BetrFS: A Compleat File System for Commodity SSDs

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Abstract

Despite the existence of file systems tailored for flash and over a decade of research into flash file systems, this paper shows that no single Linux file system performs consistently well on a commodity SSD across different workloads. We define a *compleat* file system as one where no workloads realize less than 30% of the best file system's performance, and most, if not all, workloads realize at least 85% of the best file system's performance, across a diverse set of microbenchmarks and applications. No file system is compleat on commodity SSDs. This paper demonstrates that one can construct a single compleat file system for commodity SSDs by introducing a set of optimizations over BetrFS. BetrFS is a compleat file system on HDDs, matching the fastest Linux file systems in its worst cases, and, in its best cases, improving performance by up to two orders of magnitude.

Our optimized BetrFS (i.e., v0.6) is not only compleat, it is either the fastest or within 15% of the fastest general-purpose Linux file system on a range of microbenchmarks. At best, these optimizations improve random write throughput by 6× compared to the fastest SSD file system. At worst, our file system is competitive with the other baseline file systems. These improvements translate to application-level gains; for instance, compared to other commodity file systems, the Dovecot mailserver and an rsync of the Linux source on BetrFS show speedups of 1.13× and 1.8×, respectively.

CCS Concepts: • **Information systems** → **Flash memory**; • **Software and its engineering** → **File systems management**; • **General and reference** → *Performance*.

Keywords: B^{ε}-trees, file system, solid-state drive, write optimization

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1 Introduction

Flash-based Solid State Drives (SSDs) are ubiquitous. Unfortunately, there is no single file system that performs consistently well across a range of different operations or workloads on commodity SSDs. Table 1 (details in §7) illustrates this point: among a set of common general-purpose Linux file systems, no single design offers top-of-the-line performance across the board. In each benchmark, performance tends to be bi-modal: each file system is either within 15% of the best, or very far from it.

Even F2FS [16], a log-structured file system designed explicitly for SSDs, fails to extract the device's full throughput for random-writes—a workload where log-structured designs should shine. These results are corroborated elsewhere; for instance, one study shows that ext4 is the fastest file system for blogbench, whereas F2FS is the fastest on the same SSD for compile bench, and XFS is the fastest for dbench [15].

In all of these benchmarks, the slowest file system ranged from roughly a *half to a fifth* of the performance of the fastest. The end result is that, at installation time, a system administrator decides which workloads will enjoy the underlying hardware's full performance, and which ones will be bottlenecked on the file system. Although work is ongoing to design and leverage high-end flash storage devices, such as NVMe and non-volatile main memory, this paper focuses on inexpensive SSDs because current file systems already leave performance on the table with slower SSDs. Moreover, addressing these computational bottlenecks is a prerequisite to saturating faster flash devices. Further, commodity SSDs still represent a tremendous share of deployments worldwide.

This paper investigates whether it is possible to construct a file system with consistently good performance across operations and workloads on commodity SSDs. To our knowledge, there is not an established metric for consistently good performance in a file system, versus sacrificing one operation's performance for another; we adopt the term **compleat**[1] to capture this notion of consistently good performance. Concretely, given a set of representative workloads, we set a goal of building a file system where no operation is worse than 30% of the best implementation, and most, if not all, realize at least 85% of the best implementation's performance. In Table 1, data points where a file system realizes less than 30% of the best file system's performance are shaded in red, and those that realize more than 85% of the best implementation's performance are shaded in green. Every baseline file system has at least one red cell. We note that our empirical definition of compleat is imperfect; one could select a different set of workloads, or perhaps tie file system performance targets to the performance of the underlying hardware. Our interest is in establishing a specific and measurable target. This paper demonstrates that it is possible to build a compleat file system.

Recently, file systems built using write-optimized dictionaries (WODs), such as LSM-trees or B$^{\varepsilon}$-trees, have achieved compleatness on an HDD. Specifically, BetrFS [5, 9, 39–41] contributes a number of data-structural and system optimizations to realize this goal. By using a WOD to index persistent data, a write-optimized file system can offer sequential reads and writes at disk bandwidth while performing random writes orders-of-magnitude faster than an update-in-place file system. BetrFS uses full-paths as keys [40] to ensure that logical locality in the directory hierarchy translates to physical locality on the device, minimizing seeks on a disk or minimizing total IOs on an SSD [23]. By using a WOD in combination with full-path indexing and large (2–4 MiB) nodes, BetrFS realizes top-of-line search performance and resists aging [5]. Compared to a general-purpose key-value workload, BetrFS's key-value workload features many operations that modify a contiguous range of key-value pairs, such as recursive deletion or renaming a directory; BetrFS contributes several optimizations and API extensions to ensure a performant, one-to-one mapping between file-system and key-value operations. Finally, BetrFS has innovated in data-structural techniques to batch and amortize the cost of complex operations, such as `rename` [41], as well as amortizing the cost of data structure maintenance in copy-on-abundant-write snapshots [40].

Unfortunately, many of the BetrFS performance properties do not immediately translate to SSDs. In particular, Table 1 shows that, on a commodity SSD, BetrFS only achieves a third to a sixth of the sequential bandwidth of other file systems, and the gains for searches are mixed. It may seem counter-intuitive that a file system would exhibit such different performance profiles when the only system change is a faster block device, but there are principled reasons why this is so.

This paper investigates these bottlenecks and contributes techniques that enable a file system to offer top-of-the-line performance across a wide range of benchmarks on commodity SSDs. We present and evaluate these results in a prototype file system, called **BetrFS v0.6**, available at github.com/oscarlab/betrfs (additional details in the Appendix). In this paper, we compare to version 0.4; v0.5 contributes orthogonal optimizations to implement nimble clones [41].

Consolidated layering (§3). BetrFS's B$^{\varepsilon}$-tree is stacked on ext4, essentially using ext4 as a block allocator; this stacking has acceptable costs for an HDD, but not for an SSD. This paper presents a simplified storage substrate for an in-kernel write-optimized key-value store on faster devices. In several cases, clarifying the division of labor among layers requires modifying the key-value store to implement functionality in different ways, such as moving read-ahead into the key-value store layer. In other cases, such as with metadata caching, the VFS structures are specialized and effective; minor changes to BetrFS's VFS interaction yields more effective batching of metadata updates, and better economizes B$^{\varepsilon}$-tree queries. In

[1] **compleat**, *adjective*, having all necessary or desired elements or skills.

File	Sequential I/O		Random Writes			Utility Latency		
System	Read(80g)	Write(80g)	4 KB	4 Byte	Tokubench	grep	rm	find
Btrfs	568 (0)	328 (2)	13 (0)	0.024 (0)	6.0 (0.2)	4.61 (0.21)	2.53 (0.05)	0.78 (0.16)
ext4	534 (0)	316 (6)	16 (3)	0.026 (0)	13.6 (1.5)	10.15 (0.20)	1.81 (0.08)	0.86 (0.02)
F2FS	528 (1)	320 (6)	16 (2)	0.033 (0)	4.7 (0.2)	4.72 (0.53)	2.36 (0.07)	0.83 (0.06)
XFS	531 (6)	315 (4)	19 (2)	0.027 (0)	4.5 (0.1)	6.09 (0.84)	2.74 (0.07)	0.84 (0.06)
ZFS	551 (0)	304 (7)	8 (0)	0.008 (0)	12.5 (0.1)	1.25 (0.01)	3.31 (0.37)	0.43 (0.01)
BetrFS v0.4	181 (40)	55 (6)	92 (7)	0.269 (0)	4.0 (0.1)	2.46 (0.15)	51.41 (6.96)	0.27 (0.01)
BetrFS v0.6	497 (0)	310 (3)	116 (2)	0.363 (0)	11.8 (0.2)	1.36 (0.02)	1.57 (0.04)	0.22 (0.01)

Table 1. Throughput in MB/s (left) and latency in seconds (right) of various file systems on a commodity SSD. Higher throughput and lower latency are better. Standard deviation is in parentheses. BetrFS v0.4 and BetrFS v0.6 have compression disabled. Any data points within 15% of the highest throughput or lowest latency are highlighted in green; those that are less than 30% of the best throughput (or more than 3.33× the best latency) are highlighted in red.

total, these changes improve sequential write throughput over BetrFS v0.4 by 4×, and reduce grep time by 41%.

Keyspace ranges as first-class primitives (§4). This paper presents optimizations for *range operations* that act on sets of key-value pairs that are contiguous in the keyspace. We find that, in moving from a hard drive to an SSD, range operations are too CPU intensive to keep up with a faster device. This paper contributes additional optimizations to range operations, as well as simple changes to VFS caching behavior that eliminate redundant queries. These optimizations speed up recursive deletion by 9×, making BetrFS v0.6 comparable to other file systems on this workload.

Cooperative memory management (§5). This paper describes cooperative memory management strategies for the large buffers required by write-optimized key-value stores. In particular, to aggregate small updates into large I/Os, a write-optimized key-value store must be able to efficiently allocate and potentially resize buffers that are on the order of hundreds of kilobytes to megabytes in size—because of the nature of how updates are aggregated, it is often difficult to accurately predict buffer sizes at allocation time. Yet Linux's internal kernel memory allocators are primarily optimized for pages or small objects, not buffers on the order of megabytes. Similarly, dynamically adjusting kernel mappings of large buffers can be expensive, involving TLB shootdowns across cores. By adopting new memory management strategies, BetrFS v0.6 improves performance across the board, including increases of 25% and 31% over BetrFS v0.4's already strong 4KiB and 4B random write throughput, respectively.

