BlowFish: Dynamic Storage-Performance Tradeoff in Data Stores

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Abstract

We present BlowFish, a distributed data store that admits a smooth tradeoff between storage and performance for point queries. What makes BlowFish unique is its ability to navigate along this tradeoff curve efficiently at fine-grained time scales with low computational overhead.

Achieving a smooth and dynamic storage-performance tradeoff enables a wide range of applications. We apply BlowFish to several such applications from real-world production clusters: (i) as a data recovery mechanism during failures: in practice, BlowFish requires 5.4× lower bandwidth and 2.5× lower repair time compared to state-of-the-art erasure codes, while reducing the storage cost of replication from 3× to 1.9×; and (ii) data stores with spatially-skewed and time-varying workloads (*e.g.*, due to object popularity and/or transient failures): we show that navigating the storage-performance tradeoff achieves higher system-wide utility (*e.g.*, throughput) than selectively caching hot objects.

1 Introduction

Random access and *search* are the two fundamental operations performed on modern data stores. For instance, key-value stores [3, 5, 11, 15, 16, 18, 23, 25] and NoSQL stores [1, 4, 7, 12, 13, 17, 21, 30] support random access at the granularity of records. Many of these [1,4,7,17,21,22] also support search on records. These data stores typically store an amount of data that is larger than available fast storage[1], *e.g.*, SSD or main memory. The goal then is to maximize the performance using caching, that is, executing as many queries in faster storage as possible.

The precise techniques for efficiently utilizing cache vary from system to system. At a high-level, most data stores partition the data across multiple *shards* (partitions), with each server potentially storing multiple shards [1, 7, 21, 23]. Shards may be replicated and cached across multiple servers and the queries are load balanced across shard replicas [1, 4, 7, 12, 21].

[1]To support search, many of these systems store indexes in addition to the input, which further adds to the storage overhead. We collectively refer to the indexes combined with the input as "data".

To cache more shards, many systems use compression [1, 4, 7, 21]. Unfortunately, compression leads to a hard tradeoff between throughput and storage for the cached shards — when stored uncompressed, a shard can support high throughput but takes a larger fraction of available cache size; and, when compressed, takes smaller cache space but also supports lower throughput. Furthermore, switching between these two extreme points on the storage-performance tradeoff space cannot be done at fine-grained time scales since it requires compression or decompression of the entire shard. Such a hard storage-performance tradeoff severely limits the ability of existing data stores in many real-world scenarios when the underlying infrastructure [28,29], workload [9,10,14,26,31], or both changes over time. We discuss several such scenarios from real-world production clusters below (§1.1).

We present BlowFish, a distributed data store that enables a *smooth* storage-performance tradeoff between the two extremes (uncompressed, high throughput and compressed, low throughput), allowing fine-grained changes in storage and performance. What makes BlowFish unique is that applications can navigate from one operating point to another along this tradeoff curve *dynamically* over fine-grained time scales. We show that, in many cases, navigating this smooth tradeoff has higher system-wide utility (*e.g.*, throughput per unit of storage) than existing techniques. Intuitively, this is because BlowFish allows shards to increase/decrease the storage "fractionally", just enough to meet the performance goals.

1.1 Applications and summary of results

BlowFish, by enabling a dynamic and smooth storage-performance tradeoff, allows us to explore several problems from real-world production clusters from a different "lens". We apply BlowFish to three such problems:

Storage and bandwidth efficient data repair during failures. Existing techniques either require high storage (replication) or high bandwidth (erasure codes) for data repair, as shown in Table 1. By storing multiple replicas at different points on tradeoff curve, BlowFish can achieve the best of the two worlds — in practice, BlowFish requires storage close to erasure codes while requiring re-

Table 1: Storage and bandwidth requirements for erasure codes, replication and BlowFish for data repair during failures.

	Erasure (RS) Code	Replication	BlowFish
Storage	1.2×	3×	1.9×
Repair Bandwidth	10×	1×	1×

pair bandwidth close to replication. System state is restored by copying one of the replicas and navigating along the tradeoff curve. We explore the corresponding storage-bandwidth-throughput tradeoffs in §4.2.

Skewed workloads. Existing data stores can benefit significantly using compression [1, 4, 7, 12, 21]. However, these systems lose their performance advantages in case of dynamic workloads where (i) the set of hot objects changes rapidly over time [9, 14, 26, 31], and (ii) a single copy is not enough to efficiently serve a hot object. Studies from production clusters have shown that such workloads are a norm [9, 10, 14, 26, 31]. Selective caching [8], that caches additional replicas for hot objects, only provides coarse-grained support to handle dynamic workloads — each replica increases the throughput by 2× while incurring an additional storage overhead of 1×.

BlowFish not only provides a finer-grained tradeoff (increasing the storage overhead fractionally, just enough to meet the performance goals), but also achieves a better tradeoff between storage and throughput than selective caching of compressed objects. We show in §4.3 that BlowFish achieves 2.7–4.9× lower storage (for comparable throughput) and 1.5× higher throughput (for fixed storage) compared to selective caching.

Time-varying workloads. In some scenarios, production clusters delay additional replica creation to avoid unnecessary traffic (*e.g.*, for 15 minutes during transient failures [28, 29]). Such failures contribute to 90% of the failures [28, 29] and create high temporal load across remaining replicas. We show that BlowFish can adapt to such time-varying workloads even for spiked variations (as much as by 3×) by navigating along the storage-performance tradeoff in less than 5 minutes (§4.4).

1.2 BlowFish Techniques

BlowFish builds upon Succinct [7], a system that supports queries on compressed data[2]. At a high-level, Succinct stores two *sampled* arrays, whose sampling rate acts as a proxy for the compression factor in Succinct. BlowFish introduces *Layered Sampled Array* (LSA), a new data structure that stores sampled arrays using multiple layers of sampled values. Each combination of layers in LSA correspond to a static configuration of Succinct. Layers in LSA can be added or deleted transparently, independent of existing layers and query execution, thus enabling dynamic navigation along the tradeoff curve.

Each shard in BlowFish can operate on a different point on the storage-performance tradeoff curve. This leads to several interesting problems: how should shards (within and across servers) share the available cache? How should shard replicas share requests? BlowFish adopts techniques from scheduling theory, namely back-pressure style Join-the-shortest-queue [19] mechanism, to resolve these challenges in a unified and near-optimal manner. Shards maintain request queues that are used both to load balance queries as well as to manage shard sizes within and across servers.

In summary, this paper makes three contributions:

- Design and implementation of BlowFish, a distributed data store that enables a smooth storage-performance tradeoff, allowing fine-grained changes in storage and performance for each individual shard.
- Enables dynamic adaptation to changing workloads by navigating along the smooth tradeoff curve at fine-grained time scales.
- Uses techniques from scheduling theory to perform load balancing and shard management within and across servers.

2 BlowFish Overview

We briefly describe Succinct data structures in §2.1, with a focus on how BlowFish transforms these data structures to enable the desired storage-performance tradeoff. We then discuss the storage model and target workloads for BlowFish (§2.2). Finally, we provide a high-level overview of BlowFish design (§2.3).

2.1 Succinct Background

Succinct internally supports random access and search on flat unstructured files. Using a simple transformation from semi-structured data to unstructured data [7], Succinct supports queries on semi-structured data, that is, a collection of records. Similar to other key-value and NoSQL stores [1,3,4,12,15,21,23], each record has a unique identifier `key`, and a potentially multi-attribute `value`. Succinct supports random access via `get`, `put` and `delete` operations on keys; in addition, applications can `search` along individual attributes in values.

[2]Unlike Succinct, BlowFish does *not* enforce compression; some points on the tradeoff curve may have storage comparable to systems that store indexes along with input data.

