Cloudburst: Stateful Functions-as-a-Service

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Abstract

Function-as-a-Service (FaaS) platforms and “serverless” cloud computing are becoming increasingly popular. Current FaaS offerings are targeted at stateless functions that do minimal I/O and communication. We argue that the benefits of serverless computing can be extended to a broader range of applications and algorithms. We present the design and implementation of Cloudburst, a stateful FaaS platform that provides familiar Python programming with low-latency mutable state and communication, while maintaining the autoscaling benefits of serverless computing. Cloudburst accomplishes this by leveraging Anna, an autoscaling key-value store, for state sharing and overlay routing combined with mutable caches co-located with function executors for data locality. Performant cache consistency emerges as a key challenge in this architecture. To this end, Cloudburst provides a combination of lattice-encapsulated state and new definitions and protocols for distributed session consistency. Empirical results on benchmarks and diverse applications show that Cloudburst makes stateful functions practical, reducing the state-management overheads of current FaaS platforms by orders of magnitude while also improving the state of the art in serverless consistency.

1 Introduction

Serverless computing has attracted significant attention, with a focus on autoscaling Function-as-a-Service (FaaS) systems. FaaS platforms allow developers to write functions in standard languages and deploy their code to the cloud with reduced administrative burden. The platform transparently autoscales resources from zero to peak load and back in response to workload shifts. Consumption-based pricing ensures that developers’ cost is proportional to usage of their code: there is no need to overprovision to match peak load, and there are no compute costs during idle periods. These benefits have made FaaS platforms an attractive target for research [5, 11, 28–30, 39, 45, 46, 49, 82] and industry applications [8].

The hallmark autoscaling feature of serverless platforms is enabled by an increasingly popular design principle: the disaggregation of storage and compute services [35]. Disaggregation allows the compute layer to quickly adapt resource allocation to shifting workload requirements, packing functions into VMs while reducing data movement. Disaggregation also enables allocation at multiple timescales: long-term storage can be allocated separately from short-term compute leases. Together, these advantages enable efficient autoscaling: user code consumes more expensive compute resources as needed, and accrues only storage costs during idle periods.

Unfortunately, current FaaS platforms take disaggregation to an extreme, imposing significant constraints on developers. First, the autoscaling storage services provided by cloud vendors—e.g., AWS S3 and DynamoDB—are too high-latency to access with any frequency [39, 85]. Second, function invocations are isolated from each other: these services disable point-to-point network communication between functions. Finally, and perhaps most surprisingly, current FaaS offerings provide very slow nested function calls: argument-and-result-passing is a form of cross-function communication and exhibit the high latency of current serverless offerings [5]. We return these points in §2.1, but in short, today’s popular FaaS platforms only work well for isolated stateless functions.

As a workaround, many applications—even some that were explicitly designed for serverless platforms—are forced to step outside the bounds of the serverless paradigm altogether. For example, the ExCamera serverless video encoding system [29] depends upon a single server machine as a coordinator and task assignment service. Similarly, numpywren [76] enables serverless linear algebra but provisions a static Redis machine for low-latency access to shared state for coordination. These workarounds might be tenable at small scales, but they architecturally reintroduce the scaling, fault tolerance, and management problems of traditional server deployments.

1.1 Toward Stateful Serverless via LDPC

Given the simplicity and economic appeal of FaaS, it is interesting to explore designs that preserve the autoscaling and
writes. In essence, LDPC requires multi-master (a.k.a. group) value store (providing state sharing and overlay routing) and demonstrating benefits in performance, predictable latency, as well as two application scenarios using third-party code, separate nodes. We evaluate Cloudburst via microbenchmarks to ensure consistency guarantees across functions that run on lattice structures [19, 77], and provides novel protocols to achieve logical disaggregation with physical colocation of computation and state, making it difficult to build applications, particularly latency-sensitive ones. There are three kinds of shared state concerns that we focus on in this paper: function composition, direct communication, and shared mutable storage.

1.2 Cloudburst: A Stateful Serverless Platform

In this paper, we present a new programmable serverless platform called Cloudburst that removes the shortcomings of commercial systems highlighted above, without sacrificing their benefits. Cloudburst is unique in achieving logical disaggregation and physical colocation of computation and state, and in allowing programs written in a traditional language to observe consistent state across function compositions. Cloudburst achieves this via a combination of an autoscaling key-value store (providing state sharing and overlay routing) and mutable caches co-located with function executors (providing data locality). For performant consistency, Cloudburst transparently encapsulates opaque user state into mergeable lattice structures [19, 77], and provides novel protocols to ensure consistency guarantees across functions that run on separate nodes. We evaluate Cloudburst via microbenchmarks as well as two application scenarios using third-party code, demonstrating benefits in performance, predictable latency, and consistency. In sum, this paper’s contributions include:

Figure 2. A script to create and execute a Cloudburst function.

1. The design and implementation of an autoscaling serverless architecture that combines logical disaggregation with physical co-location of compute and storage (LDPC) (§4).
2. Identification of distributed session consistency concerns and new protocols to achieve two distinct distributed session consistency guarantees—repeatable read and causal consistency—for compositions of functions (§5).
3. The ability for programs written in traditional languages to enjoy coordination-free storage consistency for their native data types via lattice capsules that wrap program state with metadata that enables automatic conflict APIs supported by Anna (§5.2).
4. An evaluation of Cloudburst’s performance and consistency on workloads involving state manipulation, fine-grained communication and dynamic autoscaling (§6).

2 Motivation and Background

Although serverless infrastructure has gained traction recently, there remains significant room for improvement in performance and state management. In this section, we discuss common pain points in building applications on today’s serverless infrastructure (§2.1) and explain Cloudburst’s design goals (§2.2).

2.1 Deploying Serverless Functions Today

Current FaaS offerings are poorly suited to managing shared state, making it difficult to build applications, particularly latency-sensitive ones. There are three kinds of shared state management that we focus on in this paper: function composition, direct communication, and shared mutable storage.