VFS and key-value store integration (§6). Finally, this paper describes a strategy for sharing versioned data, copy-on-write, between the VFS page cache and a write-optimized key-value store. Our design supports tracking multiple versions of a data block in memory without obstructing writes. This design effectively passes pages by reference through the levels of the key-value store for efficient aggregation. Sequential-write throughput improves 6× over BetrFS v0.4, elevating performance to within 15% of the fastest sequential-write implementation on an SSD file system. At a high level, this strategy can be viewed as using the kernel's page cache as a copy-on-write row cache for file contents.

Results. Our microbenchmark results are summarized in Table 1 (additional workloads presented in §7). At its best, BetrFS v0.6 shows a 10× improvement upon 4B random write performance of F2FS—a log-structured file system designed for SSDs; this is 35% higher than BetrFS v0.4. At its worst, all cells BetrFS v0.6 are within our 85%-of-best goal.

Our results appear surprising at first, because write-optimized file systems improve performance by (1) coalescing small or random writes into large sequential I/Os, and (2) preserving locality so that sequential file reads translate into large sequential I/Os. Since SSDs have good random I/O, coalescing I/Os may seem unnecessary. Yet, even on an SSD, coalescing writes significantly improves both random write performance and the efficiency of subsequent reads.

This paper presents BetrFS v0.6 as an existence proof of a compleat file system for commodity SSDs; our conjecture is that not every indexing data structure or file system implementation can be made compleat. However, some of the optimizations in this paper may generalize to other file systems or key-value stores. For instance, the Simple File Layer and cooperative memory management designs may be a useful building block for porting other key-value store implementations into an OS kernel. Our optimizations around inode instantiation and the protocol for sharing cached data with the VFS may also prove generally useful to other file systems. Our work on range queries and other features that are more specific to using a key-value substrate may prove useful in either other key-value stores (including user-level key-value stores such as RocksDB), or in file systems built over emerging key-value SSDs[11, 13, 17]

2 Background

This section presents background on BetrFS, the baseline file system to which this paper's optimizations are applied. It summarizes key details needed to understand the rest of this paper, including some details that have not been previously documented. Additional BetrFS details are available elsewhere [3, 5, 9, 39–41]

2.1 B$^\varepsilon$-tree Overview

BetrFS is an in-kernel Linux file system that uses B$^\varepsilon$-trees—a write-optimized B-tree variant—to index its on-disk data [3]. A large part of BetrFS performance stems from its mapping of file-system operations to efficient B$^\varepsilon$-tree operations. Thus, the B$^\varepsilon$-tree is at the core of the BetrFS design.

B$^\varepsilon$-trees export a key-value (i.e., dictionary) interface, similar to an LSM-tree [30]. Like a B-tree, a B$^\varepsilon$-tree stores key-value pairs in leaves. Unlike a B-tree, internal B$^\varepsilon$-tree nodes have logs for *messages*; messages are serializable objects that logically describe an operation to be performed on one or more key-value pairs (e.g., update, delete). The message abstraction is essential for the implementation of *blind writes* and *range operations* [39], discussed below.

B$^\varepsilon$-trees have good update performance because each I/O sequentially writes a large *batch* of messages. Updates are encoded as messages and inserted into the root node; messages accumulate in the root until its log buffer fills, at which time a subset of messages is *flushed* from the root to one or more children (recursing if necessary). Because B$^\varepsilon$-tree nodes are considerably large compared to nodes in a B-tree (B$^\varepsilon$-tree nodes are typically 2–4MiB), flushing moves enough data to amortize the cost of rewriting the parent and at least one child. LSM-tree compaction serves a similar role. This strategy of batching updates is called *write optimization*, and although individual updates are rewritten at each level of the tree, the rewriting costs are shared by many updates—dividing the asymptotic cost by the batch size. Thus, B$^\varepsilon$-tree updates have an average I/O cost that is much smaller than one.

A related benefit of this technique is that range queries, such as during `grep`, are I/O-efficient. Because B$^\varepsilon$-tree flushing compacts nodes, reads that have locality in the keyspace will have locality on disk [5, 6]. Combining good locality with large nodes means that B$^\varepsilon$-tree range queries require fewer total I/Os than a typical file system index structure.

Unlike a pure logging data structure, a B$^\varepsilon$-tree upholds the invariant that all messages that target a given key lie on a single root-to-leaf path. Thus, querying the latest version of a key-value pair requires reading a logarithmic number of nodes when the cache is completely cold, possibly reconstructing the value by applying messages. Of course, caching nodes reduces a query's I/O costs in practice, and caching *materialized views* of key-value pairs—versions where all relevant messages are identified and applied—reduces the CPU costs. Updates are faster than queries because updates touch just the root node—unless a flush is required—so BetrFS, whenever possible, performs blind writes (i.e., encoding a modification without first reading the old value). Consequently, things like incrementing an inode counter or modifying a small range of some file's bytes are not bottlenecked by a slower read.

B$^\varepsilon$-trees can also support range operations, which specify a start key, an end key, and an operation that is performed on all key-value pairs within the specified range. Range delete is a particularly useful operation, especially in BetrFS where a single range delete message can be used to atomically delete all of a file's blocks.

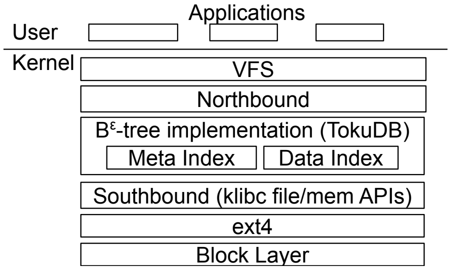

Applications
User
Kernel
VFS
Northbound
B$^\varepsilon$-tree implementation (TokuDB)
Meta Index
Data Index
Southbound (klibc file/mem APIs)
ext4
Block Layer

Figure 1. BetrFS Architecture. The "northbound" layer converts VFS operations into key-value store operations, indexed by full path. The B$^\varepsilon$-tree code maintains two indexes, which are stored on ext4.

2.2 BetrFS Architecture

Figure 1 illustrates the baseline BetrFS architecture. System calls pass through the VFS layer and caches, as in any other file system. The BetrFS "northbound" layer translates VFS operations into key-value operations and passes them to the underlying B$^\varepsilon$-tree.

BetrFS maintains two indexes: one for metadata and one for file data. The metadata index uses complete paths as keys, and stores `stat` metadata structures as values. The data index stores 4KiB file blocks using (full path, block index) tuples as keys.

Most VFS-level operations are straightforward translations to key-value operations. For example, a file is created by adding an entry to the metadata index (where the key is the full path name). One can append to a file by inserting 4KiB blocks to the data index (where the key is the full path and block number)and updating the size in the metadata index.

Our B$^\varepsilon$-tree implementation was ported into the Linux kernel from TokuDB. As a user-level key-value store and database, TokuDB was programmed against a file abstraction and some other standard user-level C programming libraries. The "southbound" layer translates TokuDB's POSIX-style file API into VFS-level requests, which it then issues to an underlying ext4 file system. In BetrFS, the B$^\varepsilon$-tree implementation only writes to 11 files, and only to three files with any frequency: one WAL log file and two DB files—one each for the metadata and data index—that store B$^\varepsilon$-tree nodes. Within the southbound layer is also a small shim, called klibc, that translates additional supporting functions, such as memory allocation, to Linux kernel APIs.

Example: File writes. When an application writes to a file, the modifications are buffered in the VFS page cache, as with any standard file system. When the VFS asks the file system to write a cached block to disk, the block's contents are sent to the B$^\varepsilon$-tree layer: a key-value pair is created and inserted into the B$^\varepsilon$-tree's root node, as well as the B$^\varepsilon$-tree's log. At this point, the in-memory B$^\varepsilon$-tree root node is dirty, and it may accumulate and flush more messages. Each time a node flushes messages to a child, the parent and child are copied and dirtied within memory.

When the B$^\varepsilon$-tree writes the dirtied nodes to disk, each node is serialized into a large, contiguous buffer, then compressed. Early versions of BetrFS relied on compression to reduce the on-disk storage costs of highly redundant keys, as well as to reduce the total I/O. More recent BetrFS versions use *lifting* [40, 41] to achieve similar space savings, both on disk and in memory, and to reduce the computational costs of in-memory key comparisons. Lifting is essentially a trie-style encoding, where the longest common prefix of all keys in a subtree is removed and stored along with the pivots and child pointer. In this paper, we disable B$^\varepsilon$-tree node compression, as the computational costs can delay I/Os for little benefit.

Example: File reads. File reads largely follow a similar path: when the VFS asks the northbound layer for a file block, the northbound layer queries the data index for the relevant file block. If they are not in memory, the B$^\varepsilon$-tree will read all of the nodes on the root-to-leaf path into memory, and apply any pending messages that affect the query.

Because nodes are much larger than a file block, reading an entire leaf node helps the performance of sequential accesses, but amplifies the I/O costs for small, random reads. In order to improve this case, leaf nodes are partitioned into multiple **basement nodes** (typically 32, each roughly 128KiB). Basement nodes are serialized as packed lists of key-value pairs, and any basement node can be read into memory without the rest of the leaf. A heuristic based on recent access patterns decides whether to read a basement node or the entire leaf.