Succinct supports random access and search using four data structures — Array-of-Suffixes (AoS), Input2AoS, AoS2Input and NextCharIdx (see Figure 1). AoS stores all suffixes in the input file in lexicographically sorted order. Input2AoS enables random access by mapping offsets in the input file to corresponding suffixes in the AoS. AoS2Input enables search by mapping suffixes in AoS to corresponding offsets in the input file. The Input2AoS and AoS2Input arrays do not possess any special structure, and require $n\lceil \log n \rceil$ space each for a file with n characters (since each entry is an integer in range 0 to $n-1$); Succinct reduces their space requirement using *sampling*. The fourth array, NextCharIdx, allows computing unsampled values in Input2AoS and AoS2Input. The AoS and the NextCharIdx arrays have certain structural properties that enable a compact representation. The description of AoS, NextCharIdx, and their compact representations is not required to keep the paper self-contained; we refer the reader to [7]. We provide necessary details on representation of Input2AoS and AoS2Input below.

Sampled Arrays: Storage versus Performance. Succinct reduces the space requirements of Input2AoS and AoS2Input using *sampling* — only a few sampled values (*e.g.*, for sampling rate α, value at indexes $0, \alpha, 2\alpha, ..$) from these two arrays are stored. NextCharIdx allows computing unsampled values during query execution.

> The tradeoff is that for a sampling rate of α, the storage requirement for Input2AoS and AoS2Input is $2n\lceil \log n \rceil / \alpha$ and the number of operations required for computing each unsampled value is α.

Succinct thus has a fixed small storage cost for AoS and NextCharIdx, and the sampling rate α acts as a proxy for overall storage and performance in Succinct.

2.2 BlowFish data model and assumptions

BlowFish enables the same functionality as Succinct (§2.1) — support for random access and search queries on flat unstructured files, with extensions for key-value stores and NoSQL stores.

Assumptions. BlowFish makes two assumptions. First, *systems are limited by capacity of faster storage*, that is operate on data sizes that do not fit entirely into the fastest storage. Indeed, indexes to support search queries along with the input data makes it hard to fit the entire data in fastest storage especially for purely in-memory data stores (*e.g.*, Redis [5], MICA [23], RAMCloud [25]). Second, BlowFish assumes that data can be sharded in a manner that a query does not require touching each server in the system. Most real-world datasets and query workloads admit such sharding schemes [14, 26, 31].

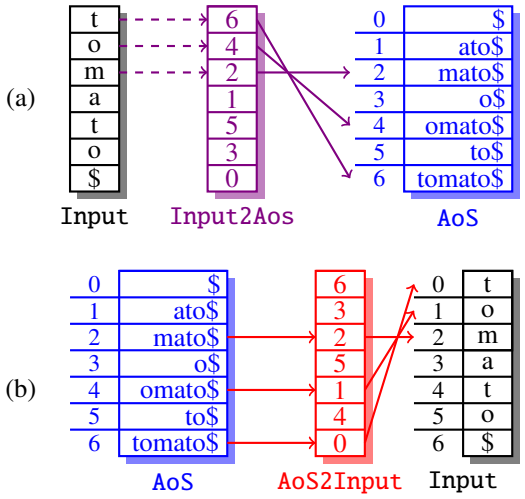


Figure 1: AoS stores suffixes in the input in lexicographically sorted order. (a) Input2AoS maps each index in the input to the index of the corresponding suffix in AoS. (b) Aos2Input maps each suffix index in AoS to the corresponding index in the input.

2.3 BlowFish Design Overview

BlowFish uses a system architecture similar to existing data stores, *e.g.*, Cassandra [21] and ElasticSearch [1]. Specifically, BlowFish comprises of a set of servers that store the data as well as execute queries (see Figure 2). Each server shares a similar design, comprising of multiple data shards (§3.1), a *request queue* per shard that keeps track of outstanding queries, and a special module *server handler* that triggers navigation along the storage-performance curve and schedules queries (§3.2).

Each shard admits the desired storage-performance tradeoff using *Layered Sampled Array* (LSA), a new data structure that allows transparently changing the sampling factor α for Input2AoS and AoS2Input over fine-grained time scales. Smaller values of α indicate higher storage requirements, but also lower latency (and vice versa). Layers can be added and deleted without affecting existing layers or query execution thus enabling dynamic navigation along the tradeoff curve. We describe LSA and the layer addition-deletion process in LSA in §3.1.

BlowFish allows each shard to operate at a different operating point on the storage-performance tradeoff curve (see Figure 3). Such a flexibility comes at the cost of increased dynamism and heterogeneity in system state. Shards on a server can have varying storage footprint and as a result, varying throughput. Moreover, storage footprint and throughput may vary across shard replicas. How should shards (within and across servers) share the available cache? How should shard replicas share requests? When should a shard trigger navigation along the storage-performance tradeoff curve?

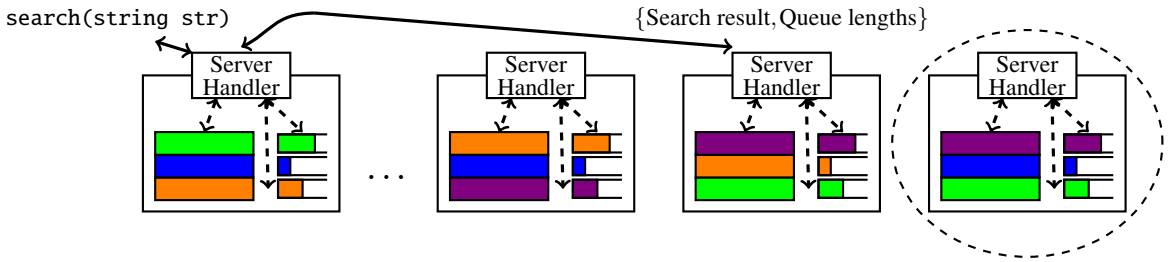


Figure 2: Overall BlowFish architecture. Each server has an architecture similar to the one shown in Figure 3. Queries are forwarded by Server Handlers to appropriate servers, and query responses encapsulate both results and queue lengths at that server.

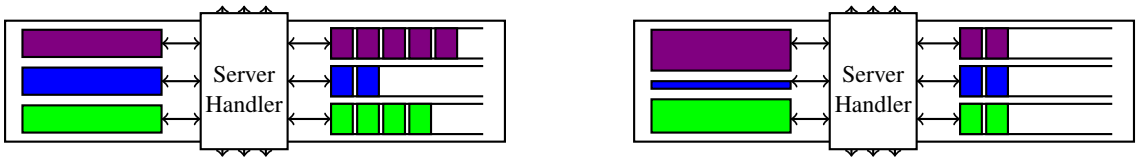


Figure 3: Main idea behind BlowFish: (left) the state of the system at some time t; (right) the state of the shards after BlowFish adapts — the shards that have longer outstanding queue lengths at time t adapt their storage footprint to a larger one, thus serving larger number of queries per second than at time t; the shards that have smaller outstanding queues, on the other hand, adapt their storage footprint to a smaller one thus matching the respective load.

BlowFish adopts techniques from scheduling theory, namely Join-the-shortest-queue [19] mechanism, to resolve the above questions in a unified manner. BlowFish servers maintain a *request queue* per shard, that stores outstanding requests for the respective shard. A server handler module periodically monitors request queues for local shards, maintains information about request queues across the system, schedules queries and triggers navigation along the storage-performance tradeoff curve.

Upon receiving a query from a client for a particular shard, the server handler forwards the query to the shard replica with shortest request queue length. All incoming queries are enqueued in the request queue for the respective shard. When the load on a particular shard is no more than its throughput at the current operating point on the storage-performance curve, the queue length remains minimal. On the other hand, when the load on the shard increases beyond the supported throughput, the request queue length for this shard increases (see Figure 3 (left)). Once the request queue length crosses a certain threshold, the navigation along the tradeoff curve is triggered either using the remaining storage on the server or by reducing the storage overhead of a relatively lower loaded shard. BlowFish internally implements a number of optimizations for selecting navigation triggers, maintaining request hysteresis to avoid unnecessary oscillations along the tradeoff curve, storage management during navigation and ensuring correctness in query execution during the navigation. We discuss these design details in §3.2.