Function Composition. For developers to embrace serverless as a general programming and runtime environment, it is necessary that function composition work as expected. Figure 1 (discussed in §6.1), shows the performance of a simple composition of side-effect-free arithmetic functions. AWS Lambda imposes a latency overhead of up to 40ms for a single function invocation, and this overhead compounds when composing functions. AWS Step Functions, which automatically chains together sequences of operations, imposes an even higher penalty. Since the latency of function composition
While point-to-point communication may seem tricky in an
well-known issues with latency and availability [15, 17]. In
A low-latency autoscaling KVS can serve as both global stor-
worse than underlying infrastructure like shared memory,
) or lightweight key-value stores (KVSs) can provide a
(DHTs) can offer appealing semantics but has
(distributed membership, distributed hashtables (DHTs) or lightweight key-value stores (KVSs) can provide a
lower-latency solution than deep storage for routing messages
between migratory function instances [69, 73, 74, 79].
Current FaaS vendors do not offer autoscaling, low-latency
DHTs or KVSs. Instead, as discussed in §1, many FaaS
applications resort to server-based solutions for lower-latency
storage, like hosted versions of Redis and memcached.

Low-Latency Access to Shared Mutable State. Recent
studies [39, 85] have shown that latencies and costs of
shared autoscaling storage for FaaS are orders of magnitude
worse than underlying infrastructure like shared memory,
networking, or server-based shared storage. Worse, the
available systems offer weak data consistency guarantees.
For example, AWS S3 offers no guarantees across multiple
clients or for inserts and deletes from a single client. This
kind of weak consistency can produce very confusing
behavior. For example, simple expressions like
\(f(x, g(x))\) may produce non-deterministic results: since \(g\) and \(f\) are
different clients, there is no guarantee about the versions of \(x\)
read by \(f\) and \(g\).

2.2 Towards Stateful Serverless

Logical Disaggregation with Physical Colocation. As a
principle, LDPC leaves significant latitude for designing
mechanisms and policy that co-locate compute and data while
preserving correctness. We observe that many of the perform-
ance bottlenecks described above can be addressed by a
simple architecture with distributed storage and local caching.
A low-latency autoscaling KVS can serve as both global stor-
age and a DHT-like overlay network. To provide better data
locality to functions, a KVS cache can be deployed on every
machine that hosts function invocations. Cloudburst’s design
includes consistent mutable caches in the compute tier (§4).
Consistency. Distributed mutable caches introduce the risk
of cache inconsistencies, which can cause significant de-
developer confusion. We could implement strong consistency
across caches (e.g., linearizability) via quorum consensus
(e.g., Paxos [53]). This offers appealing semantics but has
well-known issues with latency and availability [15, 17]. In
general, consensus protocols are a poor fit for the internals of
a dynamic autoscaling framework: consensus requires fixed
membership, and membership (“view”) change involves high-
latency agreement protocols (e.g., [13]). Instead, applications
desiring strong consistency can employ a slow-changing con-
sensus service adjacent to the serverless infrastructure.

Coordination-free approaches to consistency are a better fit
to the elastic membership of a serverless platform. Bailis, et
al.[9] categorized consistency guarantees that can be achieved
without coordination. We chose the Anna KVS [86] as Cloud-
burst’s storage engine because it supports all these guaran-
tees. Like CvRDTs [77], Anna uses lattice data types for
coordination-free consistency. That is, Anna values offer a
merge operator that is insensitive to batching, ordering and
repetition of requests—merge is associative, commutative
and idempotent. Anna uses lattice composition [19] to im-
plement consistency; we refer readers to [86] for more de-
tails. Anna also provides autoscaling at the storage layer,
responding to workload changes by selectively replicating
frequently-accessed data, growing and shrinking the cluster,
and moving data between storage tiers (memory and disk) for
cost savings [87].

However, Anna only supports consistency for individual
clients, each with a fixed IP-port pair. In Cloudburst, a request
like \(f(x, g(x))\) may involve function invocations on separate
physical machines and requires consistency across functions—
we term this distributed session consistency. In §5, we provide
protocols for various consistency levels.

Programmability. We want to provide consistency without
imposing undue burden on programmers, but Anna can only
store values that conform to its lattice-based type system. To
address this, Cloudburst introduces lattice capsules (§5.2),
which transparently wrap opaque program state in lattices
chosen to support Cloudburst’s consistency protocols. Users gain
the benefits of Anna’s conflict resolution and Cloudburst’s
distributed session consistency without having to modify their
programs.

We continue with Cloudburst’s programmer interface. We
return to Cloudburst’s design in §4 and consistency mech-
anisms in §5.

3 Programming Interface

Cloudburst accepts programs written in vanilla Python\(^1\). An
example client script to execute a function is shown in Fig-
ure 2. Cloudburst functions act like regular Python functions
but trigger remote computation in the cloud. Results by de-
fault are sent directly back to the client (line 8), in which
case the client blocks synchronously. Alternately, results can
be stored in the KVS, and the response key is wrapped in a
CloudburstFuture object, which retrieves the result
when requested (line 11-12).

Function arguments are either regular Python objects (line
11) or KVS references (lines 3-4). KVS references are trans-
parently retrieved by Cloudburst at runtime and deserialized

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\(^1\)There is nothing fundamental in our choice of Python—we simply chose to use it because it is a commonly used high-level language.
| API Name          | Functionality                                      |
|------------------|---------------------------------------------------|
| get(key)         | Retrieve a key from the KVS.                      |
| put(key, value)  | Insert or update a key in the KVS.                |
| delete(key)      | Delete a key from the KVS.                        |
| send(recv, msg)  | Send a message to another executor.               |
| recv()           | Receive outstanding messages for this function.   |
| get_id()         | Get this function’s unique ID                     |

Table 1. The Cloudburst object communication API. Users can interact with the key value store and send and receive messages.

before invoking the function. To improve performance, the runtime attempts to execute a function call with KVS references on a machine that might have the data cached. We explain how this is accomplished in §4.3.

For repeated execution, Cloudburst allows users to register arbitrary compositions of functions. We model function compositions as DAGs in the style of systems like Apache Spark [89], Dryad [44], Apache Airflow [2], and Tensorflow [1]. Each function in the DAG must be registered with the system (line 4) prior to use in a DAG. Users specify each function in the DAG and how they are composed—results are automatically passed from one DAG function to the next by the Cloudburst runtime. The result of a function with no successor is either stored in the KVS or returned directly to the user, as above. Cloudburst’s resource management system (§4.4) is responsible for scaling the number of replicas of each function up and down.

