PAIO: A Software-Defined Storage Data Plane Framework

Ricardo Macedo, Yusuke Tanimura†, Jason Haga†, Vijay Chidambaram‡, José Pereira, João Paulo
INESC TEC & University of Minho
†National Institute of Advanced Industrial Science and Technology
‡The University of Texas at Austin & VMWare Research

Abstract

We propose PAIO, the first general-purpose framework that enables system designers to build custom-made Software-Defined Storage (SDS) data plane stages. It provides the means to implement storage optimizations adaptable to different workflows and user-defined policies, and allows straightforward integration with existing applications and I/O layers. PAIO allows stages to be integrated with modern SDS control planes to ensure holistic control and system-wide optimal performance. We demonstrate the performance and applicability of PAIO with two use cases. The first improves 99th percentile latency by 4× in industry-standard LSM-based key-value stores. The second ensures dynamic per-application bandwidth guarantees under shared storage environments.

1 Introduction

Data-centric systems such as databases, key-value stores (KVS), and machine learning engines, share the need for efficient data storage and retrieval. This has led to the implementation of isolated I/O optimizations (e.g., scheduling, differentiation, caching) to address their storage requirements, such as resource fairness and throughput/latency SLOs [9, 28, 36]. This approach, however, has two main drawbacks. First, I/O optimizations are tightly integrated within the core of each solution, making it challenging to port these to other systems with similar performance goals. Second, in shared environments where multiple systems operate concurrently and compete for shared resources, individual optimizations can conflict with each other [15], leading to I/O contention and performance variation [29, 35].

The Software-Defined Storage (SDS) [21, 32] paradigm promises an appealing solution to these limitations. It aims at decoupling I/O functionality into two planes: control and data. The control plane is a logically centralized entity with system-wide visibility that enforces end-to-end policies in the I/O stack, which can be composed of different I/O layers (e.g., applications, databases, file systems, object stores) and physical storage devices (e.g., NVMe, SSD, HDD). Control algorithms, built on top of it, define the policies to be enforced at the I/O stack and generate rules directly applicable at the data plane. Examples of such control algorithms are used for achieving QoS provisioning [32, 38], performance control [30, 31], and resource fairness [18, 29].

The data plane is a multi-stage component distributed over the I/O stack. Each data plane stage (or stage, for short) implements custom I/O logic to apply over requests to meet a given policy. Stages can provide simple data transformations such as encryption and compression [13, 25], or more complex mechanisms such as token-buckets, I/O schedulers, and load balancers [18, 27, 29, 32].

However, current SDS systems including IOFlow [32], Retro [18], Crystal [13], and SafeFS [25], are designed for enforcing policies over a specific set of layers such as file systems, object stores, and hypervisors, or storage contexts (e.g., cloud-based virtualization and application-specific storage stacks), thus limiting their adoption and applicability.

In fact, introducing the ideas behind SDS over existing I/O layers, without significant system rewrite, is a challenging endeavor. Layers interact with each other through rigid interfaces that cannot be extended with ease. For example, the POSIX interface does not allow differentiating requests from different layers, or even workflows of the same layer (e.g., background and foreground tasks of a KVS [9]).¹ Thus, intercepting and propagating request information to a stage is challenging, and its absence limits the context and granularity at which workflows can be differentiated and optimized. Without this knowledge, optimizations must again be implemented individually at the layer, inhibiting code reuse and holistic tuning.

Solving these challenges requires a fundamental new abstraction, where the development of I/O optimizations should be made over a programmable and adaptable environment. As such, we propose PAIO, the first general-purpose SDS data plane framework that enables system designers to build
custom-made data plane stages.\textsuperscript{2} By promoting code reuse and straightforward integration with I/O layers, PAIO eases the implementation of complex storage mechanisms that can adapt to different workflows and policies. The chief insight behind our work is that if we are able to intercept and differentiate requests as they flow through different layers, we can enforce policies without significantly changing the layers themselves.

PAIO makes this possible through three logical components. First, a differentiation component classifies and differentiates requests at different levels of granularity. Leveraging from context propagation ideas \cite{19}, PAIO propagates additional information of a given layer to the stage, enabling per-tenant and per-context (e.g., foreground and background tasks) differentiation. Second, PAIO abstracts complex storage mechanisms into self-contained, custom-made enforcement objects, which are programmable components that contain the I/O logic to apply over requests (e.g., token-buckets, I/O schedulers). Third, PAIO exposes a control interface that allows SDS control planes to manage, monitor, and dynamically adapt each data plane stage.

We validate PAIO under two use cases. First, we implement a PAIO stage in RocksDB \cite{6}, an industry-standard Log-Structured Merge tree (LSM) KVS, and demonstrate how to prevent latency spikes by orchestrating foreground and background tasks. Results show that a PAIO-enabled RocksDB improves 99\textsuperscript{th} percentile latency by 4× under different workloads when compared to baseline RocksDB, and achieves similar tail latency performance when compared to SILK, a state-of-the-art, latency-oriented KVS \cite{9}. Second, we apply PAIO to TensorFlow \cite{7} and show how to achieve dynamic per-application bandwidth guarantees under a real shared storage scenario at the ABCI supercomputer.\textsuperscript{1} Results show that all PAIO-enabled TensorFlow instances are provisioned with their bandwidth goals.

PAIO is implemented as a user-level library so developers can create new data plane stage implementations and integrate them in different layers — porting RocksDB and TensorFlow to a PAIO-enabled environment only required adding 85 and 22 lines of code, respectively. Moreover, while this paper focuses on porting existing I/O layers to an SDS-enabled environment, PAIO can also be used to simplify the development of future data-centric systems.

In sum, the paper makes the following contributions:

- **PAIO**, a novel open-source data plane framework for building programmable and dynamically adaptable stages tailored for user-defined policies (§3–§4). PAIO is available at https://github.com/dsrhaslab/paio.
- The implementation of two data plane stages using PAIO, along with the corresponding control algorithms, to (1) prevent latency spikes in industry-standard KVS, and (2) to achieve per-application bandwidth guarantees under real shared storage deployments (§5).

![Figure 1: Operations submitted from different I/O workflwos. Example of the operation flow of a multi-layered I/O stack. Left side depicts regular information extracted from operations between the KVS and File System, while the right side includes additional request information made available through context propagation.](image)

1. **Experimental results demonstrating the performance, applicability, and feasibility of PAIO under both synthetic and realistic scenarios (§6).**

### 2 Challenges

Modern infrastructures are made of multiple independent I/O layers that operate concurrently over the same resources. To address the storage requirements specific to each layer, these implement system-specific and isolated I/O optimizations. This design however, raises several challenges.

