Abstract

In this paper we analyze the influence that lower layers (file system, OS, SSD) have on HDFS’ ability to extract maximum performance from SSDs on the read path. We uncover and analyze three surprising performance slowdowns induced by lower layers that result in HDFS read throughput loss. First, intrinsic slowdown affects reads from every new file system extent for a variable amount of time. Second, temporal slowdown appears temporarily and periodically and is workload-agnostic. Third, in permanent slowdown, some files can individually and permanently become slower after a period of time.

We analyze the impact of these slowdowns on HDFS and show significant throughput loss. Individually, each of the slowdowns can cause a read throughput loss of 10-15%. However, their effect is cumulative. When all slowdowns happen concurrently, read throughput drops by as much as 30%. We further analyze mitigation techniques and show that two of the three slowdowns could be addressed via increased IO request parallelism in the lower layers. Unfortunately, HDFS cannot automatically adapt to use such additional parallelism. Our results point to a need for adaptability in storage stacks. The reason is that an access pattern that maximizes performance in the common case is not necessarily the same one that can mask performance fluctuations.

1 Introduction

Layering is a popular way to design big data storage stacks. Distributed file systems (HDFS, GFS) are usually layered on top of a local file system (ext4, Btrfs, F2FS, XFS, ZFS) running in an OS. This approach is desirable because it encourages rapid development by reusing existing functionality. An important goal for such storage stacks is to extract maximum performance from the underlying storage. With respect to this goal, layering is a double-edge sword. On one hand, the OS and the file system can compensate for and mask inefficiencies found in hardware. On the other hand, they can introduce their own performance bottlenecks and sources of variability.

In this paper we perform a deep dive into the performance of a critical layer in today’s big data storage stacks, namely the Hadoop Distributed File System (HDFS). We particularly focus on the influence that lower layers have on HDFS’ ability to extract the maximum throughput that the underlying storage is capable of providing. We focus on the HDFS read path and on SSD as a storage media. We use ext4 as the file system due to its popularity. The HDFS read path is important because it can easily become a performance bottleneck for an application’s input stage which accesses slower storage media compared to later stages which are often optimized to work fully in memory.

Central to our exploration is the storage access pattern of a single HDFS read request: single threaded, sequential access to large files (hundreds of megabytes) using buffered IO. This access pattern is simple but tried and tested and has remained unchanged since the beginnings of HDFS. It is increasingly important to understand whether a single HDFS read using this access pattern can consistently extract by itself the maximum throughput that the underlying storage can provide. As many big data processing systems are heavily IO provisioned and the ratio of cores to disks reaches 1, relying on task-level parallelism to generate enough parallel requests to saturate storage is no longer sufficient. Moreover, relying on such parallelism is detrimental to application performance since each of the concurrent HDFS reads is served slower than it would be in isolation.

With proper parameter configuration, the HDFS read access pattern is sufficient to extract maximum performance out of our SSDs. However, we uncover and analyze three surprising performance slowdowns that can affect the HDFS read path at different timescales (short, medium and long) and result in throughput loss. All three slowdowns are caused by lower layers (file system, SSDs). Furthermore, our analysis shows that the three slowdowns can affect not only HDFS but any application that uses buffered reads.
opposed to related work that shows worn out SSDs could cause various performance problems \[8\]\[10\], our slowdowns occur on SSD with very low usage throughout their lifetime.

The first slowdown, which we call intrinsic slowdown, affects HDFS reads at short time scales (seconds). HDFS read throughput drops at the start of every new ext4 extent read. A variable number of IO requests from the start of each extent are served with increased latency regardless of the extent size. The time necessary for throughput to recover is also variable as it depends on the number of request affected.

The second slowdown, which we call temporal slowdown, affects HDFS reads at medium time scales (tens of minutes to hours). Tail latencies inside the drive increase periodically and temporarily and cause HDFS read throughput loss. While this slowdown may be confused with write-triggered SSD garbage collection \[8\], we find, surprisingly, that it appears in a workload-agnostic manner.

The third slowdown, which we call permanent slowdown, affects HDFS reads at long time scales (days to weeks). After a period of time, HDFS read throughput from a file permanently drops and never recovers for that specific file. Importantly this is not caused by a single drive-wide malfunction event but rather it is an issue that affects files individually and at different points in time. The throughput loss is caused by latency increases inside the drive, but, compared to temporal slowdown all requests are affected, not just the tail.