Cloudburst System API. Cloudburst provides developers an interface to system services—Table 1 provides an overview. The API enables KVS interactions via get and put, and it enables message passing between function invocations. Each function invocation is assigned a unique ID, and functions can advertise this ID to well-known keys in the KVS. Functions can send messages to other functions’ IDs, and the runtime automatically translates the receiver’s ID into an IP-port pair. IP-port mappings for functions are stored in the KVS and cached in the Cloudburst runtime. If a sender has not cached the IP-port pair of a receiver, or if a receiver times out, the sender queries the KVS for the correct receiver address.

4 Architecture

Cloudburst implements the principle of logical disaggregation with physical colocation (LDPC). To achieve disaggregation, the Cloudburst runtime autoscales independently of the Anna KVS. Colocation is enabled by mutable caches placed in the Cloudburst runtime for low latency access to KVS objects.

Figure 3 provides an overview of the Cloudburst architecture. There are four key components: function executors, caches, function schedulers, and a resource management system. User requests are received by a scheduler, which routes them to function executors. Each scheduler operates independently, and the system relies on a standard stateless cloud load balancer (AWS Elastic Load Balancer). Function executors run in individual processes that are packed into VMs along with a local cache per VM. The cache on each VM intermediates between the local executors and the remote KVS. All Cloudburst components are run in individual Docker [24] containers. Cloudburst uses Kubernetes [51] simply to start containers and redeploy them on failure. Cloudburst system metadata, as well as persistent application state, is stored in Anna which provides autoscaling and fault tolerance.

4.1 Function Executors

Each Cloudburst executor is an independent, long-running Python process. Schedulers (§4.3) route function invocation requests to executors. Before each invocation, the executor retrieves and deserializes the requested function and transparently resolves all KVS reference function arguments in parallel. DAG execution requests span multiple function invocations, and after each DAG function invocation, the runtime triggers downstream DAG functions. To improve performance for repeated execution (§3), each DAG function is deserialized and cached at one or more function executors. Each executor also publishes local metrics to the KVS, including the executor’s cached functions, stats on its recent CPU utilization, and the execution latencies for finished requests. We explain in the following sections how this metadata is used.

4.2 Caches

To ensure that frequently-used data is locally available, every function execution VM has a local cache process, which executors contact via IPC. Executors interface with the cache, not directly with Anna; the cache issues requests to the KVS as needed. When a cache receives an update from an executor, it updates the data locally, acknowledges the request, then asynchronously sends the result to the KVS to be merged. If a cache receives a request for data that it does not have, it makes an asynchronous request to the KVS.

Cloudburst must ensure the freshness of data in caches. A naive (but correct) scheme is for the Cloudburst caches to poll the KVS for updates, or for the cache to blindly evict data after
a timeout. In a typical workload where reads dominate writes, this generates unnecessary load on the KVS. Instead, each cache periodically publishes a snapshot of its cached keys to the KVS. We modified Anna to accept these cached keysets and construct an index that maps each key to the caches that store it; Anna uses this index to periodically propagate key updates to caches. Lattice encapsulation enables Anna to correctly merge conflicting key updates (§5.2).

4.3 Function Schedulers
A key goal of Cloudburst’s architecture is to enable low latency function scheduling. However, policy design is not a main goal of this paper; Cloudburst’s scheduling mechanisms allow pluggable policies to be explored in future work. In this section, we describe Cloudburst’s scheduling mechanisms, illustrating their use with policy heuristics that enable us to demonstrate benefits from data locality and load balancing.

Scheduling Mechanisms. All user requests to register or invoke functions and DAGs are routed to a scheduler. Schedulers register new functions by storing them in Anna and updating a shared KVS list of registered functions. For new DAGs, the scheduler verifies that each function in the DAG exists and picks an executor on which to cache each function.

For single function execution requests, the scheduler picks an executor and forwards the request to it. DAG requests require more work: The scheduler creates a schedule by picking an executor for each DAG function—which is guaranteed to have the function stored locally—and broadcasts this schedule to all participating executors. The scheduler then triggers the first function(s) in the DAG and, if the user wants the result stored in the KVS, returns a CloudburstFuture.

DAG topologies are the scheduler’s only persistent metadata and are stored in the KVS. Each scheduler tracks how many calls it receives per DAG and per function and stores these statistics in the KVS. Finally, each scheduler constructs a local index that tracks the set of keys stored by each cache; this is used for the scheduling policy described next.

Scheduling Policy. Our scheduling policy makes heuristic-based decisions using metadata reported by the executors, including cached key sets and executor load. We prioritize data locality when scheduling both single functions and DAGs. If the invocation’s arguments have KVS references, the scheduler inspects its local cached key index and attempts to pick the executor with the most data cached locally. Otherwise, the scheduler picks an executor at random.

Hot data and functions get replicated across many executor nodes via backpressure. The few nodes initially caching hot keys will quickly become saturated with requests and will report high utilization (above 70%). The scheduler tracks this utilization to avoid overloaded nodes, picking new nodes to execute those requests. The new nodes will then fetch and cache the hot data, effectively increasing the replication factor and hence the number of options the scheduler has for the next request containing a hot key.

4.4 Monitoring and Resource Management
An autoscaling system must track system load and performance metrics to make effective policy decisions. Cloudburst uses Anna as a substrate for tracking and aggregating metrics. Each executor and scheduler independently tracks an extensible set of metrics (described above) and publishes them to the KVS. The monitoring system asynchronously aggregates these metrics from storage and uses them for its policy engine.

For each DAG, the monitoring system compares the incoming request rate to the number of requests serviced by executors. If the incoming request rate is significantly higher than the request completion rate of the system, the monitoring engine will increase the resources allocated to that DAG function by pinning the function onto more executors. If the overall CPU utilization of the executors exceeds a threshold (70%), then the monitoring system will add nodes to the system. Similarly, if executor utilization drops below a threshold (20%), we deallocate resources accordingly. This simple approach exercises our monitoring mechanisms and provides adequate behavior (see §6.1.4). We discuss potential advanced auto-scaling mechanisms and policies in §8.