**Tightly coupled optimizations.** I/O optimizations implemented at data-centric systems, such as caching, tiering, and scheduling, are single-purposed as they are tightly integrated within the core of each system. Implementing these optimizations requires deep understanding of the internal operation model and significant system rewrite, reducing their portability and adoption across systems that share similar principles. For instance, porting SILK’s I/O scheduler \cite{9} to improve the tail latency performance of LevelDB \cite{12} and PebblesDB \cite{26} is not trivial, and requires profound system refactoring. As such, I/O optimizations should be disaggregated from the system’s internal logic and moved to a dedicated layer, becoming generally applicable and portable across different scenarios.

**Rigid interfaces.** The operation model of conventional I/O stacks requires layers to communicate through rigid interfaces that cannot be easily extended, discarding information that could be used to classify and differentiate requests at different levels of granularity. For instance, consider the I/O stack depicted in Fig. 1 made of an Application, a KVS, and a POSIX-compliant File System. POSIX operations submitted from the KVS can be originated from different workflows, including foreground (○) and background flows i.e., flushes...
(b) and compactions (c). From the File System’s perspective however, it can only observe the size and type of a request, making it impossible to infer its origin. For example, (b) and (c) represent two 4 KiB-sized read operations that are originated from different contexts. This loss of granularity reduces the possibility to differentiate and enforce complex policies over requests. Thus, layers should have access to additional request information to classify, differentiate, and enforce policies at a finer granularity. Considering the previous example, by propagating the context that has originated a given request, we can pinpoint each operation to its origin and handle it accordingly. Specifically, each request is now accompanied with a context field that determines the origin of a request, namely a foreground task for (b) and compaction task for (c).

Partial visibility. I/O optimizations are implemented in isolation and are oblivious of the remaining layers of the I/O stack. Under this design, layers compete for shared resources, leading to conflicting optimizations, misconfigurations, I/O contention, and performance variation. As such, optimizations should have system-wide visibility to ensure coordinated and holistic control of all storage resources.

3 PAIO Design

PAIO is a general-purpose SDS framework that enables system designers to build custom-made data plane stages. A data plane stage built with PAIO allows the classification and differentiation of I/O requests, and the enforcement of different mechanisms according to user-defined storage policies. Examples of such policies can be as simple as adjusting the workflows’ rate of greedy tenants to achieve resource fairness, or more complex ones as coordinating the rate of foreground and background workflows to ensure sustained tail latency. To achieve this, and to address the challenges pointed in §2, PAIO’s design is built over three core principles.

Programmable and extensible building blocks. The data plane must be programmable to allow developing stages tailored for each layer. It should be extensible and provide the necessary abstractions for building custom I/O mechanisms, such as caches, schedulers, and token-buckets, to employ over requests. These properties are key for supporting a wide range of I/O mechanisms tailored for the requirements of different layers.

Fine-grained control over I/O. The data plane must have granular control over I/O workflows to classify and differentiate requests at different levels, such as per-application, per-workflow, or per-request type. This allows implementing a rich set of policies over the I/O stack (e.g., QoS provisioning, resource fairness, load balancing).

Control interface. The data plane should expose a control interface that abstracts the complexity of its internal organization, and allow the SDS control plane to dynamically adapt each stage to new policies and workload variations.

Figure 2: PAIO overview. PAIO is a general-purpose SDS framework that allows implementing fine-tuned data plane stages at different points of the I/O stack.

3.1 Abstractions in PAIO

PAIO uses four main abstractions, namely enforcement objects, channels, context, and rules.

Enforcement object. An enforcement object is a self-contained, single-purposed mechanism that contains custom I/O logic to apply over requests. Examples of such mechanisms can range from performance control and resource management such as token-buckets, I/O schedulers, and caches, data transformations as compression and encryption, to data management (e.g., data prefetching, tiering). This abstraction provides to system designers the necessary flexibility and extensibility for developing new I/O mechanisms tailored for enforcing specific storage policies over requests.

Channel. A channel provides a stream-like abstraction through which requests flow. Each channel contains one or more enforcement objects, as well as a rule that maps requests to the respective enforcement object to be enforced. The combination of channels and enforcement objects is designed to ease the implementation of new storage services, while promoting their reutilization and applicability.

Context. A context represents a metadata-like object that contains a set of elements that characterize a request. These elements (or classifiers) include the workflow id (e.g., thread-1D), request type (e.g., read, open, put, get), request size, and the request context, which defines the context of a request (e.g., foreground or background tasks, flush or compaction). For each request, PAIO generates the corresponding context object that is used for classifying, differentiating, and enforcing the request over the respective mechanisms.

Rule. In PAIO, a rule represents an action that updates the state of a data plane stage. Rules are submitted by the control plane, and are organized in three types: housekeeping rules manage the internal stage organization, differentiation rules classify and differentiate I/O requests, enforcement rules adjust enforcement objects upon workload variations.

3.2 Architecture

Fig. 2 outlines PAIO’s high-level architecture, which consists of data plane stages and an external control plane. PAIO’s design targets the workflows of any given point of the I/O
stack. To orchestrate these, stages are embedded within layers to intercept requests and enforce user-defined policies.

To achieve this, PAIO is organized in four main components. First, PAIO exposes an Instance interface (§4.1) that bridges the targeted layer (App3) and the data plane stage. It intercepts all requests that are destined to the next layer (App3→File System) and generates a per-request context object that contains all request’s classifiers. Both request and context object are then submitted to the data plane stage.

Second, a differentiation module (§3.3) classifies and differentiates requests based on their context object. Requests can be differentiated at different levels of granularity, being then dispatched to the correct channel to be enforced.

Third, PAIO provides an enforcement module (§3.4) that is responsible for enforcing policies over requests and is organized with several channels and enforcement objects. For each request, the channel selects the enforcement object to employ its I/O mechanism. After being enforced, requests are returned to the original data path and submitted to the next I/O layer (File System).

Finally, PAIO exposes a control interface (§4.1) that allows the SDS control plane to orchestrate the stage lifecycle, such as creating channels and enforcement objects, propagating new enforcement rules, and collecting I/O statistics. Exposing such a control interface allows PAIO stages to be managed by existing SDS control planes [13, 18, 32].

An external control plane orchestrates each stage to cope with user-defined policies. It communicates with the data plane through PAIO’s control interface to: submit rules, either for internal management, differentiation, or fine-tuning enforcement objects; and monitoring, to keep track with the stage’s performance and ensure that all policies are met.