Crash Consistency. BetrFS uses a redo log and periodic B$^\varepsilon$-tree checkpoints to ensure crash consistency. On-disk B$^\varepsilon$-tree nodes are copy-on-write, and checkpointing ensures that there is always a persistent point-in-time consistent copy of the tree. After a crash, the redo log is replayed against the newest stable B$^\varepsilon$-tree checkpoint. Any new B$^\varepsilon$-tree nodes written to disk since that checkpoint are discarded and reconstructed from the log. The checkpointing process also deletes stale checkpoints and nodes that are not reachable from any active checkpoints. To detect potential corruptions at rest, BetrFS checksums each node on disk, and uses checksums to detect corrupted log entries.

The crash recovery semantics are roughly equivalent to full-data journaling in ext4. More precisely, all operations (including data writes) are effectively written to the log in the order they are received from the VFS. After a crash, the state is consistent with a prefix of the log, up to the last log flush. Note that `sync` variants induce a log flush, so after any sync, the log up to that point in time is durable.

Range Messages. BetrFS extends the standard key-value API with two key range operations, which in turn are encoded as messages in the B$^\varepsilon$-tree. Important operations, such as renaming or deleting files, require updating potentially many key-value pairs. In the first version of BetrFS, these operations suffered poor scaling due to the sheer volume of messages. Subsequent BetrFS versions introduced a **range message** abstraction that can operate on all key-value pairs within a contiguous key range [39]. First, a range delete atomically removes a contiguous set of keys from the B$^\varepsilon$-tree, which is more efficient than issuing a series of individual deletions for each block. Second, BetrFS adds a range rename operation, which can atomically replace the prefix on a range of keys (and associated values), potentially replacing older keys with the target names [40, 41].

The range message abstraction also unlocks further optimizations. For example, BetrFS introduced the PacMan optimization [39] as a way to reduce range delete message overheads. In the PacMan optimization, a range delete applies to all keys with some prefix *p* specified by the range delete. Suppose a range delete is inserted for all keys with prefix "/foo/*"; in the course of flushing, an older point message inserting key "/foo/bar" or range delete for the prefix "/foo/baz/*" could be dropped, or "eaten" by the new range message. More formally, we define a message as overlapping with a range delete when the message's key(s) are contained within the keyrange of the range delete message.

2.3 Performance Problems of Existing File Systems (on SSDs)

Table 1 reports several benchmarks where BetrFS v0.4 performs considerably worse than the competition on an SSD (i.e., "red" cells). In profiling and analyzing these workloads, we identified four underlying issues, some of which affect multiple workloads. This subsection explains the reasons for these problems, and indicates the sections that describe the solutions.

Sequential Writes and Excessive File Data Copies (§3 and §6). As described above, when the VFS writes file data into the northbound layer, the data is copied into a new page and added to the B$^\varepsilon$-tree as a message. With its focus on smaller values and slower disks, the B$^\varepsilon$-tree implementation copies all values (even 4KiB pages) on each flush. We note that there are already optimizations in BetrFS to avoid writing every flush *to disk* in cases where a number of writes are following the same root-to-leaf path; however, the complete data is always `memcpy`-ed at each level. Finally, there is a copy at the final write to the underlying file system. As data is flushed down each level of the tree in memory, it is also copied into a new page. Finally, when data is written into ext4 via the southbound layer, it is copied once more. Similar copying occurs on the read path.

A related issue is performance "stutters" caused by the interaction of background page eviction and double-buffering. The VFS layer employs both time-based and space-based heuristics to manage dirty-page write-back. In BetrFS, when the dirty-page threshold reaches a "high water mark" and pages are written, they are written to ext4; different pages in ext4 are then dirtied and scheduled for write-back, leading to no net change in the dirty page count.

It is common for file systems with complex on-disk formats, such as ZFS, to maintain their own caches that are distinct from the VFS page cache [8]. The design in this paper can facilitate reuse of VFS caching mechanisms in file systems that need to maintain their own node caches.

Small Writes and Double-journaling (§3). For a concrete example of the double-journaling problem, consider small, synchronous operations, such as those found in a rename-intensive microbenchmark. A `sync()` in BetrFS leads to a small, synchronous write to the BetrFS journal, which leads to a small write followed by a `sync()` in ext4, which then leads to a journal transaction to commit a metadata update in ext4. Double journaling is clearly not a best practice—one journal is sufficient.

Although the choice to stack on ext4 is specific to BetrFS, we note there is a larger, ongoing debate in the community about how to balance the need for rapid prototyping with representative performance data [21]. Most commonly, this discussion focuses on whether user-level frameworks, such as FUSE, are representative [35]. Our results indicate that, for a reasonable subset of POSIX, one can efficiently "shim" a user-level implementation into Linux, gaining the benefits of both approaches. We expect solutions to this problem would be of potential interest to developers of stacked file systems or who wish to port user-level code to the kernel.

Sequential Read and Read-Ahead (§3). Effectively every file system we studied, except BetrFS v0.4, can approach SSD bandwidth on large, sequential reads because read-ahead is a simple, effective strategy; so simple that most file systems just inherit the VFS's read-ahead heuristics. We find VFS-level read-ahead heuristics are not a good fit for BetrFS's "lower-level", which reads large B$^\varepsilon$-tree nodes from ext4, as the heuristics only operate on the order of KiB. For a B$^\varepsilon$-tree that stores data in 4 MiB nodes, ideally, while processing the current 4 MiB, one should be prefetching the entire next leaf and any additional ancestor nodes, applying messages, and materializing a view of the next leaf. Identifying read-ahead entirely at lower levels is also challenging and error-prone, as unrelated application requests may be interleaved.

File Creation and Existence Checks (§3). We observe a performance pathology in workloads that create a large number of small files, such as TokuBench. From the perspective of the key-value store, the VFS layer issues an alternating series of point queries to the metadata index—to check whether the file exists—followed by an insert message that creates the new file's inode. By default, on every query BetrFS implements a heuristic that applies messages *in memory only* to the leaf node of each root-to-leaf path traversed by the query. This effectively creates a materialized view of all pending messages at the leaf, intended to optimize subsequent queries. However, carrying a single message down the B$^\varepsilon$-tree on every existence check defeats the purpose of batching these updates.

Recursive Delete and Range Message Pathologies (§4). BetrFS implements file removal with a range delete operation. Range deletes are sufficiently fast on HDDs but become a bottleneck when performing recursive directory deletions on SSDs. For recursive delete operations that create small numbers of range messages, performance was comparable to other file systems; the recursive deletion workload examined in this paper is several times larger than prior reported results, and execution time jumps non-linearly from seconds to nearly a minute as the number of deletions scales.

Ideally, BetrFS would issue a single range delete message to compactly represent a recursive directory deletion, but that is not the case. During recursive deletion (e.g., `rm -rf`), the VFS traverses the directory hierarchy to check permissions and to delete individual file system objects in an order that ensures the file system namespace remains consistent after a system crash. Thus, the VFS deletes a directory and its contents in a bottom-up fashion (i.e., all children are deleted prior to deleting the parent). This iterative, bottom-up deletion pattern fills BetrFS's B$^\varepsilon$-tree nodes with a large number of range delete messages that have adjacent-but-not-overlapping ranges (e.g., `rangedel(dir/bar*)`, `rangedel(dir/baz*)`, . . .). So although BetrFS's PacMan optimization [39] locally compacts any overlapping range delete messages within an interior node, it cannot aggregate these messages.

Not only is PacMan unable to aggregate these range deletes, it spends considerable CPU resources trying. When the PacMan optimization runs, it compares every range message in a node to every other message in the node, consuming messages that fall within the target range (e.g., deleting a covered key-value pair or merging overlapping range delete messages into a single message with the combined range). During `rm -rf`, many range delete messages are created, but no range deletes allow for any of the other messages to be discarded. So PacMan is a quadratic algorithm that runs during every node flush but has no effect on the tree. Furthermore, BetrFS must perform flushing to make space in the root node even though, in many cases, all the range delete messages could be logically summarized as a single delete to obviate the I/O costs of flushing.

Because techniques based on modifying contiguous keyspace ranges are relatively new, they have been studied less than other WOD optimizations; but they are gaining popularity. For instance, RocksDB also recently introduced a range delete operation [20]. We expect that these optimizations, as well as analysis of the interactions among range and point operations, will be of benefit to any key-value store or file system that uses range operations in a WOD.

Small Writes and Buffer Resizing (§5). Memory management was a critical bottleneck when moving BetrFS from a hard drive to an SSD, largely because buffer sizes are difficult to predict when managing B^{ε}-tree messages in memory. For instance, flushing from a parent to a child may fill the child's buffer, and the child may need to further flush to a grandchild. In such a cascaded flush, the child may temporarily allocate a larger in-memory buffer than it will ultimately need on disk to hold these messages until flushing to the grandchild. This issue primarily affects workloads that issue small writes, which in turn serialize more messages during a flush.

The node sizes of the B^{ε}-trees in BetrFS are in the range of 2–4 MiB. BetrFS needs to allocate large buffers for storing the messages of each node as well as for serializing/deserializing nodes before/after I/Os. In the Linux kernel, `kmalloc` is the conventional way for allocating memory for kernel objects. `kmalloc` promises high performance in the scenarios that objects have standard sizes, most I/Os will be small (order of pages), and that large, irregular buffers are the exceptional case. However, `kmalloc` only supports larger allocations in a best-effort manner; in practice, they quickly fail once physically contiguous pages in the buddy allocator are exhausted. Consequently, BetrFS uses `vmalloc` to allocate large buffers. `vmalloc` is a more reliable way to allocate buffers on the order of megabytes in the kernel, though `vmalloc` is relatively expensive, as vmalloc changes the kernel's memory mapping on *every* CPU.

