB	32MB	64MB	1GB
Auxiliary data only stored on function nodes				
Throughput	3,561	10,476	11,263	11,245
Auxiliary data also backed up on storage nodes				
Throughput	11,358	11,852	12,032	12,075

Table 10. Append throughput (in KOp/s) when log appends are distributed over 128 LogBooks under a uniform or Zipf distribution.

	Uniform	**Zipf** ($s = 3$)	**Zipf** ($s = 5$)
Fixed sharding	242.7	164.0	129.6
Log index (Boki)	250.6	253.4	278.6

Table 11. Scaling read-only transactions with LogBook engines (§ 7.5). The experiment runs Retwis workload under a fixed write rate.

	Concurrent functions / LogBook engines				
	100/8E	200/16E	300/24E	400/32E	600/48E
T-put (txn/s)	6,548	12,749	18,618	23,662	30,286
Normalized	1.00x	1.95x	2.84x	3.61x	4.63x

For comparison, we modify Boki to use a fixed sharding approach, where a hashing function maps each LogBook to a log shard. Results are shown in Table 10. When log appends are uniformly distributed over LogBooks, the two approaches show no difference. However, when the distribution is skewed, fixed sharding suffers from uneven loads between log shards, while Boki's log index approach is unaffected.

Scaling LogBook engines. We then demonstrate the scalability of LogBook engines, by running read-only transactions in the Retwis workload. The workload is a mixture of read-only transactions (GetTimeline) and read-write transactions (NewTweet). In the experiment, we add more function nodes to scale LogBook engines, while always using 3 storage nodes. Every LogBook engine maintains a log index for the target LogBook. We fix the rate of NewTweet to 700 requests per second. Results are shown in Table 11. The results demonstrate Boki can scale from 8 LogBook engines to 48, thereby providing 4.63× higher read throughput.