4.5 Fault Tolerance
At the storage layer, Cloudburst relies on Anna’s replication scheme for k-fault tolerance. For the compute tier, we adopt the standard approach to fault tolerance taken by many FaaS platforms. If a machine fails while executing a function, the whole DAG is re-executed after a configurable timeout. The programmer is responsible for handling side-effects generated by failed programs if they are not idempotent. In the case of an explicit program error, the error is returned to the client. This approach should be familiar to users of AWS Lambda and other FaaS platforms, which provides the same guarantees. More advanced guarantees are a subject for future work (§8).

5 Cache Consistency
As discussed in Section 3, Cloudburst developers can register compositions of functions as a DAG. This also serves as the scope of consistency for the programmer, sometimes called a “session” [81]. The reads and writes in a session together experience the chosen definition of consistency, even across function boundaries. The simplest way to achieve this is to run the entire DAG in a single thread and let the KVS provide the desired consistency level. However, to allow for autoscaling and flexible scheduling, Cloudburst may choose to run functions within a DAG on different executors—in the extreme case, each function could run on a separate executor. This introduces the challenge of distributed session consistency: Because a DAG may run across many machines, the
executors involved in a single DAG must provide consistency across different physical machines.

In the rest of this section, we describe distributed session consistency in Cloudburst. We begin by explaining two different guarantees (§5.1), describe how we encapsulate user-level Python objects to interface with Anna’s consistency mechanisms (§5.2), and present protocols for the guarantees (§5.3).

5.1 Consistency Guarantees
A wide variety of coordination-free consistency and isolation guarantees have been identified in the literature. We focus on two guarantees here; variants are presented in §6.2 to illustrate protocol costs. In our discussion, we will denote keys with lowercase letters like \( k \); \( k_v \) is a version \( v \) of key \( k \).

We begin with repeatable read (RR) consistency. RR is adapted from the transactions literature [12], hence it assumes sequences of functions — i.e., linear DAGs. Given a read-only expression \( f(x, g(x)) \), RR guarantees that both \( f \) and \( g \) read the same version \( x_v \). More generally:

**Repeatable Read Invariant:** In a linear DAG, when any function reads a key \( k \), either it sees the most recent update to \( k \) within the DAG, or in the absence of preceding updates it sees the first version \( k_v \) read by any function in the DAG².

The second guarantee we explore is causal consistency, one of the strongest coordination-free consistency models [9, 56, 58]. In a nutshell, causal consistency requires reads and writes to respect Lamport’s “happens-before” relation [52]. One key version \( k_i \) influences another version \( l_j \) if a read of \( k_i \) happens before a write of \( l_j \); we denote this as \( k_i \rightarrow l_j \). If a function reads \( l_j \), it must not see versions of \( k \) that happened before \( k_i \); it can only see \( k_i \), versions concurrent with \( k_i \), or versions newer than \( k_i \). Prior work introduces a variety of causal building blocks that we extend. Systems like Anna [86] track causal histories of individual objects but do not track ordering between objects. Bolt-on causal consistency [10] developed techniques to achieve multi-key causal snapshots at a single physical location. Cloudburst must support multi-key causal consistency that spans multiple physical sites.

**Causal Consistency Invariant:** Consider a function \( f \) in DAG \( G \) that reads a version \( k_v \) of key \( k \). Let \( V \) denote the set of versions read previously by \( f \) or by any of \( f \)'s ancestors in \( G \). Denote the dependency set for \( f \) at this point as \( D = \{ d_i \mid d_i \rightarrow l_j \in V \} \). The version \( k_v \) that is read by \( f \) must satisfy the invariant \( k_v \rightarrow k_i \in D \). That is, \( k_v \) is concurrent to or newer than any version of \( k \) in the dependency set \( D \).

5.2 Lattice Encapsulation
As mentioned in §3, mutable shared state is a key tenet of Cloudburst’s design. Cloudburst relies on Anna’s lattice data structures to resolve conflicts from concurrent updates. Typically, Python objects are not lattices, so Cloudburst transparently encapsulates Python objects in lattices.

By default, Cloudburst encapsulates each bare program value into an Anna last writer wins (LWW) lattice — a composition of an Anna-provided vector clock and the value. Anna merges two LWW versions by keeping the value with the higher timestamp. This allows Cloudburst to achieve eventual consistency: All replicas will agree to the latest LWW value for the key [83]. It also provides timestamps for the RR protocol below.

In causal consistency mode, Cloudburst encapsulates each value in an Anna causal consistency lattice — the composition of an Anna-provided vector clock and the value. Upon merge, Anna keeps the object whose vector clock dominates; if the two versions are concurrent it keeps both. In most cases, an object has only one version. However, to de-encapsulate a causally-wrapped object with multiple concurrent versions, Cloudburst presents the user program with one version chosen via an arbitrary but deterministic tie-breaking scheme. Regardless of which version is returned, the user program sees a causally consistent history; the cache layer retains the concurrent versions for the consistency protocol described below. Applications can also choose to retrieve all concurrent versions and resolve updates manually.

5.3 Distributed Session Protocols

**Repeatable Read.** To achieve repeatable read, the Cloudburst cache on each node creates “snapshot” versions of each locally cached object upon first read, and the cache stores them for the lifetime of the DAG. When invoking a downstream function in the DAG, we propagate a list of cache addresses and version timestamps for all snapshoted keys seen so far.

When a downstream executor in a DAG receives a request, it includes this version snapshot metadata in its request to the cache. If that key has been previously read and the exact version is not stored locally, the cache queries the upstream cache that stores the correct version. If the upstream cache fails, we restart the DAG from scratch. Finally, the sink executor notifies all upstream caches of DAG completion, allowing version snapshots to be evicted.

**Distributed Session Causal Consistency.** To support causal consistency in Cloudburst, we use causal lattice encapsulation rather than LWW. We also augment the Cloudburst cache to be a causally consistent store, implementing the bolt-on causal consistency protocol [10]. The protocol ensures that each cache always holds a “causal cut”: For every pair of versions \( a_i, b_j \) in the cache, we guarantee \( a_k \rightarrow a_i \rightarrow a_k \rightarrow b_j \).