One more issue related to memory allocation is that the B^{ε}-tree implementation used in BetrFS was developed in userspace, using standard malloc, realloc, and free interfaces. In particular, most of this code was written with the assumption that `realloc` is an efficient way to dynamically grow a buffer that is hard to predict a priori. A key *implementation* assumption here is that most allocators have an efficient memoization of both allocated sizes and can often identify and reclaim fragmented space, say from rounding up to a power of two, on a `realloc` call. In Linux, however, `vmalloc` can only identify the size of an object by an expensive search of the kernel's memory mappings, and there is not an efficient way to incrementally grow a `vmalloc`'ed buffer. To be clear, these assumptions are true for small objects, using `kmalloc`; the challenge for BetrFS is efficient management of large, variable-sized objects in the kernel.

The overheads of memory management became critical for workloads that dealt with a large volume of small messages, such as TokuBench, random writes, and recursive deletion—accounting for at least 10% of execution time for each one.

More broadly, the Linux kernel's allocation interfaces are optimized for relatively small objects; managing large buffers is inefficient. Although scatter-gather style IO can mitigate this issue for large data extents or aligned pages, similar issues are likely to arise in log-structured file systems or other file systems that need to serialize variable-sized metadata or other smaller objects into larger on-disk extents. As devices continue to grow faster, the computational budget per I/O will continue to shrink. Thus, we expect these memory management techniques to be of broad utility.

Name	SuperBlock	Log	Meta Index	Data Index
Size	8 MB	2 GiB	25 GiB	223 GiB

Table 2. Simplified SFL on-disk layout. The sizes are given for a rough indication of proportion on a 250GiB disk. The SuperBlock region is abstracted as eight logical files.

3 Consolidating Storage Layers

Stacking BetrFS on ext4 is the root cause of a number of the performance issues analyzed in §2.3, such as double journaling, double buffering, copying, existence checks, and ineffective read-ahead. This section presents a simplified substrate for porting user-level code into a Linux file system. We then discuss optimizations for read-ahead and existence checks in a multi-layer file system. The changes in this section address performance bottlenecks in sequential I/O, scans, small file creation and metadata-intensive workloads (recursive deletion).

3.1 The Simple File Layer

To expedite development, BetrFS ported TokuDB [33]—a user-space B^{ε}-tree implementation—to the Linux kernel by implementing the `klibc` "shim" layer. `Klibc` translates many user-level interfaces to Linux kernel APIs, and importantly, it emulates POSIX file interfaces on top of ext4 (See Fig. 1).

We observe that running TokuDB on a complete file system is unnecessary. The BetrFS B^{ε}-tree implementation only uses 11 fixed files. Two—one per index—are large, `fallocate()`-ed files that store tree nodes; one stores the log; and the other 9 store small amounts of infrequently-changing metadata, such as whether the key-value store was shutdown cleanly or not. Effectively, these files approximate a static disk layout: a region of disk for nodes, a region for the log's circular buffer, and a superblock for global metadata. Features such as dynamic block allocation, or even dynamic file creation, are not necessary for BetrFS's write-optimized key-value store.

Based on this observation, we introduce a storage back-end, called the **Simple File Layer (SFL)**, that gives the abstraction of precisely the 11 files and APIs that the B^{ε}-tree implementation requires, and addresses all four issues mentioned above. Table 2 illustrates the SFL on-disk layout (note that several metadata files are consolidated into a single superblock-style region). SFL still provides some measure of POSIX-like APIs, e.g., named files, so that the upper layer (i.e., B^{ε}-tree indices) need not change the interfaces to SFL (i.e., klibc). Although

SFL is somewhat tailored to BetrFS v0.6's B$^\varepsilon$-tree implementation, a similar file-system shim may be used to efficiently port other user-level code into a kernel.

Finally, the SFL interface eliminates double buffering, by exporting a direct I/O-style interface.

To eliminate page copying overheads and double buffering, we design the SFL I/O interface to accept references to physical page frames, similar to direct IO, where the caller handles all buffer management, including freeing buffers after an I/O completes. The I/O interface can be used synchronously or asynchronously. We note that a similar model when stacking on ext4 requires kernel modification, as current code paths reject attempts to use direct IO on kernel addresses. SFL does not support a file handle with a cursor; rather, all read and write requests supply a file offset and a pre-allocated buffer. Each file occupies a single contiguous extent; the minimum IO size of SFL to the block layer is 4KiB, the same with ext4.

SFL eliminates double-journaling by using immutable metadata; SFL statically partitions the disk space into 11 extents, one for each of the files used by the B$^\varepsilon$-tree implementation. Crash consistency for changes to the file system-level data and metadata is already handled by the B$^\varepsilon$-tree log; SFL is only responsible for ensuring that synchronous writes are written synchronously.

We modify the B$^\varepsilon$-tree code to use a statically allocated disk region as a circular log buffer, and we converted the log engine code so that each log entry includes a sequence number and a checksum. The checksum is used to validate the integrity of a log entry. As a hint for recovery, we store a recent starting point to search for the range of valid log entries, but this is only updated periodically; the log can be reconstructed by brute force if need be.

3.2 Read-ahead

In order to ensure effective read-ahead with large nodes on disk, BetrFS v0.6 implements a cooperative read-ahead design. We use a standard sequential read heuristic in the northbound layer, which identifies a run of sequential read accesses to a file. This hint is passed to the B$^\varepsilon$-tree layer, which causes the B$^\varepsilon$-tree to asynchronously read either the next two basement nodes in the current leaf, or the next leaf node if the query hits a leaf's last basement node.

3.3 Existence Checks and File Creation

In order to address the problem where existence checks on file creation thwart batching of updates, BetrFS v0.6 defers and batches insertion of messages that create inodes into the B$^\varepsilon$-tree. Here, we use the B$^\varepsilon$-tree recovery log and the VFS to hold a newly created inode in the dirty state instead of inserting the messages directly into the tree. We first observe that logging inode creation in the BetrFS v0.6 redo log is sufficient for crash recovery, provided that the inode is inserted into the B$^\varepsilon$-tree before that region of the log is reclaimed. Further, as long as the new inode is cached in the VFS in the dirty state, subsequent queries for this inode will be serviced correctly from the VFS cache. Assuming the system does not crash, the inode will eventually be written back to the B$^\varepsilon$-tree, likely after accumulating subsequent changes, and after subsequent existence queries have moved onto different root-to-leaf paths. We call this optimization **conditional logging**.

We note that conditional logging is implemented in the northbound layer and the B$^\varepsilon$-tree, not below it, and should not violate any persistence assumptions in the B$^\varepsilon$-tree code. Moreover, this optimization is transparent to applications and does not affect the behavior of file creation from the perspective of application code.

The main additional coordination mechanism this optimization requires is an additional reference count on sections of the B$^\varepsilon$-tree redo log, tracking how many dirty inodes still require this section of log for durability. In the worst case, a dirty inode can delay reuse of a section of the circular log buffer on disk. In practice, however, the period for checkpointing in the B$^\varepsilon$-trees of BetrFS v0.6 is a minute, while the VFS keeps a dirty inode in the cache for at most 30 seconds (set by `dirty_expire_centisecs`). As a result, 50% of dirty inodes will be inserted in the next checkpoint window. We note the log file is large enough to hold all log entries written by more than 2 consecutive checkpoint windows. Therefore, in practice all dirty inodes will be written to the B$^\varepsilon$-tree before it could obstruct reuse of a portion of the log buffer.

4 Range Message Optimizations

This section presents optimizations to address the performance pathologies in how range deletion interacts with other operations that are issued by recursive file deletion.

Coalescing range delete messages. The first, and largest performance issue with range delete messages is that we discovered that for a large, recursive deletion, each range deletion message was non-overlapping. Consider the message sequence produced by a recursive deletion: for each directory deleted, there are a series of range delete messages that correspond to files in that directory. None of these range deletes will actually overlap, and the PacMan heuristic will not be able to consolidate them, as PacMan cannot efficiently infer that there are no keys between the two ranges.

To address this issue, we augment the `rmdir` implementation in the Northbound to issue a range delete for the entire directory. Previously, range deletes were only used for unlinking a file. This seems counter-intuitive and perhaps dangerous, at first, since POSIX requires that a directory be empty before it can be removed. However, the purpose of this range delete is not to delete live data; it is to coalesce or drop stale messages during flushing, including previously deleted key-value pairs from files that were once in that directory and other, disjoint range deletes.

The PacMan optimization will traverse these messages by recency—the opposite order that they were issued; in other words, PacMan will consider a directory's range delete message before it considers any narrower range delete messages for the directory's children. Thus the directory's range delete message will "gobble" the range delete messages for the files in that directory, and so on. Adding directory range deletes last lets PacMan apply more beneficial messages first.

This change alone creates an order-of-magnitude performance improvement over BetrFS in a recursive deletion benchmark, and it does so without modifying the quadratic time algorithm or reducing BetrFS v0.6's I/O activity (the recursive deletion benchmark is too small to realize any reductions in I/O activity from the discarded messages).

Bypassing B^ε-tree queries for empty directories. Rmdir semantics requires a directory to be empty, which baseline BetrFS confirms by issuing a B^ε-tree query. This query turns out to be a performance bottleneck because, in a WOD, adding a message to the tree—which is how inserts/deletes are implemented—is much faster than performing a query.