Interestingly, we find that two of the three slowdowns can be completely masked by increased parallelism in the lower layers, yet HDFS cannot trigger this increased parallelism and performance suffers. Our results point to a need for adaptability in storage stacks. An access pattern that maximizes performance in the common case is not necessarily the one that can mask unavoidable hardware performance fluctuations.

With experiments on 3 SSD based systems, we show that each of the slowdowns we identified can individually introduce at least 10-15% HDFS read throughput degradation. The effect is cumulative. In the worst case, all slowdowns can overlap leading to a 30% throughput loss.

The contributions of the paper are as follows:

- We identify and analyze the intrinsic slowdown affecting reads at the start of every new ext4 extent for a variable amount of time.
- We identify and analyze the temporal slowdown that affects reads temporarily and periodically while being workload-agnostic.
- We identify and analyze the permanent slowdown affecting reads from an individual file over time.
- We analyze the impact of these slowdowns on HDFS performance and show significant throughput loss.
- We analyze mitigation techniques and show that two of the three slowdowns can be addressed via increased parallelism.

The rest of the paper continues as follows. \[2\] presents HDFS architecture and the configuration that we use. \[3\] presents our experimental setup and the metrics used. \[4\] \[5\] and \[6\] introduce and analyze intrinsic, temporal and permanent slowdown respectively. \[7\] discusses the findings, \[8\] presents related work and \[9\] concludes.

2 Background

2.1 HDFS Architecture

HDFS is a user-level distributed file system that runs layered on top of a local file system (e.g. ext4, zfs, btrfs). An HDFS file is composed of several blocks, and each block is stored as one separate file in the local file system. Blocks are large files; a common size is 256 MB.

The HDFS design follows a server-client architecture. The server, called the NameNode, is a logically centralized metadata manager that also decides file placement and performs load balancing. The clients, called DataNodes, work at the level of HDFS blocks and provide block data to requests coming from compute tasks.

To perform an HDFS read request, a compute task (e.g. Hadoop mapper) first contacts the NameNode to find all the DataNodes holding a copy of the desired data block. The task then chooses a DataNode and asks for the entire block of data. The DataNode reads data from the drive and sends it to the task. The size DataNode’s reads is controlled by the parameter io.file.buffer.size (default 64KB). The DataNode sends as much data as allowed by the OS socket buffer sizes. A DataNode normally uses the sendfile system call to read data from a drive and send it to the task. This approach is general and handles both local tasks (i.e. on the same node as the DataNode) as well as remote tasks. As an optimization, a task can bypass the DataNode for local reads (short-circuit reads) and read data directly using standard read system calls.

2.2 HDFS Access Pattern

We now summarize the main characteristics of the HDFS read access pattern since this pattern is central to our work.

- **Single-threaded.** One request from a compute task is handled by a single worker thread in the DataNode.
- **Large files.** HDFS blocks are large files (e.g. 128MB, 256MB). Each HDFS block is a separate file in the local file system.
- **Sequential access.** The HDFS reads access data sequentially for performance reasons.
• Buffered IO. HDFS uses buffered IO in the DataNode (via sendfile or read system calls).

2.3 Removing Software Bottlenecks

We now detail the configuration changes we made to alleviate network and compute bottlenecks affecting HDFS and to eliminate sources of interference. As a result, we observed that HDFS can extract the maximum performance that our SSDs can generate.

File system configuration. We disabled access time update, directory access time update, and data-ordered journaling (we use write-back journaling) in ext4. This removes sources of interference so that we can profile HDFS in isolation.

OS configuration. Small socket buffer sizes limit the number of packets that the DataNode can send to a task and thus reduce performance by interrupting disk reads and inducing disk idleness. We increase the socket buffer size for both reads and write to match the size of the HDFS blocks.

HDFS configuration. We configured io.file.buffer.size to be equal to the HDFS block size. The default value of this parameter (64KB) results in too many sendFile system call, which in turn create a lot of context-switching between user and kernel space, which results in idleness for the IO device. We modified the HDFS code to allow the parameter to be set to 256MB as by default the maximum size is 32MB.

2.4 Maximizing Device Throughput

An important goal for HDFS is to maximize the throughput obtained from the storage devices. One way to achieve this is via multi-threading in the DataNode. This is already part of the design as different DataNode threads can serve different task requests concurrently. While this can maximize device throughput it does so at the expense of single-thread performance which reduces task performance.