### 3.3 I/O Differentiation

PAIO’s differentiation module provides the means to classify and differentiate requests at different levels of granularity, namely per-workflow, request type, and request context. The process for differentiating requests is done in two phases.

The first phase, which happens at startup time, defines how requests should be differentiated and which requests a channel receives. To do so, first PAIO specifies the context’s classifiers that will be considered at runtime, which can be a single classifier or a combination of them. For example, to use per-workflow differentiation, PAIO only considers the context’s workflow id, while to differentiate requests based on their context and type, PAIO considers both request context

| Channel  | Workflow ID | Request context | Request type |
|----------|-------------|-----------------|--------------|
| channel1 | flow1       | —               | —            |
| channel2 | —           | background tasks | read         |
| channel3 | flow5       | compaction      | write        |

and request type classifiers. Second, PAIO attributes specific context classifiers to each channel, which are used to map requests to the respective channel. Namely, it defines the exact request’s workflow id, context, and/or type that a channel receives. Table 1 provides examples of this attribution of request’s context classifier to each channel. A request belongs to a channel if its context classifier matches one of the channel’s classifiers, and is used to map requests to the respective channel. Namely, it defines the exact request’s workflow id, context, and/or type that a channel receives. Table 1 provides examples of this attribution of request’s context classifier to each channel. A request belongs to a channel if its context classifier matches one of the channel’s classifiers, and is used to map requests to the respective channel. For example, to use per-workflow differentiation, PAIO only considers the context’s workflow id, while to differentiate requests based on their context and type, PAIO considers both request context

![Figure 3: PAIO operation flow. Black filled circles depict the execution flow of a request in the PAIO stage (a→b). White filled circles depict the flow of control operations submitted from the SDS control plane to the data plane stage (c→d).](image)

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compliant File System. RocksDB’s background workflows are responsible for serving flush and compaction jobs. Before being submitted to the File System, jobs are translated into several POSIX read and write operations, leading to a loss of granularity at the operation context. To propagate this information, system designers instrument RocksDB’s critical path responsible for managing flush or compaction jobs (9) to capture their operation context (expressed as bg_flush or bg_compaction). This information is then propagated to the PAIO Instance, where the context object will be created with all classifiers (9) and submitted to the PAIO stage.

Note that this process is not mandatory, as it can be skipped for stages whose policies can be met without the propagation of additional request information (§5.2).

Channel selection. As depicted in Fig. 3 (9), for each incoming request, PAIO selects the channel that must service it. To do so, PAIO invokes a select_channel call that verifies the context’s classifiers and maps the request to the respective channel to be enforced. This mapping is done as described in the first phase of the differentiation process.

Enforcement object selection. As each channel may contain several enforcement objects, analogously to channel selection, PAIO selects the correct object to service the request. As depicted in Fig. 3 (9), for each request, the channel invokes a select_object call that verifies the context classifiers and maps the request to the respective enforcement object, which will then employ its I/O mechanism (§3.4).

### 3.4 I/O Enforcement

The enforcement module provides the building blocks for developing fine-tuned I/O services to be employed over workflow requests. It is composed of several channels, each containing one or more enforcement objects. The enforcement process begins after the channel selection. As depicted in Fig. 3, requests are forwarded to the selected channel and placed in a submission queue (9). For each request, PAIO invokes the select_object call that selects the enforcement object to use (9) and applies its I/O mechanism over the request (9). Examples of such mechanisms include token-buckets, caches, prefetching, and encryption schemes (we discuss how to build enforcement objects in the following paragraphs). Since several mechanisms can change the request’s original state, such as data transformations (e.g., encryption, compression), during this phase, the enforcement object generates a result object to store the updated request. This result is then returned to the PAIO Instance, that will unmarshall and forward it to the original data path (9).

Depending on the policies and I/O mechanisms to be employed, PAIO can enforce requests by only using context objects. While data transformations are directly applicable over the request’s content, performance control mechanisms such as token-buckets and schedulers, only require specific request’s metadata to be enforced (e.g., request type, size, priority). Thus, to avoid adding unnecessary overhead to the system execution, upon the submission of requests to the stage, PAIO allows for the request’s content to be copied to the stage’s execution path only when necessary (e.g., enforcing data transformation mechanisms).

A key feature of PAIO is that the targeted system is oblivious to the enforcement of its requests, as well as the number of channels and I/O mechanisms in the stage.

Building enforcement objects. As depicted in Table 2, PAIO exposes to system designers a simple API that allows building enforcement objects. An obj_init(s) call creates and configures an enforcement object with initial state $s$. $s$ and configures an enforcement object with initial state $s$. obj_config(s) provides the tuning knobs to update the enforcement object’s internals with a new state $s$. It enables the control plane to dynamically adapt the enforcement object to workload variations and new policies. An obj_enf(ctx, r) call, or “object enforce”, implements the actual I/O logic to apply over requests. It returns a result object that contains the updated request (r) after applying its logic. It also receives a context object (ctx) that is used to perform different actions over the I/O request.

To demonstrate the use of this abstraction, we focus on the implementation of a token-bucket mechanism [10]. We use the token-bucket to control the rate and burstiness of I/O workflows. Each workflow is served at a given token rate. The bucket is configured with a bucket size (e.g., maximum token capacity, and a refill period that defines the period to replenish the bucket. On obj_init the bucket is created and its size and refill period are set. Upon each request, the obj_enf call verifies the context’s size classifier and computes the number of tokens to be consumed, so the request can proceed. If not enough tokens are available, the request waits for the bucket to be refilled. Upon workload variations, the control plane may need to adjust the token rate, triggering a obj_config that adjusts the bucket size and/or refill period.

By default, PAIO preserves the operation logic of the targeted system (e.g., ordering, error handling), as both enforcement objects and operations submitted to PAIO follow a synchronous model. While developing asynchronous enforcement objects is feasible, one needs to ensure that both correctness and fault tolerance guarantees are preserved.

### Table 2: Interface definitions of PAIO modules.

| Interface | Description |
|-----------|-------------|
| stage_info() | Get data stage information |
| hsk_rule(t) | Housekeeping rule with tuple $t$ |
| 1. dif_rule(t) | Differentiation rule with tuple $t$ |
| enf_rule(id, s) | Enf. rule over enf. object id with state $s$ |
| collect() | Collect statistics from data plane stage |
| 2. enforce(ctx, r) | Enforce context ctx and request r |
| obj_init(s) | Initialize enf. object with state $s$ |
| obj_enf(ctx, r) | Enforce I/O mechanism over ctx and r |
| obj_config(s) | Configure enf. object with state $s$ |

*Control API. †Instance API. *Enforcement object API.
4 PAIO Interfaces and Implementation

We now detail how PAIO interacts with control planes and I/O layers, what a typical operation flow looks like in a PAIO stage, and how PAIO’s prototype is implemented.