In our optimization, we avoid these B^ε-tree queries by maintaining consistent link counts (nlink) of the in-memory directory inodes in the VFS layer. An `rm -rf` already recursively visits each child directory to identify a list of files to delete. This initial traversal warms the relevant VFS inode caches, making these checks fast. We note that the VFS already maintains this information and expects it to be correct; our primary change was ensuring that these cached values are coherent with the link counts on disk. In summary, maintaining these counters substantially improves performance by avoiding redundant B^ε-tree queries.

Removing redundant messages. The VFS protocol for removing an inode is complex, in order to handle edge cases such as open handles to unlinked files. We found the lower-level implementation of BetrFS issued two file deletion messages on two different VFS hooks (`unlink` and `evict_inode`). BetrFS v0.6 introduces a flag to the in-memory inode to avoid sending a redundant delete message for a file. Although adding messages to a write-optimized dictionary is relatively inexpensive, it is not free; removing the extra message further lowered the computational overheads of a recursive deletion.

Fully caching `readdir` ***with opportunistic inode instantiation.*** The VFS embeds several implementation assumptions into its file system API, including the assumption that a directory's metadata (inode) is stored separately from its data (listing). As a result, the VFS does not cache child metadata during a parent's `readdir`—neither directory entries nor inodes [34]; instead, separate `lookup` calls are needed. In BetrFS, a `readdir` scans contiguous items in the metadata index, and these items contain both the names and the inodes for a directory's children. Thus, the same range query that returns the file names under a directory can also populate the VFS caches without extra I/O.

We augment BetrFS v0.6 `readdir` to populate child inodes and directory entries in VFS caches. Then, subsequent `lookups` can avoid the significant overheads of redundant queries to the key-value layer, such as constructing additional keys, additional key comparisons, and checks along the the B^ε-tree's root-to-leaf path. The power of this optimization is most apparent in a cold cache recursive deletion; because `rm -rf` deletes each entry in a directory tree, bottom-up, all inodes are opportunistically cached during the top-down traversal. This optimization is measured in isolation in the evaluation (Table 3, `+DC` row), and removes more than one second of latency from recursive deletion (from 3.4s to 2.3s).

Revisiting the apply-on-query optimization. Baseline BetrFS has an optimization heuristic, that, upon a query, pushes certain messages down the B^ε-tree and applies them to *in-memory* key-value pairs in cached leaves. We call this heuristic ***apply-on-query***. The goal of this optimization is to exploit query locality: subsequent queries to the same basement node can quickly check whether an interior node has fresh and relevant pending messages, versus a CPU-intensive buffer traversal to identify the relevant messages.

Apply-on-query behaves differently depending on the cached leaf node's state. If the cached leaf node is clean, then apply-on-query searches for and applies any pending message that targets a key-value pair in the basement node involved in the query, even if no messages on the root-to-leaf path actually affect the query's result (e.g., when messages affect neighbors of the target key). Note that, in this case, the leaf's in-memory state remains clean, and the B^ε-tree's on-disk state is unchanged.

If the cached leaf node is dirty, then apply-on-query attempts to reduce I/Os by *flushing* pending messages that target any key-value pair in the entire leaf. We use the term "flush" when a message is applied to a dirty in-memory node and, ultimately, to the on-disk B^ε-tree. Apply-on-query was designed for HDDs, where it is worthwhile to spend tremendous amounts of computation to save even one additional I/O. By aggressively flushing pending messages to a leaf node that would be written back regardless, apply-on-query can reduce write amplification to this leaf.

For a workload like recursive deletion, which alternates range deletions and range queries (from `readdir`) and moves through the keyspace sequentially, this heuristic causes an interesting pathology when the leaf node is clean. Suppose the first deletion adds a range delete at the "left" of the keyspace that maps onto a clean basement node. A subsequent query to the next, disjoint key (for the next file to delete) will trigger an apply-on-query for the prior range delete, even though that range delete is non-overlapping. This process continues across the entire keyspace covered by the leaf node.

In such a workload, one incurs all of the costs of apply-on-query, and gets none of the locality benefits, as the deleted keys will not be queried again. Moreover, one must still recheck all ancestor nodes on the root-to-leaf path for relevant messages to apply. We note that checking range messages is more expensive than checking point messages, both because there are two key comparisons (versus one) and because the indexing structure is more complex to handle partially overlapping ranges. So a range-delete intensive workload exacerbates these costs. On an SSD, with a tighter computational budget per I/O, this optimization uses sufficient CPU time that it significantly increases latency of a range-delete-intensive application, with potentially marginal benefits in terms of total I/Os.

In BetrFS v0.6, we introduce a new apply-on-query policy: we only flush or apply pending messages if one or more pending messages affect the outcome of the query. Said differently, if at least one pending message in an interior node targets a key-value pair in the query, BetrFS v0.6 does apply-on-query as before; otherwise, the in-memory tree state is left unchanged. The key takeaway is that faster devices necessitate revisiting the relative weights of I/O and CPU amplification. The CPU cost of identifying all pending messages for an entire basement or leaf node is quite large, but, at least for common file system workloads, the resulting I/O savings are not. BetrFS v0.6 must already find and apply pending messages that affect the query, and this information is often a sufficient signal to exploit query locality.

After all other optimizations in this paper have been applied to the code base, this optimization alone further reduces recursive deletion latency by roughly one second (from 2.56s to 1.57s). We show the performance impact of this optimization in Table 3 in the +QRY row.

5 Cooperative Memory Management

This section describes optimizations for the management of large node buffers in the kernel. As §2.3 explains, when the B^ε-tree code writes a node to disk, it must serialize a significant amount of irregular content, such as keys and small messages, into a large (at least hundreds of KiB) buffer. Yet Linux's internal memory allocators are tuned for allocations of a page or smaller. These overheads manifest primarily in workloads that issue many small writes, such as the random write microbenchmark and TokuBench.

We address these issues through a cooperative memory management framework, where the B^ε-tree code is trusted to assist in the memory management bookkeeping, and the klibc memory allocator can also signal opportunities for more effective memory use to the B^ε-tree code.

First, we observe that most B^ε-tree code that uses large, dynamically sized buffers already tracks its own used and free space. We modify the internal free and realloc interfaces to pass this information back to our klibc allocator (a wrapper for kmalloc and vmalloc). This optimization elides the expensive searches for vmalloc sizes in the kernel code, or the need to add our own memoization, when freeing a vmalloc'ed region.

Second, and because memory management is critical to overall performance of the code, a number of side caches and allocators had developed over time as point fixes for specific bottlenecks. However, this also led to an increase in complexity and important information being lost by the time an allocation reaches the lowest level of the file system; thus, part of this work involved removing intermediate caches and memory pools, and streamlining one efficient allocator. Although baseline BetrFS had a small cache of 32 128K vmalloc'ed regions, targeting one common size, we found this was insufficient in practice, and expanded this cache of larger buffers to include additional, common powers of two.

Third, we introduce a cooperative memory management interface, where the B^ε-tree and supporting kernel code can negotiate buffer sizes that can be allocated efficiently. Previously, B^ε-tree code selected seemingly arbitrary buffer sizes, and grew them as they overflowed—typically by doubling the size. We augment our internal allocator to also return the available space at allocation time (similar to user-space malloc_size), and adapt code sites that rely heavily on realloc, often followed by relatively expensive re-initialization, to always leverage the full buffer amount at allocation time.

Unlike malloc_size, our interface can deliberately return much more space than requested. Based on profiling the behavior of the code, we found a number of sites where the final size of a buffer is bi-modal: it is either relatively small, or will grow to be megabytes in size. We found that by simply avoiding incremental powers-of-two, we could get buffers to their expected sizes quickly, and elide additional copies.

6 Sharing Pages between the VFS and B^ε-tree

This section describes how BetrFS v0.6 shares pages of file data in the VFS page cache with the B^ε-tree internal structures—realizing zero-copy I/O between the VFS and the disk, in the absence of updates to the same page during write back. These optimizations are introduced to address the issue of excessive data copying, thereby improving the performance of large, sequential reads and writes.

By default, Linux file systems place written data in the in-kernel page cache, in the "dirty" state. A dirty page may remain in the page cache for a short period, in anticipation that an application may issue additional writes to the same page. Dirty pages are eventually written to the underlying file system; during write back, the pages are locked and may not be updated by applications until the write completes, preventing on-disk consistency problems.

Zero-copy IO in a write-optimized dictionary is more complicated than a traditional file system for two reasons. In baseline BetrFS, one reason file data is copied from the VFS into a new buffer in the B^ε-tree is to avoid holding the page lock and obstructing application writes for a long time. Unlike a traditional file system, which would typically write the dirty page to disk immediately, BetrFS will hold a dirty B$^\varepsilon$-tree node (containing the dirty page) in memory for an additional period to accrue more messages. For both crash consistency and performance, BetrFS has two additional requirements:

- The same file block may exist in multiple versions, over a potentially long time. If a 4KiB page is rewritten a new copy is inserted into the tree, but multiple, older versions may exist in interior B$^\varepsilon$-tree nodes, both in memory and on disk. Once a version of a file block is in the B$^\varepsilon$-tree, it is not modified again by the B$^\varepsilon$-tree implementation. Modifying a page frame that is added to the B$^\varepsilon$-tree is equivalent to editing the history of updates.
- One does not know at the start of write-back where on disk a page will be placed. This is both because of potentially flushing messages between the start of write-back and a forcing condition (such as an `fsync`), and the fact that on disk, B$^\varepsilon$-tree nodes are copy-on-write.