3 BlowFish Design

We start with the description of Layered Sampled Array (§3.1) and then discuss the system details (§3.2).

3.1 Layered Sampled Array

BlowFish enables a smooth storage-performance tradeoff using a new data structure, Layered Sampled Array (LSA), that allows dynamically changing the sampling factor in the two sampled arrays — Input2AoS and AoS2Input. We describe LSA below.

Consider an array `A`, and let `SA` be another array that stores a set of *sampled-by-index* values from `A`. That is, for *sampling rate* α, `SA[idx]` stores `A` value at index $\alpha \times$`idx`. For instance, if `A = {6, 4, 3, 8, 9, 2}`, the sampled-by-index array with sampling rate 4 and 2 are $\texttt{SA}_4$ `= {6, 9}` and $\texttt{SA}_2$ `= {6, 3, 9}`, respectively.

LSA emulates the functionality of SA, but stores the sampled values in multiple *layers*, together with a few auxiliary structures (Figure 4). Layers in LSA can be added or deleted transparently without affecting the existing layers. Addition of layers results in higher storage (lower sampling rate α) and lower query latency; layer deletion, on the other hand, reduces the storage but also increases the query latency. Furthermore, looking up a value in LSA is *agnostic* to the existing layers, independent of how many and which layers exist (pseudo code in Appendix A). This allows BlowFish to navigate along the storage-performance curve without any change in query execution semantics compared to Succinct.

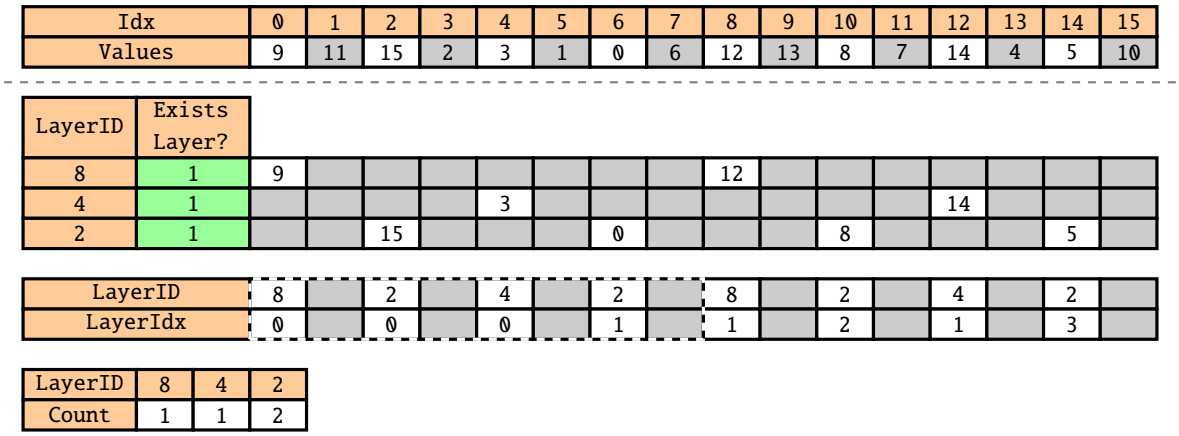


Figure 4: Illustration of *Layered Sampled Array* (LSA). The original unsampled array is shown above the dashed line (gray values indicate unsampled values). In LSA, each layer stores values for sampling rate given by `LayerID`, modulo values that are already stored in upper layers (in this example, sampling rates $8, 4, 2$). Layers are added and deleted at the bottom; that is, `LayerID=2` will be added if and only if all layers with sampling rate $4, 8, 16, ..$ exist. Similarly, `LayerID=2` will be the first layer to be deleted. The `ExistsLayer` bitmap indicates whether a particular layer exists (1) or not (0). `LayerID` and `ExistsLayer` allow checking whether or not value at any index `idx` is stored in LSA — we find the largest existing `LayerID` that is a proper divisor of `idx`. Note that among every consecutive 8 values in original array, 1 is stored in topmost layer, 1 in the next layer and 2 in the bottommost layer. This observation allows us to find the index into any layer `LayerIdx` where the corresponding sampled value is stored.

Layer Addition. The design of LSA as such allows arbitrary layers (in terms of sampling rates) to coexist; furthermore, layers can be added or deleted in arbitrary order. However, our implementation of LSA makes two simplifications. First, layers store sampled values for indexes that are *power of two*. Second, new layers are always added at the bottom. The rationale is that these two simplifications induce a certain structure in LSA, that makes the increase in storage footprint as well as time taken to add the layer very predictable. In particular, under the assumption that the unsampled array is of length $n = 2^k$ for some integer k, the number of sampled values stored at any layer is equal to the cumulative number of sampled values stored in upper layers (see Figure 4). If the sampling rate for the new layer is α, then this layer stores precisely $n/2\alpha$ sampled values; thus, the increase in storage becomes predictable. Moreover, since the upper layers constitute sampling rate 2α, computing each value in the new layer requires 2α operations (§2.1). Hence, adding a layer takes a fixed amount of time independent of the sampling rate of layer being added.

BlowFish supports two modes for creating new layers. In *dedicated layer construction*, the space is allocated for a new layer[3] and dedicated threads populate values in the layer; once all the values are populated the `ExistsLayer` bit is set to 1. The additional compute resources required in dedicated layer construction may be justified if the time spent in populating the new layer is smaller than the period of increased throughput experienced by the shard(s). However, such may not be the case for many scenarios.

The second mode for layer creation in BlowFish is *opportunistic layer construction*. This mode exploits the fact that the unsampled values for the two arrays are computed on the fly during query execution. A subset of the these values are the ones to be computed for populating the new layer. Hence, the query execution phase can be used to populate the new layer without using dedicated threads. The challenge in this mode is when to update the `ExistsLayer` flag — if set during the layer creation, the queries may incorrectly access values that have not yet been populated; on the other hand, the layer may remain unused if the flag is set after all the values are populated. BlowFish handles this situation by using a bitmap that stores a bit per sampled value for that layer. A set bit indicates that the value has already been populated and vice versa. The algorithm for opportunistic layer construction is outlined in Algorithm 2 in Appendix A.

It turns out that opportunistic layer construction performs really well for real-world workloads that typically follow a zipf-like distribution (repeated queries on certain objects). Indeed, the required unsampled values are computed during the first execution of a query and are thus available for all subsequent executions of the same query. Interestingly, this is akin to caching the query results without any explicit query result caching implementation.

[3] using free unused cache or by deleting layers from relatively lower loaded shards, as described in §3.2.4.

Layer Deletion. Deleting layers is relatively easier in BlowFish. To maintain consistency with layer additions, layer deletion proceeds from the bottom most layer. Layer deletions are computationally inexpensive, and do not require any special strategy. Upon the request for layer deletion, the `ExistsLayer` bitmap is updated to indicate that the corresponding layer is no longer available. Subsequent queries, thus, stop accessing the deleted layer. In order to maintain safety, we delay the memory deallocation for a short period of time after updating the `ExistsLayer` flag.

3.2 BlowFish Servers

We now provide details on the design and implementation of BlowFish servers.

3.2.1 Server Components

Each BlowFish server has three main components (see Figure 2 and Figure 3):

Data shards. Each server stores multiple data shards, typically one per CPU core. Each shard stores the two sampled arrays — Input2AoS and AoS2Input — using LSA, along with other data structures in Succinct. This enables a smooth storage-performance tradeoff, as described in §3.1. The aggregate storage overhead of the shards may be larger than available main memory. Each shard is memory mapped; thus, only the most accessed shards may be paged into main memory.