4.1 Interfaces

Control interface. Communication between PAIO stages and the control plane is achieved by exposing five API calls, depicted in Table 2. A stage_info call lists information about the stage, including the process identifier (PID), stage identifier, and the number of intercepted workflows.

Rule-based calls are designed to directly orchestrate PAIO’s internal mechanisms. For data plane maintenance, it defines housekeeping rules (hsk_rule) that manage the stage lifecycle (e.g., create channels and enforcement objects), and differentiation rules (dif_rule) that map requests to channels and enforcement objects. Enforcement rules (enf_rule) dynamically adjust the internal state (e.g.) of a given enforcement object (id) upon workload and policy variations.

To ensure policies are met at any given time, the control plane continuously monitors stages. A collect call gathers key performance metrics of all workflows (e.g., IOPS, bandwidth) to adjust enforcement objects to workload variations.

Through this interface, the control plane is able to define how PAIO stages handle I/O requests. Nonetheless, concerns related to the coordination and dependability of data plane stages, as well as the resolution of conflicting policies and layers are responsibility of the control plane [21], and are thus orthogonal to this paper.

Instance interface. Communication between a layer and a stage is made through the Instance interface, that establishes the connection between workflows and PAIO’s internal mechanisms. As depicted in Table 2, it provides an enforce call that intercepts requests from the layer and forwards them, along the associated context object, to the stage. To select where requests should be intercepted, system designers need to instrument the layer’s critical path that invokes the next layer’s calls. For example, to orchestrate POSIX read operations of a given application, they need to be intercepted before being submitted to the file system. Here, the context object is generated and submitted alongside the request to the PAIO stage through enforce. After enforcing the request, the original data path execution is resumed.

To simplify layer instrumentation, PAIO also provides layer-oriented interfaces (e.g., POSIX, key-value), so users only need to replace the original call for a PAIO one.

4.2 A Day in the Life of a Request

To illustrate how workflows are orchestrated by PAIO, we consider the I/O stack depicted on Fig. 3, and consider the enforcement of the following policy: “limit the rate of RocksDB flush operations to X MiB/s”. RocksDB generates foreground and background flows, containing client-based operations and internal maintenance work (e.g., flushes, compactions), respectively. Before execution, the system designer instruments RocksDB for context propagation (bg_flush) and redirecting flush-based requests to PAIO (d). In d, the path responsible for managing flush jobs is instrumented to capture the operation context, expressed as bg_flush. In d RocksDB flushes are translated into several POSIX write requests, and the PAIO Instance only handles these.

At startup time, RocksDB initializes the PAIO stage, which connects to an already deployed control plane, and identifies itself with stage_info. The control plane then submits hsk_rules(3) to create a channel and an enforcement object that contains a token-bucket mechanism whose rate is set to X MiB/s. Finally, it creates two dif_rules for the channel and enforcement object selection (3).

At execution time, upon a flush-based write request, a context object is created with its request type (write), context (bg_flush.size), and workflow id (thread-ID), and submitted, along the request, to the stage through enforce (3). Then, the stage selects the channel (3) to be used and enqueues the request (3). The channel will then select the enforcement object to service the request (3). On obj_enf (3), the token-bucket consumes tokens from the bucket and generates the result. If not enough tokens are available, the request waits until the bucket is refilled. After enforcing the request, the result is returned to the PAIO Instance (3), and the original write proceeds to the file system.

During this time, the control plane continuously monitors the data plane stage. On collect, the stage gathers performance metrics (e.g., throughput) and sends them to the control plane (3). Based on these statistics, the control plane adjusts the bucket’s rate to ensure RocksDB’s flush operations flow at X MiB/s, generating enf_rules with new rates for the enforcement object to be adjusted (3).

4.3 Implementation

We have implemented PAIO prototype with 8,000 lines of C++ code. To enforce the policies targeted in our use cases, we implemented two enforcement objects – Noop implements a pass-through mechanism (i.e., submits requests to the next layer without additional data processing), and DRL implements a token-bucket, whose goal is to dynamically rate limit I/O requests. The rate at which the bucket serves requests is given in tokens/s. A rate (r) routine, used on obj_config, changes the bucket’s size according to a function between r and refill period. On obj_enf the bucket consumes N tokens. We consider that the cost of requests is constant i.e., each byte of a read or write request represents a token. Although the I/O cost depends on several factors (e.g., workload, operation type, cache hits), we continuously calibrate the token-bucket so its rate converges to the policies’ goal. Our experiments show
that this approach works well in our scenarios, as the bucket’s rate converges within few interactions with the control plane. Nevertheless, determining the I/O cost is complementary to our work [14,28]. Combining PAIO with these could be useful under scenarios where policies are sensitive to the I/O cost.

PAIO implements per-workflow statistic counters at channels to register bandwidth of intercepted requests, number of operations, and mean throughput between collection periods. On collect, it aggregates the statistics and reports them to the control plane. Communication between the control plane and stages is established through UNIX Domain Sockets. To create the unique identifiers that map requests to channels and enforcement objects, we used a computationally cheap hashing scheme [8] (i.e., MurmurHash3) that hashes classifiers into a fixed-size token.

PAIO is provided to the community as an open-source user-space library, so developers can create new stage implementations and integrate them in different I/O layers, as shown in §5. Moreover, PAIO’s design is aligned with the current efforts of moving the storage stack to user-level through kernel-bypass technologies (e.g., SPDK, PMDK).

Control plane. We built a simple but fully-functional control plane with 3,600 lines of C++ code that enforces policies for the two use cases of this paper. Policies were implemented as control algorithms. To calibrate enforcement objects, besides stage statistics, it collects the I/O metrics generated at the targeted layer from the /proc file system [24]. Specifically, it inspects the read_bytes and write_bytes counters, which represent the number of bytes read/written from/to the block layer, and compares them with stage statistics to converge to the targeted performance goal.

5 Use Cases and Control Algorithms

We now present two use cases that showcase the applicability of PAIO for different applications and performance goals.