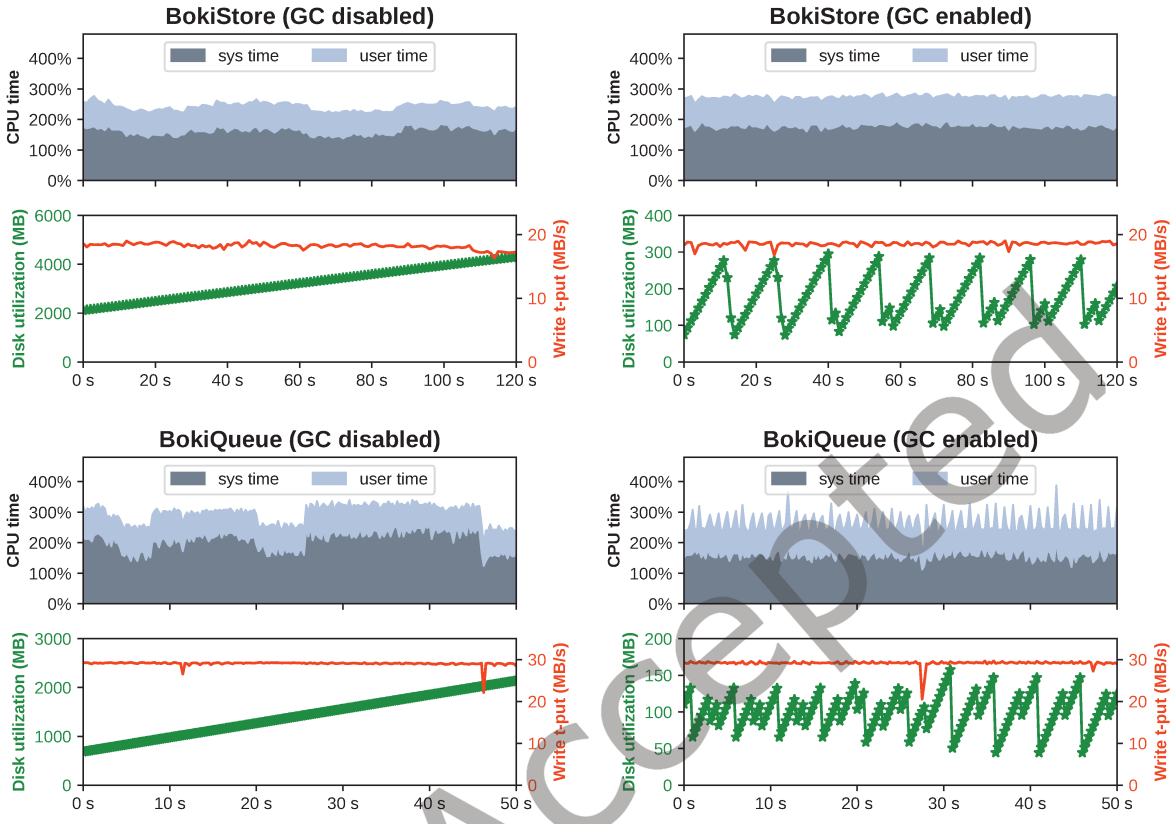


Fig. 16. Demonstration of garbage collection (GC) in BokiStore and BokiQueue (§ 7.5). All figures show the state of one storage node: the upper chart shows CPU time; and the lower chart shows disk utilization and write throughput. One storage node has 4 CPU cores. For BokiStore experiments, we show a duration of 120 seconds in the middle of running. For BokiQueue experiments, we show a duration of 50 seconds.

Garbage collection (GC). As discussed in § 5.5, Boki provides the `logTrim` API for its support libraries to reclaim space from old and useless log records. We demonstrate the effectiveness of Boki's GC mechanism in BokiStore and BokiQueue. For BokiStore, we run a workload where 96 concurrent functions modify 1,000 BokiStore objects. For BokiQueue, we run a workload with 200 producer and 200 consumer functions. Boki is configured to use JournalStore as the storage backend. Figure 16 shows the state of one storage node. From the figure, we can see GC effectively controls disk utilization, while not affecting write throughput.

For comparison, we also run the same BokiStore and BokiQueue workloads without garbage collection. In both workloads, we found GC has no influence on the throughput. However, enabling GC in BokiQueue can reduce the tail latency of message delivery from 29.5ms to 8.90ms. For the BokiStore workload, we observe no difference in request latencies.

To quantify CPU overhead, we compute the average CPU utilization over the time span shown in Figure 16. In BokiStore experiments with GC disabled, the average system and user utilization is 162% and 79% (241% total). For comparison, enabling GC increases CPU utilization by 13%: system and user utilization rise to 178% and 95%

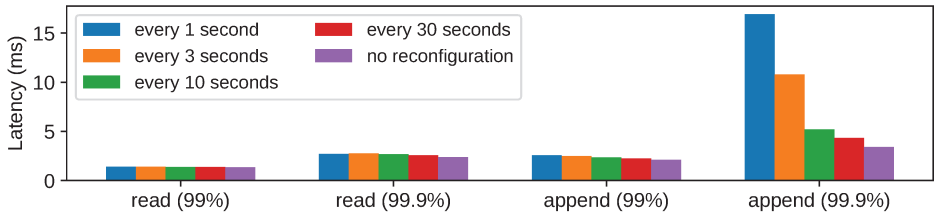


Fig. 17. Sensitivity study of LogBook latencies to reconfiguration frequency (§ 7.5). Reconfigurations have little impact on log read latencies, but can significantly affect tail latencies of log appends when they are frequent. In all tested frequencies, throughput of log reads and appends is not affected (same as "no reconfiguration"). Data are collected over a 5-minute period.

(273% total). In BokiQueue experiments with GC disabled, the average system and user utilization is 208% and 88% (296% total). Enabling GC decreases system utilization to 159% and increases user utilization to 105% (264% total). GC raises CPU utilization by 13% in BokiStore, but lowers it by 12% in BokiQueue.

Sensitivity study of reconfigurations. We finally study how reconfiguration frequency affects Boki's performance. In the experiment, Boki is configured with a single physical log using $n_{\text{meta}} = 3$. To allow reconfigurations without frequently allocating new nodes, we provision redundant nodes for Boki. In the experiment, 8 sequencer nodes are provisioned, while only 3 of them are active at one time because $n_{\text{meta}} = 3$. Reconfigurations are manually triggered periodically with a fixed frequency, from every 1 second to every 30 seconds. For each reconfiguration, 3 sequencer nodes are randomly chosen to store the metalog in the new term. We run a workload of log appends and reads (check tail), where the ratio between appends and reads is 1:4. 320 concurrent functions are executed over 8 function nodes. Results are shown in Figure 17. For read operations, we see that even frequent reconfigurations have little impact on their latencies. But for append operations, when reconfigurations become very frequent, their tail latencies increase significantly.