State-of-the-art data processing systems are heavily IO provisioned, with a ratio of CPU to disk close 1 [1]. In this context, relying on parallelism to make the most of the storage is unlikely to help because the number of tasks is roughly the same as the number of disks (tasks are usually scheduled on a separate core). As a result, it is important to understand and ensure that the HDFS access pattern (single-thread, large files, sequential access, buffered IO) can by itself extract maximum performance from SSDs.

3 Methodology

In this section, we describe the hardware and software settings, tools, workloads and metrics used in our analysis.

3.1 Experimental Setup

Hardware. We use three types of machines: Machine A has 2 Intel Xeon 2.4GHz E5-2630v3 processors, with 32 cores in total, 128GB of RAM, and a 450GB Intel DC S3500 Series (MLC) SATA 3.0 SSD. Machine B has 4 Intel Xeon 2.7GHz E5-4650 processors, with 32 cores in total, 1.5TB of RAM, and a 800GB HP 6G Enterprise SATA 3.0 SSD. Machine C has 2 Intel Xeon 2.4GHz E5-2630v3 processors, with 32 cores in total, 128GB of RAM, and a 512GB Samsung 860 Pro (V-NAND) SATA 3.0 SSD.

Our SSDs have been very lightly used throughout their lifetimes. After concluding our analysis we computed the total lifetime reads and writes performed on the drives using the "sectors read" and "sectors written" fields in /proc/diskstats in Linux. The value was less than 1TB for both reads and writes for each drive. This is orders of magnitude less than the manufacturer provided guarantees for SSDs. Thus, past heavy use of the drives is not a factor in our findings. Moreover, the disk utilization of our SSDs in the experiments is very low, under 20%.

Software. We use Ubuntu 16.04 with Linux kernel version 4.4.0. As a local file system we use ext4, one the most popular Linux file systems. We use HDFS version 2.7.1.

Monitoring Tools. To monitor IO at the storage device, we rely on block layer measurements using blktrace and blkparse. Blktrace collects IO information at the block layer, while blkparse makes the traces human readable. Where necessary we use perf and strace to analyze program behavior.

Workloads. We use HDFS via Hadoop where we run a simple WordCount job. The exact type of Hadoop job is inconsequential for our findings because we have already decoupled HDFS performance from software bottlenecks in Section 2.3. We modified the Hadoop WordCount job to not write any output so that we can reliably measure read performance. We use the FIO tool for analysis beyond HDFS. The data read by HDFS (or FIO) is composed of randomly generated strings and is divided in 8 ext4 files of 256MB each.

Our experiments consist in reading (with Hadoop or FIO) repeatedly over 24 hours the 8 ext4 files We ensure that all experiments run in isolation and are not affected by interference from any other processes.

Presenting slowdowns. For every slowdown we are able to separate its effect and present results for periods with and without that slowdown. The results without a slowdown include the effects of all other slowdowns that occur at shorter timescales. For example, when comparing results with or without temporal slowdown, the results include the effect of intrinsic slowdown but not that of permanent slowdown. This is ok because the effect of a slowdown is roughly constant over longer periods of time.

What we measure. We measure performance at the HDFS DataNode level. We measure the throughput of HDFS reads and the latency of individual block layer IO re-
quests. We do not measure end-to-end performance related to Hadoop tasks. Before every experiment we drop all caches to ensure reads actually come from the drive.

The Hadoop tasks are collocated with the HDFS DataNodes on the same machines. The DataNodes send data to the tasks via the loopback interface using the sendfile system call. We also analyzed short-circuit reads which enable Hadoop tasks to read local input directly (using standard read calls) by completely bypassing HDFS but the findings remained the same.

**Generating single requests.** In our experiments using buffered IO, two requests overlap in the device driver. In such a case, increases in request latency could be caused either by drive internals or by a sub-optimal request overlap. To distinguish such cases we tweak buffered IO to send one request at a time. To send a single request of size \( X \) KB by tuning `/sys/block/<device>/queue/read_ahead_kb`. We then use the `dd` command to read one chunk of size \( X \) (dd bs=X count=1). The influence of read ahead size on block layer size is known and discussed in related work [13].

### 3.2 Metrics

In the rest of the paper, the word "file" refers to one 256MB ext4 file. In HDFS parlance this represents one HDFS block.

- **File throughput.** The number of bytes, read from the target file, divided by the period of time. The period starts with the submission of the first block layer IO request in the file (as timestamped by blktrace) and finishes with the completion of the last block layer IO request in the file (as timestamped by blktrace). During this period we only count time when the disk is active, i.e., there is at least one IO request being serviced by or queued for the drive. This metric removes the impact of disk idle time caused by context-switches between user and kernel space in the application. Our HDFS results show no disk idle time after applying the changes in Section 2.3. Nevertheless, disk idle time appears in FIO and we chose to discard it for a fair comparison to HDFS. Overall, the disk idle time does not influence our main findings.