5.1 Tail Latency Control in Key-Value Stores

LSM KVSs such as LevelDB [12] and RocksDB [6] use foreground flows to attend client requests, which are enqueued and served in FIFO order. Background flows serve internal operations, namely flushes and compactions. Flushes are sequentially written to the first level of the tree ($L_0$) by a single thread and only proceed when there is enough space. Compactions are held in an internal FIFO queue waiting to be executed by a dedicated thread pool. Except for low level compactions ($L_0-L_1$), these can be executed in parallel.

Latency spikes. A common problem of LSM KVSs is the interference between these workflows, generating latency spikes for client requests. Latency spikes occur when flushes cannot proceed. First when $L_0-L_1$ compactions are slow, either because there is not enough disk bandwidth or because they are waiting in the compaction queue. This increases the size of $L_0$, blocking flushes when there is no more storage quota left at this level. Second whenflushes are slow, because there is not enough disk bandwidth for the operation to be executed timely. These lead the memtable to fill, stalling client writes and causing latency spikes.

SILK, a KVS built over RocksDB, addresses this with an I/O scheduler that: allocates bandwidth for internal operations when client load is low; prioritizes flushes and low level compactions, as they impact client latency; and preempts high level compactions with low level ones [9]. It employs these techniques with the following control algorithm. As these KVSs are embedded, the KVS I/O bandwidth is bounded to a given rate ($KVS_B$). It monitors clients’ bandwidth ($F_g$), and allocates any leftover bandwidth ($I_B$) to internal operations ($I_0$), given by $I_B = KVS_B - F_g$. To enforce rate $I_B$, SILK uses RocksDB’s rate limiters [3]. Flushes and $L_0-L_1$ compactions have high priority and are provisioned with minimum I/O bandwidth ($min_B$). High level compactions have low priority and can be paused at any time. Because all compactions share the same thread pool, it is possible that, at some point, all threads are handling high level compactions. As such, SILK preempts one of them to execute low level compactions.

However, implementing SILK’s I/O optimizations over RocksDB required reorganizing its internal operation flow, changing core modules made of thousands of LoC including background operation handlers, internal queueing logic, and the thread pools allocated for internal work. Further, porting these optimizations to other KVSs that would equally benefit from them would require a substantial re-implementation effort. As such, we propose an alternative approach.

PAIO. Rather than modifying the RocksDB engine, we noticed that several of these optimizations could be achieved by orchestrating I/O workflows. Thus, we implemented SILK’s design principles in SDS fashion: a PAIO data plane stage implements the I/O mechanisms for prioritizing and rate limiting background flows, while the control plane re-implements SILK’s I/O scheduling algorithm to orchestrate the stage, increasing the portability and applicability of these techniques over systems that share a similar design.

The stage intercepts all RocksDB workflows. We consider each RocksDB thread that interacts with the file system as a workflow. Differentiation is made using the workflow id and request context classifiers. We instrumented RocksDB to perform context propagation, which only required adding 47 LoC. When a flush or compaction operation is triggered, the context object is created with the respective request context (e.g., bg_flush, bg_compaction_L0_L1). Foreground flows are enforced with a Noop object that collects statistics of clients’ bandwidth. Background flows are forwarded to channels made of DRL enforcement objects. Flushes flow through a single channel. As compactions with different priorities can flow through the same channel, it contains two DRL objects configured at different rates, one for low level compactions
and another for high level ones. PAIO also collects the I/O bandwidth of flushes (F1), and low level (L0) and high level compactions (L0). Integrating PAIO in RocksDB required adding 85 LoC, as listed in Table 3.

On the control plane we implemented a SDS version of the SILK’s scheduling algorithm, as shown in Algorithm 1. The algorithm uses a feedback control loop that performs the following steps. First, it collects statistics from the stage (1) and computes leftover disk bandwidth (leftB) to assign to internal operations (2). To ensure that background flows keep flowing, it defines a minimum bandwidth threshold (3), and distributes leftB according to workflows priorities (4-11). It verifies if high priority tasks are executing, equally distributing leftB and assigning minimum bandwidth (minB) to high level compactions (5). It is important that high level compactions keep flowing to prevent low level ones from being blocked in the queue. If a single high priority task is being executed, leftB is allocated to it and minB to others (lines 6-9). It allocates leftB to low priority tasks, when high level ones are not executing (11). Then, it generates and submits enf_rules for adjusting the rate of each enforcement object (12). It first assigns rate Bf1 to those responsible for flushes. For low priority compactions it splits Bf1, between all DRL objects that handle these. Because high priority compactions are executed sequentially, it assigns Bf1 rate to the respective DRL objects.

Existing SDS systems are unable to enforce these policies, as they are either targeted for a specific layer (e.g., hypervisor, OpenStack, Ceph) and are not directly applicable over the KVS or POSIX layers [13, 18, 27, 32], or do not provide context propagation [28, 29], thus being unable to provide differentiated treatment of I/O requests.

### 5.2 Per-Application Bandwidth Control

The ABCI supercomputer is designed upon the convergence between AI and HPC workloads. One of the most used AI frameworks on it is TensorFlow [7]. To execute TensorFlow jobs, a user can allocate a full node, or a fraction of it where jobs can execute concurrently. Compute nodes are partitioned into resource-isolated instances using Linux’s cgroups [22]. Each instance has exclusive access to CPU cores, memory space, a GPU, and local disk storage quota. However, local disk bandwidth is still shared. Because each instance is agnostic of others, jobs compete for disk bandwidth leading to interference and performance variation. Even if the block I/O scheduler can ensure fairness, all instances are served with the same service level. This scenario prevents the possibility of assigning different priorities and achieving per-application bandwidth policies.

Using cgroup’s block I/O controller (blkio) allows static rate limiting read and write operations of each instance [1]. However, once the I/O rate is set it cannot be dynamically changed at execution time, as it requires stopping the jobs, adjusting the parameters, and restarting the jobs, which is prohibitively expensive. This creates a second problem where if no other job is executing in the node, the instance cannot use leftover bandwidth, leading to longer execution periods.

**PAIO.** To address this, we use a PAIO stage that implements the mechanisms to dynamically rate limit workflows at each instance, while the control plane implements a proportional sharing algorithm to orchestrate the stage and ensure all instances meet their policies. Our use case focuses on the model training phase, where each instance runs a TensorFlow job that uses a single workflow to read dataset files from the file system. TensorFlow’s read requests are intercepted and forwarded to the stage that contains a single channel with a DRL enforcement object. Contrary to §5.1, PAIO does not require context propagation, as policies can be met with the request type and size classifiers. As TensorFlow exposes different backend interfaces (e.g., POSIX, HDFS, AWS S3), we extended the POSIX file system to enforce requests at the stage. This was achieved by adding 22 LoC, as listed in Table 3.