Correctness test of BokiStore transactions. As mentioned in § 6.2, we use unit tests to validate Boki support libraries and the underlying Boki shared log implementation. We describe the results of one representative test which validates the correctness of BokiStore's transaction protocol (Figure 9). In this test, we create 32 BokiStore objects, each of which is used as a counter. Then we write a function to repeatedly choose k counters at random ($k = 2, 3, 5$ are tested), and add them to random values in a transaction. We run 48 concurrent instances of this function for 30 seconds. Within each function instance, it accumulates local deltas for each counter given the outcome of transactions. Local deltas of all counters are returned by every function instance. The test checks if all counters' final values match the sum of the local deltas. When 3 objects are updated in each transaction, 48 function instances create 148,216 transactions during the 30-second period, and 52,165 transactions commit successfully without conflicts.

8 Related Work

Stateful serverless computing. State management remains a key challenge in the current serverless environment [38, 52]. To meet the increasing demand for stateful serverless, there are recent attempts from industry, e.g., Cloudflare's Durable Objects [18] and Azure's Entity Functions [9]. These systems are still in their early stages and have seen limited adoption.

There are also proposals from academia, e.g., Pocket [46], Cloudburst [57], Faasm [56], and Jiffy [44]. These projects have different focus, e.g., heterogeneous storage technology [46], lightweight isolation [56], auto-scaling [57], and supporting far memory [44]. These systems all export put-get interfaces (i.e., a key-value store) for functions to manage state (Jiffy [44] also supports file and FIFO queue interfaces). Boki is the first to study a different interface for serverless state management, the shared log API. Boki's shared log approach is motivated by the fault-tolerance and consistency challenges encountered by stateful serverless applications, which the put-get interface cannot easily address.

A recent article [52] argues future serverless abstractions will be general-purpose, where cloud providers expose a few basic building blocks, e.g., cloud functions (FaaS) for computation and serverless storage for state management. The shared log and key-value store are both promising storage building blocks, which can work together to enable new serverless applications.

Distributed shared logs. Recent studies on distributed shared logs [24–27, 32, 47, 60] heavily inspire the design of Boki. A shared log is a powerful primitive for achieving strong data consistency in the presence of failures, because it can be used for state machine replication (SMR) [53], the canonical approach for building fault-tolerant services.

Boki leverages Scalog [32]'s high-throughput ordering protocol. Virtual consensus in Delos [24] inspires Boki's design of metalogs. Materialized streams in vCorfu [60] inspire the design of log tags in the LogBook API, and LogBook's virtualization. However, Boki's metalog design distinguishes it from these prior works. The logical decoupling provided by the metalog allows existing techniques to be adopted smoothly, while enabling new techniques, e.g., the log index for read efficiency. For applications, Tango [26]'s techniques enable serverless durable objects [18] backed by shared logs.

Fault-tolerant workflows. Orchestrating serverless functions as workflows is an important serverless paradigm, provided by all major cloud providers [5, 10, 19]. Workflows aim at providing *exactly-once* execution semantics, but stateful serverless functions (SSF) complicate this goal.

Beldi [61] proposes solutions for current serverless platforms. Beldi's mechanism is inspired by Olive [54]'s log-based fault tolerance protocol. In a Beldi workflow, during execution of SSF operations, the actions are logged. Beldi periodically re-executes SSFs that encounter failures. The operation log is used to prevent duplicated execution of operation, so that *at-most-once* execution semantics are guaranteed. On the other hand, re-execution for failed SSFs ensures *at-least-once* execution semantics.

Beldi's log-based fault-tolerant mechanism motivates Boki's shared log approach for stateful serverless computing. However, their techniques would need to be adapted for use with shared logs (§ 5.1), mostly because the workflow log is not co-located with user data in the same database.

9 Conclusion

State management has become a major challenge in serverless computing. Boki is the first system that allows stateful serverless functions to manage state using distributed shared logs. Boki's shared log abstraction (i.e., LogBooks) can support diverse serverless use cases, including fault-tolerant workflows, durable object storage, and message queues. Boki's shared logs achieve elasticity, data locality, and resource efficiency, enabled by a novel metalog design. The metalog is a unified solution to the problems of log ordering, consistency, and fault tolerance in Boki. Evaluations of Boki and its support libraries demonstrate the performance advantages (up to 4.2×) of the shared-log-based approach for serverless state management.

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