Request Queues. BlowFish servers maintain a queue of outstanding queries per shard, referred to as *request queues*. The length of request queues provide a rough approximation to the load on the shard — larger request queue lengths indicate a larger number of outstanding requests for the shard, implying that the shard is observing more queries than it is able to serve (and vice versa).

Server Handler. Each server in BlowFish has a server handler module that acts as an interface to clients as well as other server handlers in the system. Each client connects to one of the server handlers that handles the client query (similar to Cassandra [21]). The server handler interacts with other server handlers to execute queries and to maintain the necessary system state. BlowFish server handlers are also responsible for query scheduling and load balancing, and for making decisions on how shards share the cache available at the *local* server. We discuss these functionalities below.

3.2.2 Query execution

Similar to existing data stores [1, 4, 21], an incoming query in BlowFish may touch one or more shards depending on the sharding scheme. The server handler handling the query is responsible for forwarding the query to the server handler(s) of the corresponding shard(s); we discuss query scheduling across shard replicas below. Whenever possible, the query results from multiple shards on the same server are aggregated by the server handler.

Random access and search. BlowFish does *not* require changes in Succinct algorithms for executing queries at each shard, with the exception of looking up values in sampled arrays[4]. In particular, since the two sampled arrays in Succinct — Input2AoS and AoS2Input — are replaced by LSA, the corresponding lookup algorithms are replaced by lookup algorithms for LSA (§2.3, Figure 4). We note that, by using `ExistsLayer` flag, BlowFish makes LSA lookup algorithms transparent to existing layers and query execution.

Updates. BlowFish implements data appends exactly as Succinct [7] does. Specifically, BlowFish uses a multi-store architecture with a write-optimized LogStore that supports fine-grained appends, a query-optimized SuffixStore that supports bulk appends and a memory-optimized SuccinctStore. LogStore and SuffixStore, for typical cluster configurations, store less than 0.1% of the entire dataset (the most recently added data). BlowFish does not require changes in LogStore and SuffixStore implementation, and enables the storage-performance tradeoff for data only in SuccinctStore. Since the storage and the performance of the system is dominated by SuccinctStore, the storage-performance tradeoff curve of BlowFish is not impacted by update operations.

3.2.3 Scheduling and Load Balancing

BlowFish server handlers maintain the request queue lengths for each shard in the system. Each server handler periodically monitors and records the request queue lengths for *local* shards. For non-local shards, the request queue lengths are collected during the query phase — server handlers encapsulate the request queue lengths for their local shards in the query responses. Upon receiving a query response, a server handler decapsulates the request queue lengths and updates its local metadata to record the new lengths for the corresponding shards.

Each shard (and shard replica) in BlowFish may operate on a different point on the storage-performance curve (Figure 3). Thus, different replicas of the same shard may have different query execution time for the same query. To efficiently schedule queries across such a heterogeneous system, BlowFish adopts techniques from scheduling theory literature — a back-pressure scheduling style Join-the-shortest-queue [19] mechanism. An incoming query

[4]The description of these algorithms is not required to keep the paper self-contained; we refer the reader to [7] for details.

for a shard is forwarded to the replica with the smallest request queue length. By conceptually modeling this problem as replicas having the same speed but varying job sizes (for the same query), the analysis for Join-the-shortest-queue [19] applies to BlowFish, implying close to optimal load balancing.

3.2.4 Dynamically Navigating the Tradeoff

BlowFish uses the request queues not only for scheduling and load balancing, but also to trigger navigation along the storage-performance tradeoff curve for each individual shard. We discuss below the details on tradeoff navigation, and how this enables efficient cache sharing among shards within and across servers.

One challenge in using request queue lengths as an approximation to load on the shard is to differentiate short-term spikes from persistent overloading of shards (Figure 5). To achieve this, BlowFish server handlers also maintain exponentially averaged queue lengths for each local shard — the queue lengths are monitored every δ time units, and the exponentially averaged queue length at time t is computed as:

$$Q_t^{avg} = \beta \times Q_t + (1-\beta) \times Q_{t-\delta}^{avg} \quad (1)$$

The parameters β and δ provide two knobs for approximating the load on a shard based on its request queue length. β is a fraction ($\beta < 1$) that determines the contribution of more recent queue length values to the average — larger β assigns higher weight to more recent values in the average. δ is the periodicity at which queue lengths are averaged — smaller values of δ (i.e., more frequent averaging) results in higher sensitivity to bursts in queue length. Note that a small exponentially average queue length implies a persistently underloaded shard.

We now describe how shards share the available cache within and across servers by dynamically navigating along the storage-performance tradeoff curve. We start with the relatively simpler case of shards on the same server, and then describe the case of shards across servers.

Shards on the same server. Recall that BlowFish implementation adds and deletes layers in a bottom-up fashion, with each layer storing sampled values for powers of two. Thus, at any instant, the sampling rate of LSA is a power of two $(2,4,8,\ldots)$. For each of these sampling rates, BlowFish stores two *threshold* values. The *upper threshold* value is used to trigger storage increase for any particular shard — when the exponentially averaged queue length of a shard S crosses the upper threshold value, S must be consistently overloaded and must increase its throughput.

However, the server may not have extra cache to sustain the increased storage for S. For such scenarios, BlowFish stores a *lower threshold* value which is used to trigger storage reduction. In particular, if the exponentially averaged queue length *and* the instantaneous request queue length for one of the other shards S' on the same server is below the lower threshold, BlowFish reduces the storage for S' before triggering the storage increase for S. If there is no such S', the server must already be throughput bottlenecked and the navigation for S is not triggered.

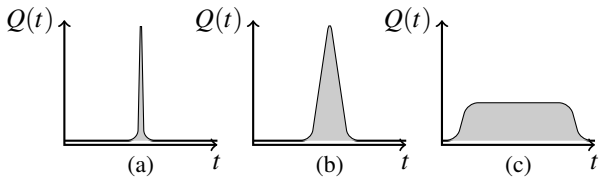


Figure 5: Three different scenarios of queue length ($Q(t)$) variation with time (t). (a) shows a very short-lasting "spike", (b) shows a longer lasting spike while (c) shows a persistent "plateau" in queue-length values. BlowFish should ideally ignore spikes as in (a) and attempt to adapt to the queue length variations depicted in (b) and (c).

We make two observations. First, the goals of exponentially averaged queue lengths and two threshold values are rather different: the former makes BlowFish stable against temporary spikes in load, while the latter against "flap damping" of load on the shards. Second, under stable loads, the above technique for triggering navigation along the tradeoff curve allows each shard on the same server to share cache proportional to its throughput requirements.

Shard replicas across servers. At the outset, it may seem like shards (and shard replicas) across servers need to coordinate among themselves to efficiently share the total system cache. It turns out that local cache sharing, as described above, combined with BlowFish's scheduling technique implicitly provides such a coordination.

Consider a shard S with two replicas R1 and R2, both operating at the same point on the tradeoff curve and having equal queue lengths. The incoming queries are thus equally distributed across R1 and R2. If the load on S increases gradually, both R1 and R2 will eventually experience load higher than the throughput they can support. At this point, the request queue lengths at R1 and R2 start building up at the same rate. Suppose R2 shares the server with other heavily loaded shards (that is, R2 can not navigate up the tradeoff curve). BlowFish will then trigger a layer creation for R1 only. R1 can thus support higher throughput and its request queue length will decrease. BlowFish's scheduling technique kicks in here: incoming queries will now be routed to R1 rather than equal load balancing, resulting in lower load at R2. It is easy to see that at this point, BlowFish will load balance queries to R1 and R2 proportional to their respective throughputs.

4 Evaluation

BlowFish is implemented in ≈ 2K lines of C++ on top of Succinct [7]. We apply BlowFish to application domains outlined in §1.1 and compare its performance against state-of-the-art schemes for each application domain.