At the control plane, we implemented a max-min fair share algorithm to ensure per-application bandwidth guarantees, as shown in Algorithm 2, which is typically used for resource fairness policies [18, 32]. Rather than assigning the minimum I/O bandwidth to each instance, it distributes leftover bandwidth whenever it is available (leftB). The algorithm uses a feedback control loop that performs the following steps. First,

---

**Algorithm 1** Tail Latency Control Algorithm

| Initialize: KVSB = 200; minB = 10 |
|---|
| 1: \{Fg, Fl, L0, Lg\} ← collect () |
| 2: leftB ← KVSB - Fg |
| 3: leftB ← max \{leftB | minB\} |
| 4: if F1 > 0 ∧ L0 > 0 then |
| 5: \{Bf1, Bl0, Lf1\} ← \{leftB/2, leftB/2, minB\} |
| 6: else if F1 > 0 ∧ L0 = 0 then |
| 7: \{Bf1, Bl0, Lf1\} ← \{leftB, minB, minB\} |
| 8: else if F1 = 0 ∧ L0 > 0 then |
| 9: \{Bf1, Bl0, Lf1\} ← \{ minB, leftB, minB\} |
| 10: else |
| 11: \{Bf1, Bl0, Lf1\} ← \{ minB, minB, leftB\} |
| 12: enf_rule ((Bf1, Bl0, Lf1)) |
| 13: sleep (loop_interval) |

---

**Table 3:** Lines of code added to RocksDB and TensorFlow.

| Lines added | RocksDB† | TensorFlow† |
|---|---|---|
| Initialize PAIO stage | 10 | 15 |
| Context propagation instr. | 47 | – |
| Serialize context object | 7 | 3 |
| Instrument operation calls | 17 | 2 |
| Deserialize result object | 4 | 2 |
| **Total** | 85 | 22 |

†RocksDB [4] and TensorFlow [5] codebases consist of approximately 335K LoC and 2.3M LoC, respectively.
Algorithm 2: Max-min Fair Share Control Algorithm

Initialize: \( \text{MaxB} = 1 \text{GiB}; \text{Active} > 0; \text{demand}_i > 0 \)
1: \( \{I_1, I_2, I_3, I_4\} \leftarrow \text{collect}() \\
2: \text{leftB} \leftarrow \text{MaxB} \\
3: \text{for } i = 0 \text{ in } [0, \text{Active} - 1] \text{ do} \\
4: \quad \text{if } \text{demand}_i \leq \text{leftB}_i / \text{Active}_i \text{ then} \text{then} \\
5: \quad \quad \text{rate}_i \leftarrow \text{demand}_i \\
6: \quad \text{else} \\
7: \quad \quad \text{rate}_i \leftarrow \left(\frac{\text{leftB}_i}{\text{Active}_i}\right) \\
8: \quad \text{leftB} \leftarrow \text{leftB} - \text{rate}_i \\
9: \text{for } i = 0 \text{ in } [0, \text{Active} - 1] \text{ do} \\
10: \quad \text{rate}_i \leftarrow \text{leftB}_i / \text{Active}_i \\
11: \text{env_rule} (\{\text{rate}_1, I_1\}, \{\text{rate}_2, I_2\}, \{\text{rate}_3, I_3\}, \{\text{rate}_4, I_4\}) \\
12: \text{sleep} (\text{loop_interval})

the overall disk bandwidth available (\( \text{MaxB} \)) and bandwidth demands of each application (\( \text{demand} \)) are defined a priori by the system administrator or the mechanism responsible for managing resources of different job instances [37]. The control plane starts collecting statistics of active instances, given by \( I_i \) (1), as well as the bandwidth generated by each TensorFlow job (collected at /proc). Then, it computes the rate limit of each active instance (3-10). If an instance’s \( \text{demand} \) is less than its fair share, the control plane assigns the \( \text{demand} \) (4-5), assigning its fair share otherwise (6). It then distributes \( \text{leftB} \) between all instances (9-10). Having computed all rates, the control plane calibrates the bucket rate of each instance in a function of \( I_i \) and \( \text{rate}_i \), generating the \( \text{env规则} \) to be submitted to each stage (11). Finally, the control plane sleeps for \( \text{loop_interval} \) before beginning a new control cycle (12).

Existing SDS solutions that target the virtualization layer could be used for enforcing these policies under cloud-based environments [17, 30, 32]. However, under scenarios that require bare-metal access to resources such as HPC infrastructures (e.g., ABCI) and bare-metal cloud servers, these solutions are unfit for ensuring such objectives.

6 Evaluation

Our evaluation seeks to demonstrate the performance and scalability of PAIO (§6.1), and its ability and feasibility of enforcing I/O policies over different scenarios (§6.2 – §6.3). Unless stated otherwise, experiments were conducted in a compute node of the ABCI supercomputer with the following hardware specifications: two 20-core Intel Xeon processors with 2-way multi-threading, four NVidia Tesla V100 GPUs, 384GiB of RAM, and a 1.6TiB Intel SSD DC P4600. It uses CentOS 7.5 with Linux kernel 3.10 and the \( \text{xfst} \) file system.

6.1 PAIO Performance and Scalability

We developed a simple benchmark that simulates an application whose requests are enforced with a PAIO stage. This benchmark aims to demonstrate the maximum performance achievable with PAIO by stress-testing it in a loop-back manner. It generates and submits multi-threaded requests in a closed loop through Instance’s \( \text{enforce} \) call, under a varying number of clients (e.g., workflows) and request sizes. Request size and number of client threads range between 0-128KiB and 1-128, respectively. A PAIO stage is configured with varying number of channels (matching the number of client threads), each containing a Noop enforcement object that copies the request’s buffer to the result object. All reported results are the mean of at least ten runs, and standard deviation is kept below 5%. Experiments were conducted using a machine with two 18-core Intel Xeon processors with 2-way multi threading, configured with Ubuntu Server 20.04 and Linux kernel 5.8.9.

IOPS and Bandwidth. Fig. 4 depicts the cumulative IOPS ratio with respect to a single channel. Absolute IOPS value is shown above the 1 channel bar. A 0B request size represents a context-only request (i.e., no content), as described in §3.4.