However, a causal cut in a single node’s cache is not sufficient. To achieve distributed session causal consistency across caches, the set of versions read across all caches must form a causal cut globally. Consider a DAG with two functions \( f(k) \) and \( g(l) \), which are executed in sequence on different
machines. Assume $f$ reads $k_v$ and there is a dependency $l_u \rightarrow k_v$. If the causal-cut cache of the node executing $g$ is unaware of the constraint on valid versions of $l$, $g$ could read an old version $l_w : l_w \rightarrow l_u$, thereby violating causality. The following protocol solves this challenge: In addition to shipping read-set metadata (as in RR), each executor ships the set of causal dependencies (pairs of keys and their associated vector clocks) of the read set to downstream executors. Caches upstream store version snapshots of these causal dependencies.

For each key in the read set, the downstream cache first checks whether the locally-cached key’s vector clock is causally concurrent with or dominates that of the version snapshot stored at the upstream cache. If so, the cache returns the local version; otherwise, it queries the upstream cache for the correct version snapshot. This protocol constructs a distributed causal cut across the caches involved in the DAG execution, achieving distributed session causal consistency.

6 Evaluation

We now present a detailed evaluation of Cloudburst. We first study the individual mechanisms implemented in Cloudburst (§6.1), demonstrating orders of magnitude improvement in latency relative to existing serverless infrastructure for a variety of tasks. Next we study the overheads introduced by Cloudburst’s consistency mechanisms (§6.2), and finally we implement and evaluate two real-world applications on Cloudburst: machine learning prediction serving and a Twitter clone (§6.3).

All experiments were run in the us-east-1a AWS availability zone (AZ). Schedulers were run on AWS c5.large EC2 VMs (2 vCPUs and 4GB RAM), and function executors were run on c5.2xlarge EC2 VMs (8 vCPUs and 16GB RAM); hyperthreading was enabled. Our function execution VMs used 4 cores—3 for Python execution and 1 for the cache. Clients were run on separate machines in the same AZ. All Redis experiments were run using AWS ElastiCache, using a cluster with two shards and three replicas per shard.

6.1 Mechanisms in Cloudburst

6.1.1 Function Composition

To begin, we compare Cloudburst’s function composition overheads with other serverless systems, as well as a non-serverless baseline. We chose functions with minimal computation to isolate each system’s overhead. The pipeline was composed of two functions: `square(increment(x: int))`. Figure 1 shows median and 99th percentile measured latencies across 1,000 requests run in serial from a single client.

Cloudburst stored results in Anna, as discussed in Section 3 and has the lowest latency of all systems measured. We first compared against SAND [5], a new serverless platform that achieves low-latency function composition by using a hierarchical message bus. We could not deploy SAND ourselves because the source code is unavailable, so we used a hosted offering [75]. Our client was not in the same data center as the SAND service; to account for client-server latency we measured the end-to-end request latency and subtracted the latency of an empty HTTP request. SAND is an order of magnitude slower than Cloudburst, but we acknowledge that the experiment is not well-controlled. To further validate Cloudburst, we compared Dask, a serverful, open-source distributed Python execution framework. We deployed Dask on AWS using the same instances used for Cloudburst and found that performance was comparable to Cloudburst. Given Dask’s relative maturity, this gives us confidence that our overheads are reasonable.

Finally, we compared against four AWS implementations, three of which used AWS Lambda. Lambda (Direct) returns results directly to the user, while Lambda (S3) and Lambda (Dynamo) store the results in the corresponding storage service. All Lambda implementations pass arguments using the Lambda API. The fastest AWS implementation was Lambda (Direct) as it avoided interacting with high-latency storage; the storage systems added a roughly 200ms latency penalty. We also compare against AWS Step Functions, which constructs a DAG similar to Cloudburst’s and returns results directly to the user. The Step Functions implementation over 2× slower than Lambda and 158× slower than Cloudburst.

**Takeaway:** Cloudburst’s function composition matches state-of-the-art Python runtime latency and outperforms commercial serverless infrastructure by 1-3 orders of magnitude.

6.1.2 Data Locality

Next, we study the performance benefit of Cloudburst’s caching techniques. We chose a representative task, with significant input data but light computation: return the sum

![Figure 4. Median and 99th percentile latency to calculate the sum of elements in 10 arrays, comparing Cloudburst with caching, without caching, and AWS Lambda over AWS ElastiCache (Redis) and AWS S3. We vary array lengths from 1,000 to 1,000,000 by multiples of 10 to demonstrate the effects of increasing data retrieval costs.](image)
Latency (ms)

|           | Cloudburst (gossip) | Cloudburst (gather) | Lambda | Redis (gather) | Dynamo (gather) |
|-----------|--------------------|--------------------|--------|---------------|----------------|
| 200       | 314                | 515                | 266    | 689           |                |
| 400       |                    |                    |        |               |                |
| 600       |                    |                    |        |               |                |
| 800       |                    |                    |        |               |                |
| 1000      |                    |                    |        |               |                |

Figure 5. Median and 99th percentile latencies for distributed aggregation. The Cloudburst implementation uses a distributed, gossip-based aggregation technique [48], and the Lambda implementations share state via the respective key-value stores. Cloudburst outperforms communication through storage, even for a low-latency KVS.

of all elements across 10 input arrays. We implemented two versions on AWS Lambda, which retrieved inputs from AWS ElastiCache (using Redis) and AWS S3 respectively. ElastiCache is not an autoscaling system, but we include it in our evaluation because it offers best-case latencies for data retrieval for AWS Lambda. We compare two implementations in Cloudburst. One version, Cloudburst (Hot) passes the same array in to every function execution, guaranteeing that every retrieval after the first is a cache hit and achieving optimal latency. The second, Cloudburst (Cold), creates a new set of inputs for each request; every retrieval is a cache miss, and this measures worst-case latencies of fetching data from the Anna KVS. All measurements are reported across 12 clients issuing 3,000 requests each. We run Cloudburst with 7 function execution nodes and 2 schedulers.

The Cloudburst (Hot) bars in Figure 4 show that system’s performance is consistent across the first two data sizes for cache hits, rises slightly for 8MB of data, and degrades significantly for the largest array size as computation costs begin to dominate. Cloudburst performs best at 8MB, improving over Cloudburst (Cold)’s median latency by about 10×, over Lambda on Redis’ by 40×, and over Lambda on S3’s by 79×.