To implement zero-copy I/O and satisfy these requirements, BetrFS v0.6 moves pages through the tree by reference to the physical frame number while in memory, rather than by value. This design ensures that there is, at most, one copy per write to a page. We note that SFL (§3) is also a necessary building block for zero-copy I/O. Although a seemingly simple change, this introduces some design challenges.

Tracking Messages. We add a new message type to the B$^\varepsilon$-tree implementation for insert messages, called `insertByRef(key, reference, derefMem())`, which accepts a key, an opaque reference to a value, and a function to convert the reference back to a value. In the case of BetrFS v0.6, we use page frame numbers as our reference, and a function such as `kmap()` to copy memory contents, if needed.

VFS-level Copy-on-Write. When a page is inserted to the B$^\varepsilon$-tree using the `insertByRef` message, we need to ensure that page contents do not change again until any references to the page are released by the B$^\varepsilon$-tree, as the B$^\varepsilon$-tree expects messages to be immutable until they are obviated.

In order to avoid obstructing subsequent writes, we modify the "northbound" code that interacts with the VFS layer to change write-back to copy-on-write using the `PG_private` flag and file-system level hooks. The B$^\varepsilon$-tree implementation will not write this page; if a VFS operation (e.g., a write() system call or a write via `mmap`) occurs, the VFS will call into a lower-level function which first checks the private fields, giving BetrFS v0.6 the opportunity to allocate a new page to accept the write. In the case where the B$^\varepsilon$-tree releases all references to the page before a subsequent write, the copy can be elided and, the existing VFS page can accept the write.

On-disk Node Format. Zero-copy I/O is not possible in the BetrFS node layout. Within a basement node, key-value pairs are packed in a series of key1, value1, key2, value2, etc. We modify the basement node (sub-leaf node, §2) layout to first pack keys and any small values at the front of the basement node, and then place all 4KiB values in aligned sectors at the end of the basement node. With this layout, when a node is read into a buffer, all file blocks in a typical file will already be placed in 4KiB-aligned buffers in memory.

In the case of writing a node, this also reduces the serialization cost when combined with scatter-gather style I/O. The keys and small values must still be serialized, but a list of page reference can be directly passed to SFL.

Interior B$^\varepsilon$-tree nodes follow a similar design, with small messages packed at the front of the node, and page-sized values in aligned locations at the end of the node.

Reads and Caching. When a node is read into memory in BetrFS v0.6, we allocate a virtually contiguous region of kernel memory to map the node if needed, but do not necessarily require the pages in that region to be physically contiguous. Node contents, including data blocks, can be cached, copy-on-write, by both the B$^\varepsilon$-tree internally, and in the page cache. Each layer may also free memory independently. For instance, suppose a single page is shared between the VFS and a larger B$^\varepsilon$-tree node; here, the B$^\varepsilon$-tree node can be freed, except for the one page, which becomes exclusively owned by the VFS.

7 Evaluation

In this section, we evaluate BetrFS v0.6 performance using a combination of microbenchmarks and application workloads. Our evaluation seeks to answer the following questions:

- To what degree does each optimization described in the paper improve performance?
- Do these optimizations translate into application-level performance improvements?

All experiments were conducted on a PowerEdge T130 with a 4-core 3.00 GHz Intel Xeon E3-1220 v6 CPU, and 32 GB RAM. The system runs 64-bit Ubuntu 18.04.6 with Linux kernel version 4.19.99 when we test BetrFS v0.4 and BetrFS v0.6 variants and 5.9.15 for other file systems, in order to give the competition the advantage of any recent advances. We boot with the root file system on a 500 GB TOSHIBA DT01ACA0 HDD. The SSD under test is a 250 GB Samsung EVO 860 SSD with a 512-byte page size and 12 GB write cache; we measure a peak raw sequential bandwidth at 567 MB/s for reads. For writes, the peak bandwidth is 502 MB/s when the data size is smaller than 12 GB and drops to 392 MB/s when the data size is larger than 12 GB, which we attribute to device-internal operations.

We compare BetrFS v0.6 with several general-purpose file systems, including BetrFS, Btrfs, F2FS, ext4, XFS, and ZFS. We mount these file systems with default parameters, unless otherwise specified. We use the versions of XFS, Btrfs, ext4, and F2FS that are part of the Linux 5.9.15 kernel, and zfs version 0.8.6 from zfsonlinux.org.

File	Sequential I/O		Random Writes			Utility Latency		
System	Read(80g)	Write(80g)	4 KB	4 Byte	Tokubench	grep	rm	find
Ext4	534 (0)	316 (6)	16 (3)	0.026 (0)	13.6 (1.5)	10.15 (0.20)	1.81 (0.08)	0.86 (0.02)
Btrfs	568 (0)	328 (2)	13 (0)	0.024 (0)	6.0 (0.2)	4.61 (0.21)	2.53 (0.05)	0.78 (0.16)
Xfs	531 (6)	315 (4)	19 (2)	0.027 (0)	4.5 (0.1)	6.09 (0.84)	2.74 (0.07)	0.84 (0.06)
f2fs	528 (1)	320 (6)	16 (2)	0.033 (0)	4.7 (0.2)	4.72 (0.53)	2.36 (0.07)	0.83 (0.06)
zfs	551 (0)	304 (7)	8 (0)	0.008 (0)	12.5 (0.1)	1.25 (0.01)	3.31 (0.37)	0.43 (0.01)
BetrFS v0.4	181 (40)	55 (6)	92 (7)	0.269 (0)	4.0 (0.1)	2.46 (0.15)	51.41 (6.96)	0.27 (0.01)
BetrFS v0.6+SFL	462 (0)	222 (1)	96 (2)	0.262 (0)	5.4 (0.1)	1.44 (0.07)	44.71 (4.58)	0.19 (0.00)
+RG	462 (1)	226 (0)	97 (1)	0.274 (0)	5.3 (0.1)	1.44 (0.06)	5.02 (0.31)	0.21 (0.01)
+MLC	463 (0)	226 (1)	115 (2)	0.352 (0)	8.3 (0.1)	1.44 (0.02)	4.21 (0.13)	0.24 (0.04)
+PGSH	497 (0)	310 (3)	118 (1)	0.360 (0)	7.7 (0.1)	1.46 (0.06)	3.41 (0.10)	0.20 (0.00)
+DC	496 (1)	312 (1)	116 (2)	0.358 (0)	7.8 (0.1)	1.33 (0.02)	2.30 (0.10)	0.20 (0.01)
+CL	497 (1)	306 (1)	118 (1)	0.364 (0)	11.7 (0.2)	1.42 (0.08)	2.56 (0.06)	0.22 (0.00)
+QRY	497 (0)	310 (3)	116 (2)	0.363 (0)	11.8 (0.2)	1.36 (0.02)	1.57 (0.04)	0.22 (0.01)

Table 3. Throughput in MB/s (left) and latency in seconds (right) of various file systems on a commodity SSD. Higher throughput and lower latency is better. Standard deviation is in parentheses. BetrFS v0.4 and BetrFS v0.6 have compression disabled. Each optimization in BetrFS v0.6 is added with one row with the name of "+" followed by the abbreviation of this optimization in the table. "SFL" is short for Simple File Layer; "RG" range; "MCL" malloc; "PGSH" page sharing; "DC" dentry cache; "CL" conditional logging; "QRY" query path optimization. All BetrFS v0.6 optimizations are applied cumulatively. For instance, "+RG" adds the range message optimizations to BetrFS v0.6 with SFL. Any data points within 15% of the highest throughput or lowest latency are highlighted in green; those that are less than 30% of the best throughput (or more than 3.33× the best latency) are highlighted in red.

In terms of crash consistency, ext4 is configured with ordered mode; XFS and Btrfs have similar semantics. BetrFS v0.4, BetrFS v0.6, ZFS, and F2FS have semantics comparable to full data journaling. BetrFS v0.4, BetrFS v0.6, Btrfs, and ZFS include checksumming to detect on-disk corruptions.

7.1 File System Microbenchmarks

We first conduct a series of file system microbenchmarks to understand how each optimization contributes to BetrFS v0.6 performance. In the sequential I/O tests, we used fio to sequentially write a single 80GiB file, and then re-read it after clearing the VFS caches, reporting average throughput and standard deviation. In the random write tests, we wrote to 256K randomly selected, block-aligned offsets within a 10GiB file, followed by a single `fsync()`. The first column shows the performance of random writes at a 4KiB granularity; the second column shows writes at 4 byte granularity. The TokuBench [7] benchmark creates three million 200-byte files in a balanced directory tree with a fanout of 128. We run TokuBench with 4 threads since our machine has 4 cores. For `rm`, we recursively delete a directory with 2 copies of Linux 3.11.10 source code. For `grep`, we search for the string “cpu_to_be64” in the directory of Linux source code. For `find`, we search for the files with the name `wait.c` in the directory of Linux source code.

Table 3 shows the file system throughput for sequential reads, sequential writes, random writes, and TokuBench, as well as latency of grep, recursive deletion, and find on an SSD. We note that our goal, as stated in §1, is, ideally, to build a single file system that is within 15% of the top performing file system for each operation (shaded in green). Cells shaded in red are more than 70% worse than the best file system.