When using a 0B request size, a single PAIO channel achieves an average throughput of 3.43 MOps/s. Since the workload is CPU-bound, client threads start competing for processing time, and thus, PAIO achieves higher throughput when using 64 channels. Under this configuration, PAIO achieves a cumulative throughput of 102.7 MOps/s, representing a 30× performance increase.

As the request size increases so does the total bytes processed by PAIO. When configured with 64 channels, PAIO is able to process 489 GiB/s for 128KiB-sized requests. As for a single channel, PAIO processes requests at 2.5 GiB/s and 14.7 GiB/s for 1KiB and 128KiB request sizes, respectively.

Profiling. We measured the execution time of each PAIO operation that appears in the main execution path. Context object creation takes approximately 17 ns, while the channel and enforcement object selection take 85 ns to complete (each). The duration of \( \text{obj\_enf} \) ranges between 20 ns and 7.45 μs when configured with 0B and 128KiB request sizes.

Summary: This section showcases the maximum performance achieved with PAIO when enforcing context-only oper-
We now demonstrate how PAIO achieves tail latency control under several workloads and how does it compare to other systems. We compare the performance of RocksDB with Auto-tuned (i.e., a version of RocksDB with auto-tuned rate limiting of background operations [16]), SILK, and PAIO (i.e., a PAIO-enabled RocksDB). We tuned all KVS with the following configurations. The memtable-size was set to 128MiB. 

We used 8 worker threads for client operations and 8 background threads for flush (1) and compactions (7). The minimum bandwidth threshold for background operations was set to 10MiB/s. To simplify results compression and commit logging are turned off. All experiments were conducted using the db_bench benchmark suite [2], and resources were limited using Linux cgroups [1, 22]. We limit memory usage to 1GiB and I/O bandwidth to 200MiB/s, as used in the SILK testbed, which is based on Nutanix production environments [9]. Conducting experiments with higher limits would lead to similar results, however it would require longer execution periods and a larger dataset to generate a similar backlog.

We focus on workloads made of bursty clients, to better simulate existing services in production [9, 11]. Client re-
quests are issued in a closed loop through a combination of
peaks and valleys. An initial valley of 300 seconds submits
operations at 5kops/s, and is used for executing the KVS in-
ternal backlog. Peaks are issued at a rate of 20kops/s for 100
seconds, followed by 10 seconds valleys at 5kops/s. All data-
stores were preloaded with 100M key-value pairs, using a
uniform key-distribution, 8B keys and 1024B values.

We use three workloads with different read:write ratios,
namely mixture with 50:50, read-heavy with 90:10, and write-
heavy with 10:90. Mixture represents a commonly used YCSB
workload (i.e., workload A) and provides a similar ratio as
Nutanix production workloads [9]. Read-heavy provides an
operation ratio similar to those reported at Facebook [11].
To present a comprehensive testbed, we included a write-
heavy workload. For each system, workloads were executed
three times over 1-hour with a uniform key-distribution. For
figure clarity, we present the first 20 minutes of a single run.
Similar performance curves were observed for the rest of
the execution. Fig. 5–7 depict throughput and 99th percentile
latency of all systems under each workload. Theoretical client
load is presented as a red dashed line. Mean throughput is
shown as an horizontal dashed line.

**Mixture workload.** Fig. 5 depicts the results of each system
under the mixture workload. Due to accumulated backlog of
the loading phase, throughput achieved in all systems does
not match the theoretical client load. RocksDB presents high
tail latency spikes due to constant flushes and low level comp-
actions. Auto-tuned presents less latency spikes but degrades
overall throughput, which occurs due to the rate limiter be-
ing agnostic of background tasks’ priority, and because it
increases its rate when there is more backlog, contending for
disk bandwidth. SILK achieves low tail latency but suffers
periodic drops in throughput due to accumulated backlog.

Compared to RocksDB (11.9 kops/s), PAIO provides similar
mean throughput (12.4 kops/s). Regarding tail latency, while
RocksDB experiences peaks that range between 3–20 ms, PAIO and SILK observe a 4x decrease in absolute tail latency,
with values ranging between 2–6 ms.

**Read-heavy workload.** Fig. 6 depicts the results under the
read-heavy workload. Throughput-wise all systems perform
identically. At different periods, all systems demonstrate a
temporary throughput degradation due to accumulated back-
log. As for tail latency, the analysis is twofold. RocksDB and
Auto-tuned present high tail latency up to the 400 s mark. Af-
er that mark, RocksDB does not have more pending backlog
and achieves sustained tail latency that ranges between 1–
3 ms, while on Auto-tuned, some compactions are still being
performed due to rate limiting, thus increasing latency by 1
to 2 ms. SILK and PAIO have similar tail latency curves. Dur-
ing the initial valley both systems significantly improve tail
latency when compared to RocksDB. After the 400 s mark,
SILK pauses high level compactions and presents a tail la-
tency between 1–2 ms. By preempting high level compactions
and serving low level ones through the same thread pool as
flushes, it ensures that high priority tasks are rarely stalled.
SILK achieves this by modifying the original RocksDB queu-
ing mechanism. In PAIO, while sustained, its tail latency is
1 ms higher than SILK’s in the same observation period. Since
PAIO does not modify the RocksDB engine, it cannot preempt
compactions, resulting in a small increase on client latency.

**Write-heavy workload.** Fig. 7 depicts the results under the
write-heavy workload. As high write proportions continu-
ously generate latency-critical background tasks, RocksDB is
not able to endure this load, resulting in high latency spikes.
Auto-tuned limits all background writes, which degrades la-
tency spikes, but still achieves 5 ms tail latencies in several
periods. SILK pauses all high level compactions and only
latency-critical tasks are served, improving mean throughput
and keeping latency spikes below the 5 ms mark. In PAIO,
since flushes occur more frequently, the control plane slows
down high level compactions more aggressively, which leads
to low level ones to be temporary halted at the compaction
queue, waiting to be executed. While degrading mean through-
put, PAIO still decreases tail latency, never exceeding 7 ms.
The throughput difference between PAIO and SILK is justi-
fied by the latter preempting high level compactions over low
level ones, as described in the read-heavy workload.

**Takeaway.** We demonstrate that by abstracting a minimal
amount of the application’s semantics (i.e., context) and prop-
agating it to the data plane stage with minor changes to com-
plex codebases (i.e., 47 LoC), PAIO outperforms RocksDB,
an industry-standard KVS, by at most 4× in tail latency, and
enables as much control and performance as system-specific
optimizations (SILK) that required profound refactoring to
the original codebase.