While Lambda on S3 is the slowest configuration for smaller inputs, it is more competitive at 80MB. Here, Lambda on Redis’ latencies rise significantly. While Cloudburst (Cold)’s median latency is the second fastest, its 99th percentile latency is comparable with S3’s and Redis’. This validates the common wisdom that S3 is efficient for high bandwidth tasks. At this size, Cloudburst (Hot)’s median latency is still 9× faster than Cloudburst (Cold) and 24× faster than S3’s.

**Takeaway:** While performance gains vary, avoiding network roundtrips to storage services improves performance by orders of magnitude.

### 6.1.3 Low-Latency Communication

Another key feature in Cloudburst is low-latency communication, allowing developers to leverage distributed systems protocols that are infeasibly slow in other serverless platforms.

As an illustration, we consider the implementation of distributed aggregation: the simplest form of distributed statistics. Our scenario is to periodically average a floating-point performance metric across the set of functions that are running at any given time. Kempe et al. [48] developed a simple gossip-based protocol for approximate aggregation that uses random message passing among the current participants in the protocol. The algorithm is designed to provide correct answers even as the membership changes. We implemented the algorithm in 60 lines of Python and ran it over Cloudburst. We compute 1,000 rounds of aggregation in sequence and measure the time until the result converges to within 5% error.

The gossip algorithm involves repeated small messages, making it highly inefficient on stateless platforms like AWS Lambda that only allow communication via high-latency storage systems. Instead, we compare against a more natural approach for centralized storage: Each lambda publishes its metrics to a KVS, and a predetermined leader gathers the published information and returns it to the client. We refer to this algorithm as the “gather” algorithm. Note that this algorithm, unlike [48], requires the population to be fixed in advance, and is therefore not a good fit to an autoscaling setting. But it requires less communication, so we use it as a workaround to enable the systems that forbid direct communication to compete. We implement the same protocol on Lambda over Redis for similar reasons as in § 6.1.2—although serverful, Redis offers best-case performance for Lambda. We also implement the gather algorithm over Cloudburst and Anna for reference.

Figure 5 shows our results. Cloudburst’s gossip based protocol is 3× faster than the gather protocol using Lambda and DynamoDB. Although we expected gather on serverful Redis to outperform Cloudburst’s gossip algorithm, our measurements show that gossip on Cloudburst is actually about 10% faster than gather on Redis at median and 40% faster at the 99th percentile. Finally, gather on Cloudburst is 22× faster than gather on Redis and 53× faster than gather on DynamoDB. There are two reasons for these discrepancies. First, Lambda has very high function invocation costs (see §6.1.1). Second, Redis is single-mastered and forces serialized writes, creating a queuing delay for writes.

**Takeaway:** Cloudburst’s low latency communication mechanisms enable developers to build fast distributed algorithms with fine-grained communication. These algorithms can have notable performance benefits over workarounds involving even relatively fast shared storage.

### 6.1.4 Autoscaling

Finally, we validate Cloudburst’s ability to detect and respond to workload changes. The goal of any serverless system is to smoothly scale program execution up and down in response to changes in request rate. As described in Section 4.4, Cloudburst uses a heuristic-based policy that accounts for incoming
request rates, request execution times, and executor load. We simulate a relatively computationally intensive function by deploying a function that sleeps for 50ms before returning.

The system starts with 10 executor nodes (30 threads) and one replica of the function deployed. Figure 6 shows our results. At time 0, 60 client threads simultaneously begin issuing requests. The jagged curve measures system throughput (requests processed per second), and the dotted line tracks the number of threads allocated to the function. Over the first 30 seconds, Cloudburst is able to take advantage of the idle resources in the system, and throughput reaches around 300 requests per second. At this point, the management system detects that all nodes are saturated with requests and adds more EC2 instances, which take about 2 minutes to complete; this is seen in the plateau that lasts until time 3. As soon as resources become available, they are allocated to our sleep function, and throughput rises by 100 requests a second.

This process repeats itself twice more, with the throughput rising to 500 and 600 requests per second with each increase in resources. After 11.5 minutes, the workload finishes, and by time 12, the system has drained itself of all outstanding requests. The management system detects the sudden drop in request rate and, within 30 seconds, reduces the number of threads allocated to the sleep functions from 66 to 2. Within 5 minutes, the number of EC2 instances drops from a max of 22 back to the original 10. We are currently bottlenecked by the latency of spinning up EC2 instances; we discuss that limitation and potential improvements in Section 8.

Takeaway: Cloudburst’s mechanisms for autoscaling enable policies that can quickly detect and react to workload changes. We are mostly limited by the high cost of spinning up new EC2 instances. The policies and cost of spinning up instances can be improved in future without changing Cloudburst’s architecture.

6.2 Consistency Models

In this section, we evaluate the overheads of Cloudburst’s consistency models. For comparison, we also implement and measure weaker consistency models to understand the costs involved in distributed session causal consistency. Single-key causality tracks causal order of updates to individual keys (omitting the overhead of dependency sets). Multi-key causality is an implementation of Bolt-On Causal Consistency [10], avoiding the overhead of distributed session consistency.

We populate Anna with 1 million keys, each with a payload of 8 bytes, and we generate 250 random DAGs which are 2 to 5 functions long, with an average length of 3. Our benchmark is designed to isolate the latency overheads of each consistency mode by avoiding expensive computation; it uses small data to highlight any metadata overheads. Each function takes two string arguments, performs a simple string manipulation task, and outputs another string. Function arguments are either KVS references (drawn from the set of 1 million keys with a Zipfian coefficient of 1.0) or the result of a previous function execution. The sink function of the DAG writes its result to the KVS into a key chosen randomly from the read set. We use 8 concurrent benchmark threads, each sequentially issuing 500 requests to Cloudburst.

6.2.1 Latency Comparison

Figure 7 shows the latency of each DAG execution under five consistency models normalized by the longest path in the DAG. Median latency is nearly uniform across all modes, but performance differs significantly at the 99th percentile.

Last-writer wins has the lowest overhead, as it only stores the timestamp associated with each key and requires no remote version fetches. The 99th percentile latency of distributed session repeatable read is 1.8x higher than last-writer wins’. This is because repeated reference to a key across functions requires an exact version match; even if the key is cached locally, a version mismatch will force a remote fetch.