- **Request Latency.** The time between the timestamp when a block layer request is sent to the drive (D symbol in blktrace) and the timestamp of its completion (C symbol in blktrace). Both timestamps are taken from blktrace.

- **Fragmentation.** The number of extents an ext4 file has. Note that all of our files are 256MB. The maximum extent size in ext4 is 128MB. Therefore, the minimum possible number of extents in a file is 2.

- **Recovery Time.** The period of time during which IO requests have higher than usual latency due to intrinsic slowdown. This is measured starting from the first IO read request of an ext4 extent until either the latency of the requests decreases to normal or the extent is fully read, whichever comes first.

### 4 Intrinsic Slowdown

In this section, we introduce the intrinsic slowdown, a performance degradation that predictably affects files at short time scales (seconds to minutes). This slowdown is related to the logical file fragmentation. Every time a new file system extent is read, a number of IO requests from the start of the extent are served with increased latency and that is correlated with throughput drops. Interestingly, even un-fragmented files are affected since a file has to have at least one extent and every extent is affected by the slowdown. The more fragmented a file is, the more extents it has, and the bigger is the impact of the slowdown.

Intrinsic slowdown appears on all the machines we tested and causes a drop in throughput of 10-15% depending on the machine. The slowdown lasts a variable amount of time but there is no correlation with extent size. This slowdown affects not only HDFS but all applications using buffered IO.

The remainder of this section presents an overview of a throughput loss, an analysis of the results, a discussion on causes and an analysis of mitigation strategies.

#### 4.1 Performance Degradation at a Glance

Figure 1 illustrates the influence that an increased number of extents has on throughput for each of the 3 machines. In this figure, each point represents the average file throughput of a set of files with the same number of extents in one machine. Files were created using ext4’s default file allocation policies so we had no control over the number of extent each file was allocated. We observed that ext4 allocations result in highly variable fragmentation levels even on our drives which were less then 20% full. We often saw cases where one file was allocated 30 extents and a file created seconds after was allocated 2 extents. A thorough analysis of ext4 allocation patterns is, however, beyond the scope of this work.

The figure shows that an increase in fragmentation is correlated with a loss in throughput. This finding holds on all 3 machines but the magnitude of the throughput loss is different because the SSDs are different. With 29 extents, throughput drops by roughly 13% for machines A and B, but by less than 5% for machine C. There is a limit to the throughput loss and that is best exemplified by the fact that throughput drops very slowly for machines A and B after 20 extents. The reason is that the extents are smaller but the recovery period is not correlated with the extent size so a very large percentage of the IO requests is affected by the slowdown.

#### 4.2 Analysis

**Correlations.** We next analyze IO request latency. Figure 2 presents the request latencies on machines A, B and C, during an HDFS read. The dashed lines correspond to request latencies after the intrinsic slowdown disappeared while the
Temporal and Spatial Spillover: Figure 3 shows the correlation between increased latency and request overlap imbalance. The imbalance is corrected around request 22 and soon after latency drops under 1 ms which is the latency we normally see outside of intrinsic slowdown.

Characterization of recovery periods: We next analyze the duration and variability of the recovery periods. There are two main insights. First, even for a single extent size and one machine, there can be significant variation in the duration of the recovery period. Second, the duration of the recovery period is not correlated to the extent size.

Figure 4 shows CDFs of the duration of the recovery period on the 3 machines. For each machine we show large extents (128 MB) with continuous lines and smaller extents (32-40 MB) with dashed lines. We aggregated results from extents from multiple files if they have the target size and reside on the same machine. We measure the recovery duration in number of requests. The request size is 256 KB.

The CDFs for any one of the machines show a similar pattern in the recovery period despite the different extent size. Therefore, extent size is not a factor with respect to the duration of the recovery period.

There is significant variability in the recovery period for every extent size on machines A and B. The worst-case recovery duration is more than 5x that of the best-case. In contrast, machine C shows much less variability.

If we compute the recovery period relative to extent size (not illustrated) we find that for the smallest extents (e.g. 8 MB) it is common for at least 50% of the requests in the extent to be affected by intrinsic slowdown. In the worst case, we have seen 90% of an extent being affected.