### 6.3 Per-Application Bandwidth Control

We now show how PAIO ensures per-application bandwidth
 guarantees under a shared storage environment. Our setup
was driven by the requirements of the ABCI supercomputer.
Experiments ran using TensorFlow 2.1.0 with the LeNet train-
ing model, configured with a batch size of 64 TRecords. We
used the ImageNet dataset. Each instance runs with a dedi-
cated GPU and dataset, and its memory is limited to 32GiB.
Overall disk bandwidth is rate limited to 1GiB/s.

At all times, a node executes at most four instances with
equal resource shares in terms of CPU, GPU, and RAM. Each
instance executes a TensorFlow job, is assigned with a band-
width policy, and executes a given number of training epochs.
Namely, instances 1 to 4 are assigned with minimum band-
width guarantees of 150, 200, 300, and 350 MiB/s, and exec-
tute 6, 5, 5, and 4 training epochs, respectively.

Experiments were conducted under three setups. Baseline
represents the current setup supported at the ABCI supercom-
puter, where all instances execute without bandwidth guaran-
tees. In Blkio, the bandwidth requirements are defined using
throughput (MiB/s) through (MiB/s) through (MiB/s) through (MiB/s) through (MiB/s)

250 250 500 750 750

a new rate, and resume from the latest checkpoint. However, checkpoint the instance’s execution, reconfigure blkio with it takes 95 minutes to complete its execution in Blkio. Experiments were executed over 95 minutes. During this phase, P...I/O bandwidth at 421 MiB/s. Whenever a new instance is added, it reads at 421 MiB/s. Whenever a new instance is added, the I/O bandwidth is shared across all (2). At 3, the aggregate instance throughput matches the disk limit. At 4, instance performance converges to approximately 256 MiB/s, leading to all instances experiencing the same service level. However, I3 and I4 cannot meet their goal, since I1 and I2 have more than their fair share. After 46 minutes of execution (5), I3 terminates, and leftover bandwidth is shared with the remainder. Again, I4 cannot achieve the targeted service level. At 6 and 7, active instances have access to leftover bandwidth and finish their execution. Summary: Instances I3 and I4 were unable to achieve their bandwidth guarantees, missing their deadlines during 31 and 34 minutes, respectively.

Blkio. Experiments were executed over 95 minutes. During the execution (5) to (7), whenever a new instance is added, it is provisioned with its bandwidth limit. However, because the rate of each instance is set using blkio, instances cannot use leftover bandwidth to speed up their execution. For example, while on Baseline I1 executes under the 50-minutes mark, it takes 95 minutes to complete its execution in Blkio. To overcome this, a possible solution would require to stop and checkpoint the instance’s execution, reconfigure blkio with a new rate, and resume from the latest checkpoint. However, doing this process every time a new instance joins or leaves the compute node would significantly delay the execution time of all running instances.

Summary: All instances achieve their bandwidth guarantees but cannot be dynamically provisioned with available disk bandwidth, leading to longer periods of execution.

PAIO. Experiments were executed over 59 minutes. At 1 and 2, instances are assigned with their proportional I/O share, as the control plane first meets each instance demands and then distributes leftover bandwidth proportionally. Contrary to Baseline, where all active instances experience the same service level, at 3, the control plane bounds the bandwidth of I1 and I2 to a mean throughput of 245 MiB/s and 313 MiB/s, respectively. At 4, instances are set with their bandwidth limit. During this phase, PAIO provides the same properties as blkio. From 5 to 7, as instances end their execution, active ones are provisioned as in 1 to 4.

Summary: All instances met their bandwidth objectives. When all instances are active, PAIO matches the performance of Blkio. When leftover bandwidth is available, PAIO shares it across all active instances, speeding up their execution. Compared to Blkio, PAIO finishes 36, 13, and 2 minutes faster for I1, I2, and I3, and performs identically for I4.

Takeaway. We demonstrate that PAIO can ensure per-application bandwidth guarantees under real shared storage environments. Compared to Baseline, which represents the current setup at the ABCI supercomputer, PAIO ensures that policies are met at all times. Compared to Blkio, as PAIO distributes leftover bandwidth proportionally across active instances, it significantly reduces the overall execution time.

Figure 8: Per-application bandwidth limits under shared storage for Baseline, Blkio, and PAIO setups.
7 Related Work

Several SDS systems are targeted for specific I/O layers and storage contexts. IOFlow [32], sRoute [30], and PSLO [17] tackle the virtualization layer. PriorityMeister [38] intercepts requests at the Network File System to enforce rate limiting services. At the block layer, Mesnier et al. [23] classify requests and employ caching optimizations. Pisces [29] and Libra [28] enforce bandwidth guarantees under multi-tenant KVS. Malacology [27] improves the programmability of Ceph [34] to allow building custom applications on top of it. Retro [18] and Cake [33] implement resource management services at the Hadoop stack. PAIO advances these by being applicable over different I/O layers (we demonstrate this by implementing PAIO stages over RocksDB and TensorFlow), and providing a programmable and extensible library that allows developers to implement data plane stages with ease.

SafeFS [25] and Crystal [13] are the only two systems that share similar principles with PAIO, in terms of programmability and extensibility. SafeFS provides a framework for stacking FUSE-based file systems on top of each other, each providing a different service to be enforced over storage requests. However, both systems are bounded to a specific I/O layer (i.e., user-level file systems and OpenStack Swift), while PAIO ensures wider applicability. Moreover, as these systems do not allow additional layer information to be propagated to the data plane, they are unable to enforce policies at a finer granularity, such as those demonstrated in the RocksDB use case (§5.1).

8 Conclusion

In this paper we present PAIO, the first general-purpose SDS data plane framework. It enables system designers to build custom-made data plane stages employable over different I/O layers. PAIO provides differentiated treatment of requests and allows implementing fine-tuned storage services to cope with varied storage policies.

By combining ideas from SDS and context propagation, we demonstrate that PAIO allows decoupling system-specific I/O optimizations to a more programmable environment, promoting their portability and applicability to other systems and I/O layers, while also enforcing policies at a finer granularity. We show this by implementing SILK’s design principles in SDS fashion over RocksDB. Results show that a PAIO-enabled RocksDB improves tail latency at the 99th by 4× under different workloads, and performs similarly to SILK. Also, we demonstrate that by having global visibility of resources, PAIO-enabled deployments can achieve per-application dynamic bandwidth guarantees under a shared storage supercomputer environment.

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Availability

PAIO user-level library, along with tests and scripts used for conducting the experiments of this paper, are publicly available at https://github.com/dsrhaalab/paio.

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