Single-key causality does not involve metadata passing or data retrieval, but each key maintains a vector clock that tracks the causal ordering of updates performed across clients.
Since the size of the vector clock grows linearly with the number of clients that modified the key, hot keys tend to have larger vector clocks—the hottest key in our benchmark had a 240× longer vector clock than the cold keys—leading to higher retrieval latency at the tail. Multi-key causality forces each key to track its dependencies in addition to maintaining the vector clock, adding slightly to its worst-case latency.

Finally, distributed session causal consistency incurs the cost of passing causal metadata along the DAG as well as retrieving version snapshots to satisfy causality. In the worst case, a DAG with 5 functions performs 4 extra network round-trips to retrieve version snapshots. This leads to a 1.7× slowdown in 99th percentile latency over single- and multi-key causality and a 9× slowdown over last-writer wins.

**Takeaway:** Although Cloudburst's non-trivial consistency models increase tail latencies, median latencies are over an order of magnitude faster than DynamoDB and S3 for similar tasks, while providing stronger consistency.

### 6.2.2 Inconsistencies

Stronger consistency models introduce overheads but also prevent anomalies that would otherwise arise in weaker models. Table 2 shows the number of inconsistencies observed over the course of 4000 DAG executions run in LWW mode, tracking anomalies for other levels.

| Inconsistencies Observed | LWW | Causal | DSRR |
|--------------------------|-----|--------|------|
|                          | SK  | MK     | DSC  |
| 0                        | 904 | 939    | 1043 |
|                          | 46  |        |      |

Table 2. The number of inconsistencies observed by Cloudburst consistency levels relative to what is observed at the weakest level (LWW). The causal levels are increasingly strict, so the numbers accrue incrementally left to right. The DSRR anomalies are independent.

Figure 8. A comparison of Cloudburst against native Python, AWS SageMaker, and AWS Lambda for serving a prediction pipeline.

### 6.3 Case Studies

In this section, we discuss the implementation of two real-world applications on top of Cloudburst. We first consider low-latency prediction serving for machine learning models and compare Cloudburst to a purpose-built cloud offering, AWS SageMaker. We then implement a Twitter clone called Retwis, which takes advantage of our consistency mechanisms, and we report both the effort involved in porting the application to Cloudburst as well as some initial evaluation metrics.

#### 6.3.1 Prediction Serving

ML model prediction is a computationally intensive task that can benefit from elastic scaling and efficient sparse access to large amounts of state. For example, the prediction serving infrastructure at Facebook [37] needs to access per user state with each query and respond in real time. Furthermore, many prediction pipelines combine multiple stages of computation—e.g., clean the input, join it with reference data, execute one or more models, and combine the results [20, 54].

We implement a basic prediction serving pipeline on Cloudburst and compare against a fully-managed, purpose-built prediction serving framework (AWS SageMaker) and AWS Lambda. We also compare against a single Python process to measure serialization and communication overheads. Lambda does not support GPUs, so all experiments are run on CPUs.

We use the MobileNet [43] image classification model in Tensorflow [1] and construct a three-stage pipeline: resize an input image, execute the model, and combine features to render a prediction. Porting this pipeline to Cloudburst was easier than porting it to other systems. The native Python implementation was 23 lines of code (LOC). Cloudburst required adding 4 LOC to retrieve the model from Anna. AWS SageMaker required adding serialization logic (10 LOC) and a Python web-server to invoke each function (30 LOC). Finally, AWS Lambda required significant changes: managing serialization (10 LOC) and manually compressing Python dependencies to fit into Lambda’s 512MB container limit.

Figure 8 reports median and 99th percentile latencies. Cloudburst is only about 30ms slower than the Python
We ported Retwis to our system as a set of six Cloudburst web serving workloads are closely aligned with the capabilities Cloudburst provides. For example, Twitter provisions server capacity of up to 10x the typical daily peak in order to accommodate unusual events such as elections, sporting events, or natural disasters [36]. Furthermore, causal consistency is a good model for many consumer internet workloads because it matches well with end-user expectations for information propagation: e.g., Google has adopted it as part of a universal model for privacy and access control [68].

To this end, we considered an example web serving workload. Retwis [70] is an open source Twitter clone built on Redis and is often used to evaluate distributed systems [21, 42, 78, 88, 91]. Conversational “threads” like those on Twitter naturally exercise causal consistency: It is confusing to read the response to a post (e.g., “lambda!”) before you have read the post it refers to (“what comes after kappa?”).

We adapted a Python Retwis implementation called retwis-py [71] to run on Cloudburst and compared its performance to a vanilla “serverful” deployment on Redis. We ported Retwis to our system as a set of six Cloudburst functions. The port was simple: We changed 44 lines, most of which were removing references to a global Redis variable.

We created a graph of 1000 users, each following 50 other users (zipf=1.5, a realistic skew for online social networks [63]) and prepopulated 5000 tweets, half of which were replies to other tweets. We compare Cloudburst in LWW mode, Cloudburst in causal consistency mode, and Retwis over Redis; all configurations used 6 executor threads (webservers for Retwis) and 1 KVS node. Cloudburst used 1 scheduler. We run Cloudburst in LWW mode and Redis with 6 clients and stress test Cloudburst in causal mode by running 12 clients to increase causal conflicts. Each client issues 1000 requests—20% PostTweet (write) requests and 80% GetTimeline (read) requests.

Figure 9 summarizes our performance results. In LWW mode, Cloudburst achieved comparable median latencies (about 10% slower) than Redis but had 2× and 1.83× faster 99th percentile latencies for reads and writes, respectively. In causal mode, read latencies are comparable to the other two configurations while writes are slower due to the overhead of propagating causal metadata. Nonetheless, the 99th percentile latencies are in fact better than Redis’ for both reads and writes, despite the doubled load.

Cloudburst’s LWW version incurred over 9,000 anomalies (reply tweets without the original post) in this benchmark. Redis is a serverful linearizable system, so it did not create any anomalies. However, in cluster mode, Redis partitions data but does not coordinate across partitions. As a result, Redis in cluster mode would be susceptible to the same anomalies as Cloudburst in LWW mode—while Cloudburst in causal mode would scale naturally, as demonstrated in §6.2.

Takeaway: An ML algorithm deployed in Cloudburst delivers low, predictable latency comparable to a single Python process, out-performing a purpose-built commercial service.