Evaluation Setup. We describe the setup used for each application in respective subsections. We describe here what is consistent across all the applications: dataset and query workload. We use the TPC-H benchmark dataset [6], that consists of records with 8 byte keys and roughly 140 byte values on an average; the values comprise of 15 attributes (or columns). We note that several of our evaluation results are independent of the underlying dataset (*e.g.*, bandwidth for data repair, time taken to navigate along the tradeoff curve, etc.) and depend only on amount of data per server.

We use a query workload that comprises of 50% random access queries and 50% search queries; we discuss the impact of varying the fraction of random access and search queries in §4.1. Random access queries return the entire value, given a key. Search queries take in an (attribute, value) pair and return all keys whose entry for the input attribute matches the value. We use three query distributions in our evaluation for generating queries over the key space (for random access) and over the attribute values (for search). First, *uniform distribution* with queries distributed uniformly across key space and attribute values; this essentially constitutes a worst-case scenario for BlowFish[5]. The remaining two query workloads follow *Zipf distribution with skewness* 0.99 *(low skew) and* 0.01 *(heavily skewed)*, the last one constituting the best-case scenario for BlowFish.

All our distributed experiments run on Amazon EC2 cluster comprising of c3.2xlarge servers, with 15GB RAM backed by two 80GB SSDs and 8 vCPUs. Unless mentioned otherwise, all our experiments shard the input data into 8GB shards and use one shard per CPU core.

4.1 Storage Performance Tradeoff

We start by evaluating the storage-performance tradeoff curve enabled by BlowFish. Figure 6 shows this tradeoff for query workload comprising of 50% random access and 50% search queries; Appendix B presents the curves for other workloads. Note that the tradeoff for mixed workload has characteristics similar to 100% `search` workload (Appendix B) since, similar to other systems, execution time for search is significantly higher than random access. The throughput is, thus, dominated by search latency.

[5]Intuitively, queries distributed uniformly across shards and across records alleviates the need for shards having varying storage footprints.

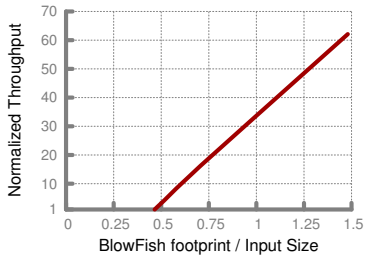


Figure 6: Storage-throughput tradeoff curve (per thread) enabled by BlowFish. The y-axis is normalized by the throughput of smallest possible storage footprint (71ops) in BlowFish.

We make two observations in Figure 6. First, BlowFish achieves storage footprint varying from 0.5× to 8.7× the input data size (while supporting search functionality; the figure shows only up to 1.5× the data size for clarity)[6]. In particular, BlowFish does not enforce compression. Second, increase in storage leads to super-linear increase in throughput (moving from ≈ 0.5 to ≈ 0.75 leads to 20× increase in throughput) due to non-linear computational cost of operating on compressed data [7].

4.2 Data Repair During Failures

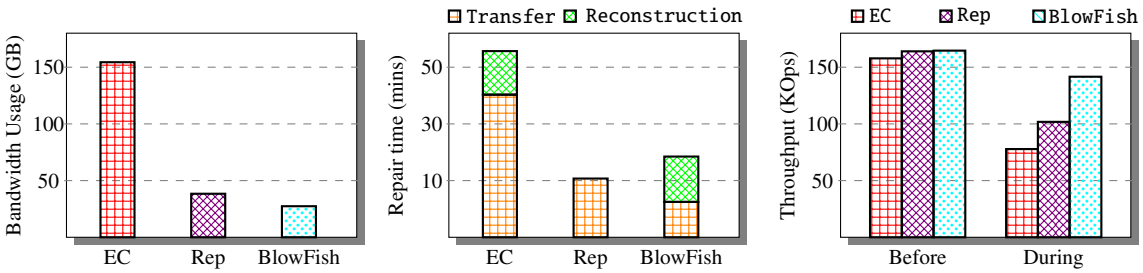
We now apply BlowFish to the first application: efficient data recovery upon failures.

Existing techniques and BlowFish tradeoffs. Two techniques exist for data repair during failures: replication and erasure codes. The main tradeoff is that of storage and bandwidth, as shown in Table 1. Note that this tradeoff is hard; that is, for both replication and erasure codes, the storage overhead and the bandwidth for data repair is fixed for a fixed fault tolerance. We discuss related work in §5, but note that erasure codes remain inefficient for data stores serving small objects due to high repair time and/or bandwidth requirements.

4.2.1 Experimental Setup

We perform evaluation along four metrics: storage overhead, bandwidth and time required for data repair, and throughput before and during failures. Since none of the open-source data stores support erasure codes, we use an implementation of Reed-Solomon (RS) codes [2]. The code use 10 data blocks and 2 parity blocks, similar to those used at Facebook [24, 29], but for two failure case. Accordingly, we use 3× replication. For BlowFish, we use an instantiation that uses three replicas with storage 0.9×, 0.5× and 0.5×, aggregating to 1.9× storage — an operating point between erasure codes and replication.

[6]The smallest footprint is 0.5× since TPC-H data is not very compressible, achieving compression factor of 3.1 using gzip.



(a) Bandwidth (b) Repair Time (c) Throughput

Figure 7: Comparison of BlowFish against RS erasure codes and replication (discussion in §4.2.2). BlowFish requires 5.4× lower bandwidth for data repair compared to erasure codes, leading to 2.5× faster repair time. BlowFish achieves throughput comparable to erasure codes and replication under no failures, and $1.4-1.8\times$ higher throughput during failures.

We use 12 server EC2 cluster to put data and parity blocks on separate servers; each server contains both data and parity blocks, but not for the same data. Replicas for replication and BlowFish were also distributed similarly. We use 160GB of total raw data distributed across 20 shards. The corresponding storage for erasure codes, replication and BlowFish is, thus, 192, 480 and 310GB. Note that the cluster has 180GB main memory. Thus, all data shards for erasure codes fit in memory, while a part of BlowFish and replication data is spilled to disk (modeling storage-constrained systems).

We use uniform query distribution (across shards and across records) for throughput results. Recall that this distribution constitutes a worst-case scenario for BlowFish. We measure the throughput for the mixed 50% random access and 50% search workload.

4.2.2 Results

Storage and Bandwidth. As discussed above, RS codes, replication and BlowFish have a storage overhead of 1.2×, 3× and 1.9×. In terms of bandwidth, we note that the three schemes require storing 16, 40 and 26GB of data per server, respectively. Figure 7(a) shows the corresponding bandwidth requirements for data repair for the three schemes. Note that while erasure codes require 10× bandwidth compared to replication *for each individual failed shard*, the overall bandwidth requirements are less than 10× since each server in erasure coded case also stores lesser data due to lower storage footprint of erasure codes (best case scenario for erasure codes along all metrics).

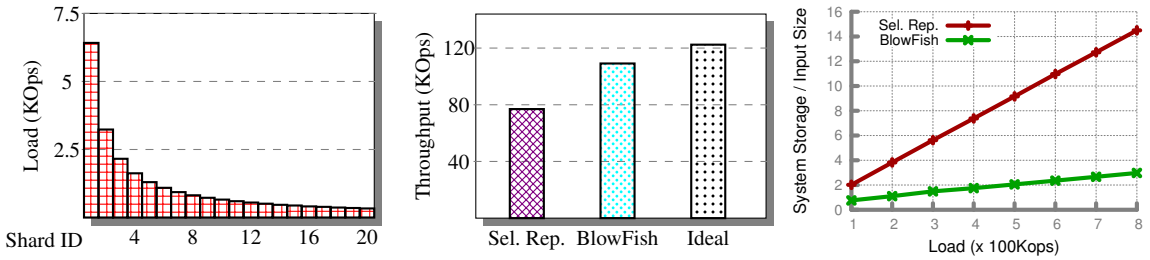
Repair time. The time taken to repair the failed data is a sum of two factors — time taken to copy the data required for recovery (transfer time), and computations required by the respective schemes to restore the failed data (reconstruction time). Figure 7(b) compares the data repair time for BlowFish against replication and RS codes.