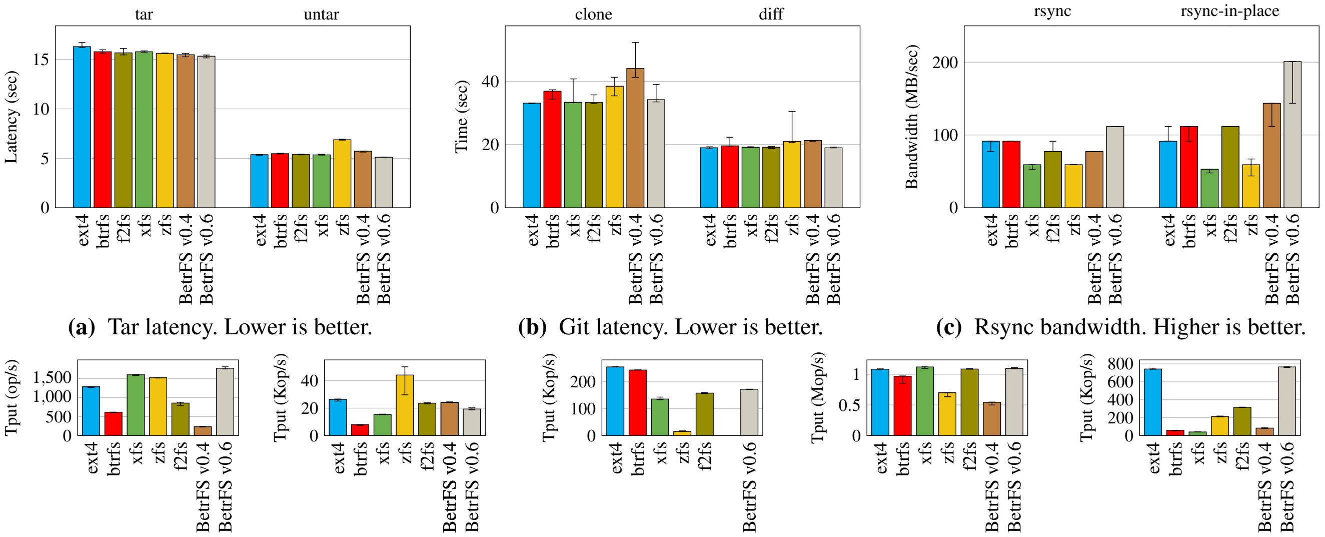
Since BetrFS v0.6 augments the BetrFS design with a series of optimizations, we evaluate BetrFS v0.6 performance with an increasing number of these optimizations enabled.

Simple File Layer (SFL). We find that the impact of switching the “southbound” file system from ext4 to SFL (§3) significantly improved sequential read (by 2.5× and within 20% of disk bandwidth) and reduces `grep` latency by 41%, as the read-ahead heuristics in the B$^\varepsilon$-tree were more effective than the prior read-ahead behavior. Replacing ext4 with SFL also removes double journaling and double caching, which yields significant improvements to several write-intensive workloads, including sequential write (+2.5× throughput), TokuBench (+35%), and recursive deletion (–13% latency).

Range (RG) and Query Path (QRY) Optimizations. As expected, the main beneficiary of the range optimizations is recursive deletion (§4), which is dominated by range deletion messages. These optimizations reduce the `rm` time by an order of magnitude. Reworking the apply-on-query heuristic (also §4) brings BetrFS v0.6 to be the fastest file system on this microbenchmark, and marginally reduces grep time and increases sequential write throughput.

Memory Allocation (MLC). The memory allocation optimizations (§5) primarily benefit workloads that issue many small messages, such as random writes (19% and 28% increased throughput for 4KiB and 4B, respectively), TokuBench (57%), and recursive deletion (–16% latency). For these workloads, the overheads of managing large buffers of small objects become a first-order cost.

Page Sharing (PGSH). Page sharing (§6) primarily improves sequential IO performance, although it helps other



(a) Tar latency. Lower is better.

(b) Git latency. Lower is better.

(c) Rsync bandwidth. Higher is better.

(d) Dovecot mailserver.

(e) OLTP.

(f) Fileserver.

(g) Webserver.

(h) Webproxy.

Figure 2. Application benchmarks. Figures 2c–2h are all throughput, and higher is better.

update intensive workloads. Sequential read improves by over 30 MBps, and sequential write improves by nearly 100 MBps, making sequential writes competitive with other file systems. With an 80 GiB sequential write (needed to more than double DRAM size), the SSD appears bottlenecked on internal operations, well below the advertised peak bandwidth. This is independent of the file system under test. On shorter writes (e.g., 10 GiB, omitted for brevity), this optimization more than doubles the throughput compared to no page sharing.

Directory Cache (DC) and Conditional Logging (CL). We present the directory cache optimization (§4) for read-ahead separately; it removes more than an second of execution time from a recursive deletion. Similarly, the conditional logging optimization (§3.3) increases small file creation (TokuBench) throughput by 50%.

In total, each of these optimizations is necessary to meet our performance goal. Most notably, these optimizations further improve random write and search performance over both BetrFS v0.4 and other standard Linux file systems, indicating that relying solely on faster device-level random write behavior without corresponding data structural changes leaves over 6× the throughput on the table.

7.2 Applications and Benchmarks

We measure the end-to-end performance of BetrFS v0.6 on a range of applications and FileBench [32] server-side workloads, running on an SSD.

Rsync copies the Linux 3.11.10 source tree from a source to a destination directory within the same partition and file system. With the –in-place option, rsync writes data directly to the destination file rather than creating a temporary file and updating via atomic rename. **Tar** unpacks a tarball of Linux 3.11.10 source code and **untar** creates a tarball out of a copy of Linux 3.11.10 source code. **Git clone** clones the latest Linux source repository from one directory to another on the local system. **Git diff** workload reports the time to diff between the v4.14 and v4.07 Linux source tags. The Dovecot **mailserver** 2.2.13 is run with 8 threads. We initialize the mailserver with 10 folders, each containing 2,500 messages. Each of 8 clients performs 10,000 operations with 50% reads and 50% updates (marks, moves, or deletes).

The results are presented in Figures 2a–2d. In the best case, the throughput of an in-place rsync is nearly double the competition, including BetrFS v0.4. Similarly, in Dovecot mailserver, BetrFS v0.6 is much faster than any other file system, unlike BetrFS v0.4. Among these workloads, BetrFS v0.6 is able to roughly match the fastest file system.

Filebench. Figures 2e–2h show the performance for four FileBench benchmarks: OLTP, WebServer, WebProxy, and FileServer. Note that BetrFS v0.4 crashes on FileServer.

BetrFS v0.6 performs as well as the best file systems for Webserver and Webproxy, whereas for OLTP and Fileserver the performance of BetrFS v0.6 is in the middle. In the case of OLTP, the primary bottleneck in BetrFS v0.6 is heavy use of `fsync`, combined with some code paths for log writing that are synchronous in BetrFS v0.6 but asynchronous in other file systems. Profiling indicates that the lost relative performance on FileServer is a mixture of smaller overheads for sequential writes (commensurate with Table 3) and smaller, random reads. We believe these OLTP and Fileserver performance issues are not fundamental can be improved in future work.

8 Related Work

File Systems for SSDs. The flash era has intensified interest in log-structured file systems [29], largely due to flash's faster random reads and the observation that flash translation layers perform best with sequential writes. SFS [22] is a log-structured file system based on NILFS2 (a log-structured file system tuned for HDDs). SFS co-locates data blocks with similar update likelihoods to minimize segment cleaning overheads. FlashLight [12] is a log-structured file system that introduces a hybrid indexing scheme, intra-inode index logging, and a GC scheme that adopts fine-grained data separation. These techniques reduce indexing overheads. F2FS [16] uses a flash-friendly on-disk layout, cost-effective indexing structures, and both multi-head and adaptive logging to optimize log-structured file system performance for modern SSDs.

Orthogonal to this work, some file systems exploit internal SSD parallelism. For instance, ParaFS [42] proposes 2-D data allocation as a way to maintain hot/cold data separation while exploiting channel-level parallelism.

More recently, there has been considerable interest in tiered storage architectures, often using byte-addressable non-volatile memory to first ingest data that is later migrated to capacity-optimized SSDs (or HDDs). NVMFS [25] is one such experimental file system that assumes two distinct types of storage media: NVRAM and NAND flash SSD. The fast NVRAM is used to store hot data and metadata, and writes to the SSD are sequential, as in a log-structured file system. Strata [14] is a multi-tiered user-space file system that exploits NVMM as the high-performance tier, and SSDs/HDDs as the lower tiers. Nova [38] is a file system designed for hybrid memory systems, using log-structured file system techniques to exploit the fast random access that NVMs provide.

Anvil [37] exposes fine-grained control over storage address remapping within an SSD, facilitating efficient snapshots, deduplication, and single-write journaling. Transactional Flash [24] extends SSDs with a transactional API, supporting transactional operations in file and database systems.

BlueStore [1] replaces local file systems as the Ceph storage backend and addresses similar metadata performance issues caused by stacking file systems.