6.3.2 Retwis

Web serving workloads are closely aligned with the capabilities Cloudburst provides. For example, Twitter provisions server capacity of up to 10x the typical daily peak in order to accommodate unusual events such as elections, sporting events, or natural disasters [36]. Furthermore, causal consistency is a good model for many consumer internet workloads because it matches well with end-user expectations for information propagation: e.g., Google has adopted it as part of a universal model for privacy and access control [68].

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Takeaway: It was straightforward to adapt a standard social network application to run on Cloudburst. Performance was comparable to serverful baselines at the median and better at the tail, even with causal consistency overheads.

7 Related Work

Serverless Systems. In addition to commercial offerings, there are many open-source serverless platforms [40, 50, 66, 67], all of which provide standard stateless FaaS guarantees. Among platforms with new guarantees [5, 41, 60], SAND [5] is most similar to Cloudburst, reducing overheads for low-latency function compositions. Cloudburst achieves better latencies (§6.1.1) and adds shared state and communication abstractions that enable a broader range of applications.

Recent work has explored faster, more efficient serverless platforms. SOCK [65], introduces a generalized-Zygote provisioning mechanism to cache and clone function initialization; its library loading technique could be integrated with Cloudburst. Also complementary are strong, low-overhead sandboxing mechanisms including gVisor [34] and Firecracker [27].

Language-Level Consistency Programming languages also offer solutions to distributed consistency. One option from functional languages is to prevent inconsistencies by making state immutable [18]. A second is to constrain updates to be deterministically mergeable, by requiring users to write associative, commutative, and idempotent code (ACID 2.0 [38]),
use special-purpose types like CRDTs [77] or DSLs for distributed computing like Bloom [19]. As a platform, Cloudburst does not prescribe a language or type system, though these approaches could be layered on top of Cloudburst.

Causal Consistency. Several existing storage systems provide causal consistency [4, 6, 25, 26, 56, 57, 61, 90]. However, these are fixed-deployment systems that do not meet the autoscaling requirements of a serverless setting. In [4, 6, 25, 26, 61], each data partition relies on a linear clock to version data and uses a fixed-size vector clock to track causal dependencies across keys. The size of these vector clocks is tightly coupled with the system deployment—specifically, the shard and replica counts. Correctly adjusting this metadata requires an expensive coordination protocol, which we rejected in Cloudburst’s design (§2.2). [56] and [57] reveal a new version only when all of its dependencies have been retrieved. [90] constructs a causally consistent snapshot across an entire data center. All of these systems are susceptible to “slow-down cascades” [61], where a single straggler node limits write visibility and increases the overhead of write buffering.

In contrast, Cloudburst implements causal consistency in the cache layer as in Bolt-On Causal Consistency [10]. Each cache creates its own causally consistent snapshot without coordinating with other caches, eliminating the possibility of a slow-down cascade. The cache layer also tracks dependencies in individual keys’ metadata rather than tracking the vector clocks of fixed, coarse-grained shards. This comes at the cost of increased dependency metadata overhead. Various techniques including periodic dependency garbage collection [56], compression [61], and reducing dependencies via explicit causality specification [10] can mitigate this issue, though we do not measure them here.

Distributed Execution Frameworks Research in systems for distributed computing systems has a long history [14] and has seen recent advances, with frameworks such as Ray [64], Dask [72], and Orleans [16] providing rich task-parallel and actor-based abstractions. The serverless perspective drives new considerations for autoscaling, and motivates novel caching and consistency models in Cloudburst. There are also numerous distributed execution frameworks specialized to big data batch processing [3, 23, 62, 89]. Some commercial batch processing systems are offered as serverless products.

The remaining challenge is to provide performant correctness. Cloudburst embraces coordination-free consistency as the appropriate class of guarantees for an autoscaling system. We confront challenges at both the storage and caching layer. We use lattice capsules to allow opaque program state to be merged asynchronously into replicated coordination-free persistent storage. We develop distributed session consistency protocols to ensure that computations spanning multiple caches provide uniform correctness guarantees. Together, these techniques provide a strong contract to users for reasoning about state—far stronger than the guarantees offered by cloud storage that backs commercial FaaS systems. Even with these guarantees, we demonstrate performance that rivals and often beats baselines from inelastic server-centric approaches.

The feasibility of stateful serverless computing suggests a variety of potential future work.

Isolation and Fault Tolerance As noted in §5.1, storage consistency guarantees say nothing about concurrent effects between DAGs, a concern akin to transactional isolation (the “I” in ACID). On a related note, the standard fault tolerance model for FaaS is to restart on failure, ignoring potential problems with non-idempotent functions. Something akin to transactional atomicity (the “A” in ACID) seems desirable here. It is well-known that serializable transactions require coordination [9], but it is interesting to consider whether sufficient notions of Atomicity and Isolation are achievable without coordination schemes like quorum consensus.

Auto-Scaling Mechanism and Policy. In this work we present and evaluate a simple auto-scaling heuristic. However, there are significant opportunities to reduce boot time by warm pooling [84] and more proactively scale computation [31, 47, 80] as a function of variability in the driving workloads. We believe that cache-based co-placement of computation and data presents promising opportunities for research in elastic auto-scaling of compute and storage.

Streaming Services Cloudburst’s internal monitoring service is based on components publishing metadata updates to well-known KVS keys. In essence, the KVS serves a rolling snapshot of an update stream. There is a rich literature on distributed streaming that could offer more, e.g. as surveyed by [32]. The autoscaling environment of FaaS would introduce new challenges, but this area seems ripe for both system internals and user-level streaming abstractions.

Security and Privacy. As mentioned briefly in §4, Cloudburst’s current design provides container-level isolation, which is susceptible to well-known attacks [55, 59]. This is unacceptable in multi-tenant cloud environments, where sensitive user data may coincide with other user programs. It is interesting to explore how Cloudburst’s design would address these concerns.

8 Conclusion and Future Work

In this paper we demonstrate the feasibility of general-purpose “stateful” serverless computing. We enable autoscaling via Logical Disaggregation of storage and compute; we achieve performant state management via Physical Colocation of storage caches with compute services. Cloudburst demonstrates that disaggregation and colocation are not inherently in conflict. In fact, the LDPC design pattern is key to our solution for stateful serverless computing.
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