RS codes require roughly 5× higher transfer time compared to BlowFish. Although erasure codes read the required data in parallel from multiple servers, the access link at the server where the data is being collected becomes the network bottleneck. This is further exacerbated since these servers are also serving queries. The decoding time of RS codes is similar to reconstruction time for BlowFish. Overall, BlowFish is roughly 2.5× faster than RS codes and 1.4× slower than replication in terms of time taken to restore system state after failures.

Throughput. The throughput results for the three schemes expose an interesting tradeoff (see Figure 7(c)).

When there are no failures, all the three schemes achieve comparable throughput. This is rather non-intuitive since replication has three replicas to serve queries while erasure codes have only one and BlowFish has replicas operating at smaller storage footprints. However, recall that the cluster is bottlenecked by the capacity of faster storage. If we load balance the queries in replication and in BlowFish across the three replicas, many of these queries are executed off SSD, thus reducing the overall system throughput (much more for replication since many more queries are executed off SSD). To that end, we evaluated the case of replication and BlowFish where queries are load balanced to only one replica; in this case, as expected, all the three schemes achieve comparable throughput.

During failures, the throughput for both erasure codes and replication reduces significantly. For RS codes, 10 out of (remaining) 11 servers are used to both read the data required for recovery as well as to serve queries. This severely affects the overall RS throughput (reducing it by 2×). For replication, note that the amount of failed data is 40GB (five shards). Recovering these shards results in replication creating two kinds of interference: interfering



(a) Load distribution across shards (b) Throughput for a fixed storage (c) Storage required to sustain load

Figure 8: Comparison of BlowFish and selective caching for skewed workload application. See §4.3 for discussion.

with queries being answered on data unaffected by failures *and* queries answered on failed server now being answered off-SSD from remaining servers. This interference reduces the replication throughput by almost 33%. Note that both these interferences are minimal in BlowFish: fewer shards need be constructed, thus fewer servers are interfered with, and fewer queries go to SSD. It turns out that the interference is minimal, and BlowFish observes minimal throughput reduction (less than 12%) during failures. As a result, BlowFish throughput during failures is is $1.4-1.8\times$ higher than the other two schemes.

4.3 Skewed Workloads

We now apply BlowFish to the problem of efficiently utilizing the system cache for workloads with skewed query distribution across shards (*e.g.*, more queries on hot data and fewer queries on warm data). The case of skew across shards varying with time is evaluated in next subsection.

State-of-the-art. The state-of-the-art technique for handling spatially-skewed workloads in Selective caching [8] that caches, for each object, number of replicas proportional to the load on the object.

4.3.1 Experimental Setup

We use 20 data shards, each comprising of 8GB of raw data, for this experiment. We compare BlowFish and Selective caching using two approaches. In the first approach, we fix the cluster (amount of fast storage) and *measure* the maximum possible throughput that each scheme can sustain. In the second approach, we vary the load for the two schemes and *compute* the amount of fast storage required by each scheme to sustain that load.

For the former, we use a cluster with 8 EC2 servers. A large number of clients generate queries with a Zipf distribution with skewness 0.01 (heavily skewed) across the shards. As shown in Figure 8(a), the load on the heaviest shard using this distribution is $20\times$ the load on the lightest shard — this models the real-world scenario of a few shards being "hot" and most of the shards being "cold". For selective caching, each shard has number of replicas proportional to its load (recall, total storage is fixed); for BlowFish, the shard operates at a point on the tradeoff curve that can sustain the load with minimal storage overhead. We distribute the shards randomly across the available servers. For the latter, we vary the load and compute the amount of fast storage required by the two schemes to meet the load assuming that the entire data fits in fast storage. Here, we increase the number of shards to 100 to perform computations for a more realistic cluster size.

4.3.2 Results

For fixed storage. The storage required for selective caching and BlowFish to meet the load is 155.52GB and 118.96GB, respectively. Since storage is constrained, some shards in selective caching can not serve queries from faster storage. Intuitively, this is because BlowFish provides a finer-grained tradeoff (increasing the storage overhead fractionally, just enough to meet the performance goals) compared to the coarse-grained tradeoff of selective replication (throughput can be increased only by $2\times$ by adding another replica requiring $1\times$ higher storage overhead). Thus, BlowFish utilizes the available system cache more efficiently. Figure 8(b) shows that this leads to BlowFish achieving $1.5\times$ higher throughput than selective caching. Interestingly, BlowFish achieves 89% of the ideal throughput, where the ideal is computed by taking into account the load skew across shards, the total system storage, the maximum possible per-shard throughput per server, and by placing heavily loaded shards with lightly loaded shards. The remaining 11% is attributed to the random placement of shards across servers, resulting in some servers being throughput bottlenecked.

Fixed load. Figure 8(c) shows that, as expected, BlowFish requires $2.7-4.9\times$ lower amount of fast storage compared to selective caching to sustain the load.

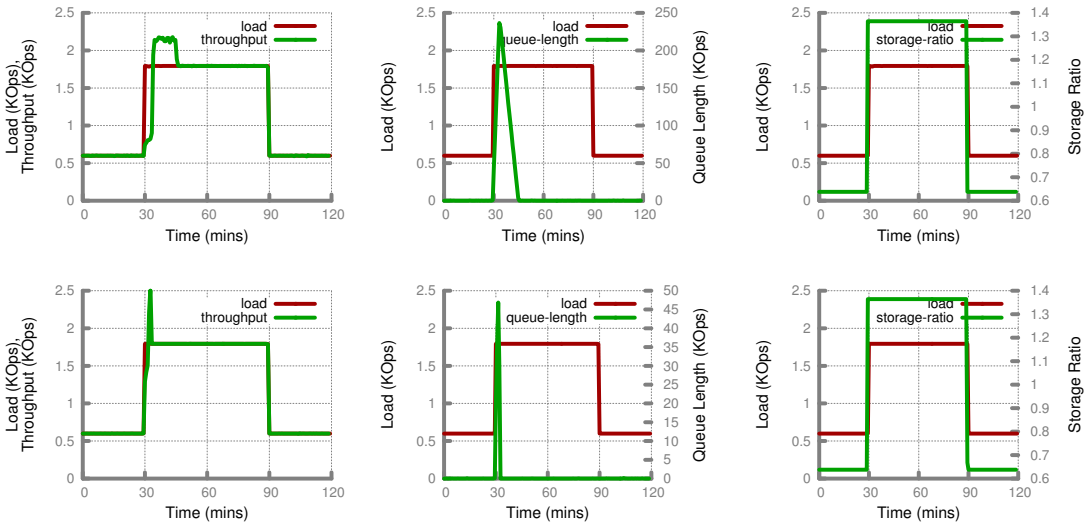


Figure 9: Opportunistic layer construction with spiked changes in load for uniform workload (top three) and skewed workload (bottom three). The figures show variation in throughput (left), request queue length (center) and storage footprint (right).

4.4 Time-varying workloads

We now evaluate BlowFish's ability to *adapt* to time-varying load, in terms of time taken to adapt and queue stability. We also evaluate the performance of BlowFish's scheduling technique during such time-varying loads.