Optimizing WODs for Flash Storage. LSM-trees are a popular write-optimized dictionary (WOD), used in popular key-value stores, including RocksDB. RocksDB [20] recently implemented a range delete operation that is similar to the operation optimized in this paper. Several projects have looked at optimizations for running an LSM-tree on flash. bLSM [30], a general-purpose log-structured merge tree for both HDDs and SSDs, introduced a new merge scheduler to minimize write latency and maintain write throughput; it also uses Bloom filters [4] to improve performance. VT-Trees [31] use indirection to avoid unnecessarily rewriting already-sorted data during compaction. LOCS [36] exposes internal flash channels to the LSM-tree key-value store so that compactions can exploit the abundant parallelism. Wisckey [19] separates keys from values in a persistent LSM-tree-based KV-store to minimize I/O amplification for SSD-conscious storage. PebblesDB [26] fragments interior levels of the LSM tree in order to reduce the overheads of compaction. SILK [2] is a key-value store, based on RocksDB, that incorporates the notion of an I/O scheduler to reduce interference and thus prevent latency spikes. KVell [18] presents a novel persistent key-value design for modern block-addressable NVMe SSDs; it adopts a shared-nothing philosophy to avoid synchronization overheads, batches device accesses, and maintains an inexpensive partial sort in memory. All of these techniques are complementary to the techniques described in this paper.

VFS Directory Cache Optimization. Tsai et al. [34] propose caching the result of a `readdir`, which Linux does not do by default. Our `readdir` optimization is complementary: it does not reduce the number of `readdir` calls, but uses these results to reduce subsequent child lookup costs.

Write-Optimized File Systems. TableFS [27] and IndexFS [28] store file system metadata in an LSM-tree with a column-style schema to speed up insertion throughput. TableFS and IndexFS demonstrate that write-optimized dictionaries can accelerate file system metadata operations for HDDs while BetrFS demonstrates write-optimized dictionaries can be a useful tool for building general-purpose file systems for both HDDs and SSDs. TokuFS [7] is a FUSE-based file system, also built using B$^\varepsilon$-trees. TokuFS showed that a write-optimized file system can support efficient write-intensive and scan-intensive workloads. KVFS [31] uses VT-trees. It is also FUSE-based, supports transactions, and has comparable performance to the in-kernel ext4 file system. Different from both KVFS and TokuFS, BetrFS integrates write-optimized dictionaries into the Linux kernel's storage stack, which elides performance issues imposed by FUSE.

9 Conclusion

Although trade-offs are often considered fundamental in file system design, this paper demonstrates that one can build a compleat file system for commodity SSDs. Further, this paper demonstrates that the choice of persistent indexing data structure has a first-order impact on performance, even on faster flash devices—legacy data structures forego up to 6× the random write throughput that one can realize with a B$^\varepsilon$-tree on the same hardware. This is built on the basic technique of batching smaller I/Os into larger ones, but requires considerable infrastructure improvements and other optimizations to meet the computational budget required by flash storage.

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A Artifact Appendix

A.1 Abstract

This artifact contains a set of scripts that reproduce the experiments in the EuroSys 2022 paper "A Compleat File System for Commodity SSDs", which introduces BetrFS version 0.6. BetrFS is an in-kernel Linux file system that uses a B$^{\varepsilon}$-tree to index on-disk data and BetrFS v0.6 performs consistently well on an SSD across different workloads.

A.2 Description & Requirements

A.2.1 How to access. The artifact consists of two public GitHub repositories. The first repository, https://github.com/oscarlab/betrfs (hereinafter *betrfs*), contains all public releases of the BetrFS source code; this is the repository where future bugfixes and maintenance updates will be posted. BetrFS version 0.6, which is the version of BetrFS where all of the paper's optimizations applied, is denoted by the tag *v0.6*. Versions of BetrFS with the paper's optimizations cumulatively applied can be found in this repository's eurosys22/sfl-kernel-4.19.99, eurosys22/range-kernel-4.19.99, eurosys22/malloc-opts-kernel-4.19.99, eurosys22/page-sharing, eurosys22/dc-kernel-4.19.99, eurosys22/cond-log-opt, and eurosys22/query-path-opt branches.

The second repository, https://github.com/oscarlab/betrfs-eurosys22-artifact [10] (hereinafter *betrfs-eurosys22-artifact*), contains scripts that automate the process of downloading, compiling, and installing dependencies; switching Linux kernels; running experiments; and aggregating experiment results. The `README.md` file in this repository contains detailed instructions, including Unix commands, that run the scripts provided to complete these tasks.

A.2.2 Hardware dependencies. Since the paper compares Linux file system performance on commodity SATA SSDs, the testing environment should have an independent SATA SSD that is sufficiently large, i.e., with least 250GiB of usable capacity, as well as a root file system partition with at least 250GiB of space.

A.2.3 Software dependencies. The artifact is known to work on the stock version of Ubuntu 18.04.6.

BetrFS v0.4, BetrFS v0.6, and the set of comparison file systems use different kernels. In particular,

- BetrFS v0.4: stock Linux v4.19.99
- BetrFS v0.6: patched Linux v4.19.99
- All other file systems: stock Linux v5.9.15 (the newest Linux kernel version at the time of development).

The artifact provides scripts to build and switch among the required kernels. The artifact also provides scripts to install required dependencies from Ubuntu repositories or public web sources, including git, bison, flex, gcc-7, g++7, valgrind, zlib, f2fs-tools, ZFS, the Dovecot mailserver, and Filebench.

A.2.4 Benchmarks. The Filebench benchmarking tool is used in this evaluation. The *betrfs* repository contains all required Filebench workload personalities used in the experiments.

A.3 Set-up

To prepare the environment, the user should run the `install-deps.sh` script in the *betrfs-eurosys22-artifact* repository.

In addition, the user should confirm that the `install-deps.sh` script set meaningful values for the configuration variables in the *betrfs* repository's `benchmarks/fs-info.sh` file. More importantly, the user should set `sb_dev` in `benchmarks/fs-info.sh` to the devfs path of the SSD on which experiments will be run.

A.4 Evaluation workflow

To compare performance of the different file systems and optimizations across workloads, the experiments should be run in an appropriate environment for each file system. There are scripts in the *betrfs-eurosys22-artifact* repository to complete these general steps:

- install and reboot into the appropriate kernel
- run the comprehensive evaluation script

The `pre-*.sh` scripts install the required kernel and any other dependencies, after which the machine must be rebooted.

The `eval-*.sh` scripts run the actual benchmarks. Results of the experiments are placed into CSV files in a directory named `results/`.

If desired, the *betrfs-eurosys22-artifact* repository also includes instructions for running individual tests from among the set of tests that are part of the comprehensive evaluation script.

A.4.1 Major Claims.

- *(C1)*: On commodity SATA SSDs, BetrFS v0.6 performs consistently well across a range of workloads that test file system performance. This is demonstrated by microbenchmarks in experiment set (E1).
- *(C2)*: BetrFS v0.6's consistently strong performance on common file system tasks corresponds to good performance on applications. This is demonstrated by the experiments (E2) through (E6).

A.4.2 Experiments.

- *Experiment (E1): [FS microbenchmarks]:* file system microbenchmarks correspond to Table 3. Microbenchmarks include sequentially reading and writing large files, random writes, creating many small files in a balanced directory tree (Tokubench), recursive directory traversal (find, grep), and recursive directory deletion (rm).

- *Experiment (E2): [tar/untar]:* the time to create and expand tar archives of the Linux 3.11.10 source code, corresponding to Figure 2(a).
- *Experiment (E3): [git]:* Git latency, corresponding to Figure 2(b). Git clone reports the time to clone the latest Linux source repository from one directory to another on the local system, and Git diff reports the time to diff between the v4.14 and v4.07 Linux source tags.
- *Experiment (E4): [rsync]:* rsync throughput, corresponding to Figure 2(c). Rsync copies the Linux 3.11.10 source tree from a source to a destination directory within the same partition and file system. With the `-in-place` option, rsync writes data directly to the destination file rather than creating a temporary file and updating via atomic rename.
- *Experiment (E5): [Dovecot mailserver]:* mailserver throughput, corresponding to Figure 2(d). The Dovecot mailserver 2.2.13 is run with 8 threads. The mailserver is initialized with 10 folders, each containing 2,500 messages. Each of 8 clients performs 10,000 operations with 50% reads and 50% updates (marks, moves, or deletes).
- *Experiment (E6): [Filebench]:* Filebench performance on a set of different simulated workloads, corresponding to Figures 2(e) through 2(h). The workloads include scaled versions of the OLTP, Fileserver, Webserver, and Webproxy workload personalities.

[Preparation] Before running any experiment, execute the *betrfs-eurosys22-artifact* repository's `pre-betrfs-v0.4.sh` script to prepare the environment for BetrFS v0.4, `pre-betrfs-v0.6.sh` script for BetrFS v0.6, and `pre-other.sh` for Btrfs, ext4, XFS, ZFS, and F2FS.

[Execution] To run all experiments for a given environment, execute the *betrfs-eurosys22-artifact* repository's `eval-betrfs-v0.4.sh` for BetrFS v0.4, `eval-betrfs-v0.6.sh` for BetrFS 0.6, and `eval-other.sh` for btrfs, ext4, xfs, zfs, and f2fs.

[Results] All results are placed in CSV files in the `results/` directory.

[Run-time] Although there is variation among the individual file systems, executing all experiments on a single file system takes approximately eight hours on the hardware described in the paper. This run-time estimate includes multiple experiment runs as executed by the scripts.

A.5 General Notes

The *betrfs* repository branches described above correspond to the cumulative application of the paper's optimizations. BetrFS v0.6 is the version of the file system that includes all optimizations; BetrFS v0.6 should be considered the final product of this study.