4.4.1 Experimental Setup

We perform micro-benchmarks to focus on adaptation time, queue stability and per-thread shard throughput for time-varying workloads. We use a number of clients to generate time-varying load on the system. We performed four sets of experiments: uniform and skewed (Zipf with skewness 0.01) query distribution (across queried keys and search terms); and, gradual and spiked variations in load. It is easy to see that (uniform, spiked) and (skewed, gradual) are the worst-case and the best-case scenario for BlowFish, respectively. We present results for spiked variations in load (*e.g.*, due to transient failures) for both uniform and skewed query distribution; the remaining results are in Appendix C. We perform micro-benchmarks by increasing the load on the shard from 600ops to 1800ops suddenly (3× increase in load models failures of two replicas, an extremely unlikely scenario) at time $t = 30$ and observe the system for an hour before dropping down the load back to 600ops at time $t = 90$.

4.4.2 Results

BlowFish adaptation time and queue stability. As the load is increased from 600ops to 1800ops, the throughput supported by the shard at that storage ratio is insufficient to meet the increased load (Figures 9(a) and 9(d)). As a result, the request queue length for the shard increases (Figures 9(b) and 9(e)). At one point, BlowFish triggers *opportunistic layer creation* — the system immediately allocates additional storage for the two sampled arrays (increased storage ratio in Figures 9(c) and 9(f)); the sampled values are filled in gradually as queries are executed.

At this point, the results for uniform and skewed query distribution differ. For the uniform case, the already filled sampled values are reused infrequently. Thus, it takes BlowFish longer to adapt (≈ 5 minutes) before it starts draining the request queue (the peak in Figure 9(b)). BlowFish is able to drain the entire request queue within 15 minutes, making the system stable at that point.

For the skewed workload, the sampled values computed during query execution are reused frequently since queries repeat frequently. Thus, BlowFish is able to adapt much faster (≈ 2minutes) and drain the queues within 5 minutes. Note that this is akin to caching of results, explicitly implemented in many existing data stores [1, 4, 21] while BlowFish provides this functionality inherently.

BlowFish scheduling. To evaluate the effectiveness and stability of BlowFish scheduling, we turn our attention to a distributed setting. We focus our attention on three replicas of the same shard. We make the server storing one of these replicas storage constrained (replica #3); that is, irrespective of the load, the replica cannot trigger navigation along the storage-performance tradeoff curve. We then gradually increase the workload from 3KOps to 8KOps in steps of 1KOps per 30 minutes (Figure 10) and observe the behavior of request queues at the three replicas.

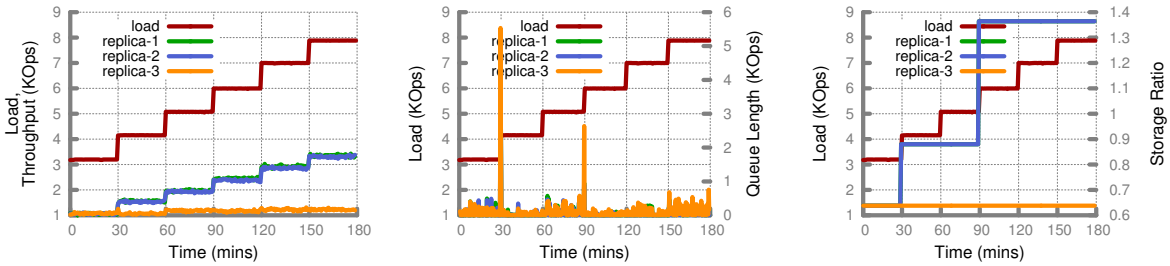


Figure 10: The effectiveness and stability of BlowFish's query scheduling mechanism in a replicated system (discussion in §4.4). Variation in throughput (left), request queue lengths (center) and storage-footprints (right) for the three replicas.

Initially, each of the three replicas observe a load of 1KOps since queue sizes are equal, and BlowFish scheduler equally balances the load. As the load is increased to 4KOps, the replicas are no longer able to match the load, causing the request queues at the replicas to build up (Figure 10(c)). Once the queue lengths cross the threshold, replica #1 and #2 trigger layer construction to match higher load (Figure 10(a)).

As the first two replicas opportunistically add layers, their throughput increases; however, the throughput for the third replicas remains consistent (Figure 10(b)). This causes the request queue to build up for the third replica at a rate higher than the other two replicas (Figure 10(c)). Interestingly, the BlowFish reduces quickly adapts, and stops issuing queries to replica#3, causing its request queue length to start dropping. We observe a similar trend when the load increases to 5KOps. BlowFish does observe queue length oscillations during adaptation, albeit of extremely small magnitude.

5 Related Work

BlowFish's goals are related to three key areas:

Storage-performance tradeoff. Existing data stores usually support two extreme operating points for each cached shard — compressed but low throughput, and uncompressed but high throughput. Several compression techniques (*e.g.*, gzip) can allow achieving different compression factors by changing parameters. However, these require decompression and re-compression of the entire data on the shard. As shown in the paper, a smooth and dynamic storage-performance tradeoff not only provides benefits for existing applications but can also enable a wide range of new applications.

Data repair. The tradeoff between known techniques for data repair — replication and erasure codes — is that of storage overhead and bandwidth. Studies have shown that the bandwidth requirement of traditional erasure codes is simply too high to use them in practice [29]. Several research proposals [20, 27, 29] reduce the bandwidth requirements of traditional erasure codes for batch processing jobs. However, these codes remain inefficient for data stores serving small objects. As shown in §4, BlowFish achieves storage close to erasure codes, while maintaining the bandwidth and repair time advantages of replication.

Selective Caching. As discussed in §1 and §4, selective caching can achieve good performance for workloads skewed towards a few popular objects. However, it only provides a coarse-grained support — increasing the throughput by 2× by increasing the storage overhead by 1×. BlowFish, instead, provides a much finer-grained control allowing applications to increase the storage fractionally, just enough to meet the performance goals.

6 Conclusion

BlowFish is a distributed data store that enables a smooth storage-performance tradeoff between two extremes — compressed but low throughput and uncompressed but high throughput. In addition, BlowFish allows applications to navigate along this tradeoff curve over fine-grained time scales. Using this flexibility, we explored several problems from real-world production clusters from a new "lens" and showed that the tradeoff exposed by BlowFish can offer significant benefits compared to state-of-the-art techniques for the respective problems.

Acknowledgments

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A Layered Sampled Array Lookup, and Opportunistic layer creation

We outline how lookups are performed on the LSA (§3.1) in Algorithm 1. At a high level, given the LSA index, we obtain the layer ID and index into the corresponding layer using LSA's auxiliary structures (see Figure 4). We use the layer ID to locate the layer, and obtain the required value using the index into the layer.

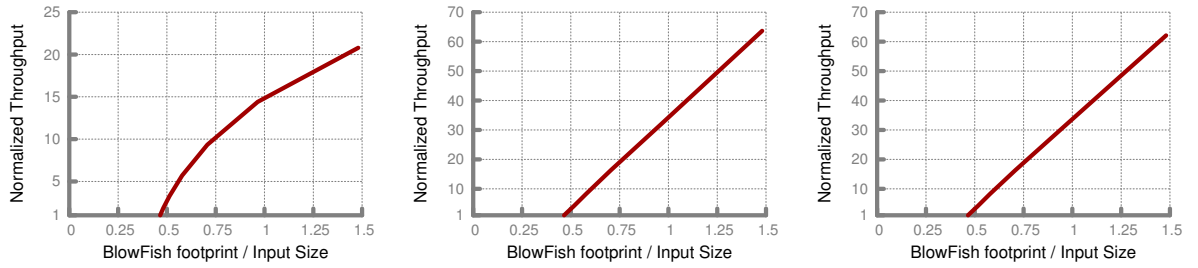
Algorithm 2 describes how BlowFish creates new layers *opportunistically* (§3.1); that is, rather than using dedicated resources to compute the required sampled values upon a new layer creation, BlowFish uses the computations performed during query execution to opportunistically populate the sampled values in the new layer.

Algorithm 1 `LookupLSA`

```
1:  procedure GetLayerID (idx)   ▷ Get the layer ID given the index into the sampled array; α is the sampling rate.
2:      return LayerID[idx % α]
3:  end procedure
4:  procedure GetLayerIdx(idx) ▷ Get the index into LayerID given the index into the sampled array; α is the sampling rate.
5:      count ← Count[LayerID(idx)]
6:      return count × (idx / α) + LayerIdx[idx % α]
7:  end procedure
8:  procedure LookupLSA (idx)        ▷ Performs lookup on the LSA.
9:      if IsSampled(idx) then
10:         l_id ← GetLayerID(idx)                ▷ Get layer ID.
11:         l_idx ← GetLayerIdx(idx)              ▷ Get index into layer.
12:         return SampledArray[l_id][l_idx]
13:     end if
14: end procedure
```

B Storage-throughput Tradeoff for different workloads

Figure 6 in §4 shows the storage-throughput tradeoff enabled by BlowFish for query workload comprising of 50% random access and 50% search queries. Figure 11 shows this tradeoff for other workloads. In particular, Figure 11(a) and Figure 11(b) show the storage-throughput tradeoff for workloads comprising of 100% random access and 100% search queries, respectively. Note that the tradeoff for mixed workload has characteristics similar to 100% `search` workload since, similar to other systems, execution time for search is significantly higher than random access. The throughput of the system is, thus, dominated by latency of search queries.



(a) 100% `random access` (b) 100% `search` (c) 50% `random access` + 50% `search`

Figure 11: Storage-throughput tradeoff curve (per thread) enabled by BlowFish for three workloads with varying fraction of `random access` and `search` queries. The y-axis is normalized by the throughput of smallest possible storage footprint in BlowFish (3874ops for random access only, 37ops for search only, and 71ops for the mixed workload).

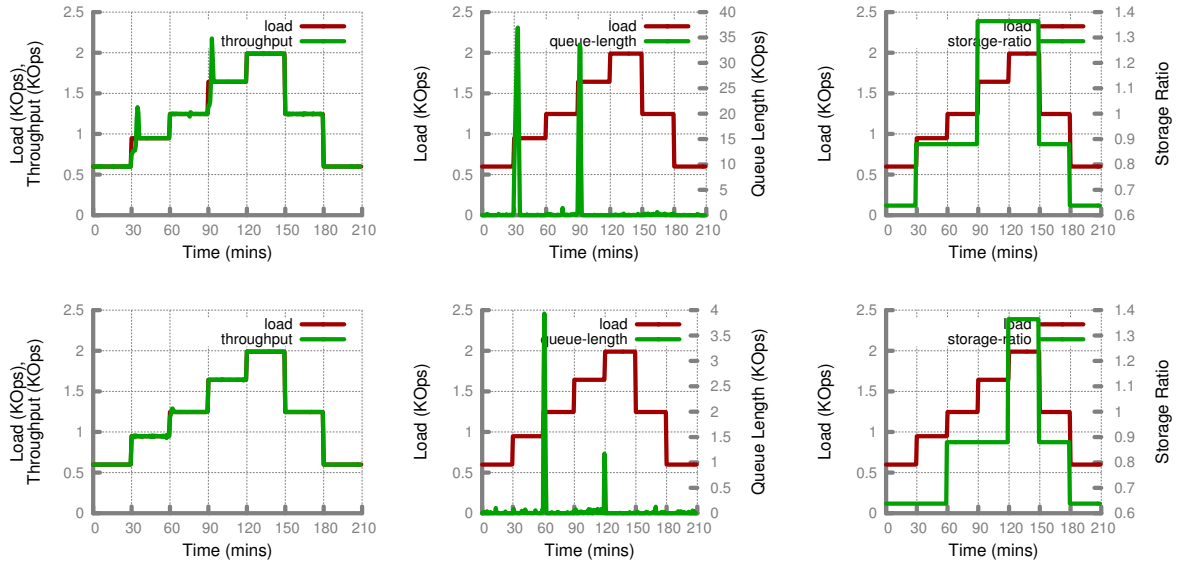


Figure 12: Opportunistic layer construction with gradual changes in load for uniform workload (top three) and skewed workload (bottom three). The figures show variation in throughput (left), request queue length (center) and storage footprint (right).

C Gradual Workload Variation

We present the results for how BlowFish adapts to time-varying workloads with a setup identical to §4.4, but for slightly different variations in the workload. In particular, instead of increasing the load on the shard from 600ops to 1800ops suddenly (as in the results of Figure 9), we increase the load from 600ops to 2000ops, with a gradual increase of 350ops at 30 minute intervals. This granularity of increase in load is similar to those reported in real-world production clusters [9], and constitutes a much easier case for BlowFish compared to the spiked increase in load considered in §4.4.

Uniform query distribution (Figure 12, top). As the load increases from 600ops to 950ops (Figure 12(a)), the load becomes higher than the throughput supported by the shard at that storage ratio (800ops). Consequently, the request queue length starts building up (Figure 12(b)), and BlowFish triggers a layer addition by allocating space for the new layers (Figure 12(c)). BlowFish opportunistically fills up values in the new layer, and the throughput for the shard increases gradually. This continues until the throughput matches the load on the shard; at this point, however, the throughput continues to increase even beyond the load to deplete the outstanding requests in the queue until the queue length reduces to zero and the system resumes normal operation. A similar trend can be seen when the load is increased to 1650ops.

Algorithm 2 `CreateLayerOpportunistic`

1: **procedure** `CreateLayerOpportunistic`(l_{id}) ▷ Marks layer l_{id} for creation, and initializes bitmap marking layer's sampled values; α is the sampling rate.
2: Mark layer l_{id} for creation.
3: LayerSize ← InputSize/2α
4: **for** l_{idx} in (0, LayerSize − 1) **do**
5: `IsLayerValueSampled`[l_{id}][l_{idx}] ← `0`
6: **end for**
7: **end procedure**
8: **procedure** `OpportunisticPopulate(val, idx)` ▷ Exploit query execution to populate layers opportunistically; `val` is the unsampled values computed during query execution, and `idx` is its index into the unsampled array.
9: l_{id} ← `GetLayerID(idx)` ▷ Get layer ID.
10: **if** layer l_{id} is marked for creation **then**
11: l_{idx} ← `GetLayerIdx(idx)` ▷ Get index into layer.
12: `SampledArray`[l_{id}][l_{idx}] ← *val*
13: `IsLayerValueSampled`[l_{id}][l_{idx}] ← 1
14: **end if**
15: **end procedure**

Skewed query distribution (Figure 12, bottom). The trends observed for the skewed workload are similar to those for the uniform worklod, with two key differences. First, we observe that BlowFish triggers layer creation at different points for this workload. In particular, the throughput for the skewed workload at the same storage footprint (0.8 in Figure 12(c) and 12(f)) is higher than that for the uniform workload. To see why, note that the performance of `search` operations varies significantly based on the queries; while the different queries contribute equally for the uniform workload, the throughput for the skewed workload is shaped by the queries that occur more frequently. This effect attributes for the different throughput characteristics for the two workloads at the same storage footprint.

Second, as noted before (§4.4), BlowFish adaptation benefits from the repetitive nature of queries in the skewed workload, since repeated queries can reuse the values populated during their previous execution. In comparison to uniform query distribution, this leads to faster adaptation to increase in load and quicker depletion of the increased request queue lengths.

Comparison with results for the spiked case. Note the difference in results for the case of spiked increase in load (Figure 9) and gradual increase in load (Figure 12). In the former case, the increase in load leads to significantly higher request queue lengths and hence, it takes much longer for the sytem to return to normal operations. In the latter, however, due to gradual increase in load, the system can drain the outstanding request queue significantly faster, can resume normal operations faster, and thus provides adaptation at much finer time granularity.