Discussion on internal SSD root cause: Since we do not have access to the proprietary SSD FTL design we cannot directly search for the root cause internal to the drive. We believe that sub-optimal request overlap leads to throughput loss because it forces the drive to be inefficient by serving both overlapping requests in parallel when the most efficient strategy would sometimes be to focus on the oldest one first. The request stream enters in this state due to the initial requests at the start of the extent. The stream self-corrects by eventually reaching the optimal (balanced) request overlap and remaining there. The software does not help in the cor-
Throughput

Average File Throughput (MB/s)

Percentiles

sent in parallel to the drive. Results in both larger requests as well as more requests being buffered IO, by increasing the read ahead size. This setting

We observe the same effect when increasing parallelism in requests, direct IO better leverages the device parallelism. Slowdown. The reason is that by sending more and larger extents with direct IO. The tendency holds across all machines tested. In other words, direct IO can mask intrinsic slowdown. We consider mitigation strategies that are more aggressive than the self-correction happens solely due to timing, based on the request latencies. This also explain the variability in the recovery periods.

4.3 Mitigation Strategies

We consider mitigation strategies that are more aggressive in generating request level parallelism in the hope that they could compensate for the loss in throughput due to the slowdown. We find that both direct IO as well as increasing the number of requests sent in parallel with buffered IO can mask intrinsic slowdown.

Figure 5 compares average file throughput vs number of extents, when using direct IO across different machines. The files are the same as in Figure 4. The figure shows that average throughput is maintained across different numbers of extents with direct IO. The tendency holds across all machines tested. In other words, direct IO can mask intrinsic slowdown. The reason is that by sending more and larger requests, direct IO better leverages the device parallelism. We observe the same effect when increasing parallelism in buffered IO, by increasing the read ahead size. This setting results in both larger requests as well as more requests being sent in parallel to the drive.

5 Temporal Slowdown

In this section, we introduce the temporal slowdown, a periodic and temporary performance degradation that affects files at medium timescales (minutes to hours). At the high level, the pattern in which temporal slowdown manifests might we confused with write-induced SSD garbage collection (GC). However, temporal slowdown is not always GC. Surprisingly, on machine A, it always manifests even in read-only workloads. On machine B, it is indeed triggered by writes but interestingly it takes a very small amount of writes relative to the drive capacity to trigger temporal slowdown. Moreover, our SSDs have a very low utilization (under 20%). We link the slowdown to tail latency increases inside the drive. Temporal slowdown causes a throughput drop of up to 14%. Temporal slowdown affects not only HDFS but all applications using either direct or buffered IO.

The remainder of this section presents an overview of a throughput loss, an analysis of the results, a discussion on causes and an analysis of mitigation strategies.

5.1 Performance Degradation at a Glance

Figure 6 presents the throughput timeline of a file affected by temporal slowdown on machine A. It shows three instances of the slowdown around the 1:00, 3:30 and 5:40 marks. The rest of the throughput variation is caused by inherent slowdown. The average throughput of the periods not affected by the slowdown is 430 MB/s. The first instance of slowdown causes a drop in throughput to 370 MB/s, a 14% drop from the 430 MB/s average. On machine A, temporal slowdown appears on average every 130 min and last on average 5 min.

Figure 7 shows the same experiment on machine B. There are 5 instances of temporal slowdown clearly visible due to the pronounced drops in throughput. The average throughput of the periods not affected by the slowdown is 455 MB/s. The biggest impact is caused by the third slowdown instance which causes a drop to 390 MB/s, almost 15% down from the average. On machine B, temporal slowdown appears on average every 18 min and last for 1.5 min.
Correlations. We next analyze IO request latency. Figure 8 shows a CDF of the request latencies for one file. One line shows latencies during temporal slowdown while another shows latencies during periods not affected by the slowdown. The difference lies in the tail behavior. During temporal slowdown a small percentage of the requests show much larger latency. This is consistent with the impact of background activities internal to the drive.

The experiments in Figures 6 and 7 do introduce writes and they responsible for triggering temporal slowdown on machine B. Even though from the application perspective (i.e., Hadoop) the workload is read-only, a small number of writes appear due to HDFS metadata management. These are the only writes in the system as we explicitly turned off journaling and metadata updates in ext4. Interestingly, a small amount of writes relative to the drive size is sufficient to trigger temporal slowdown. On machine B, temporal slowdown occurs approximately every 120MB. That amounts to only 0.015% of the disk size.

Temporal slowdown without writes. Our main finding related to temporal slowdown is that it can occur in the complete absence of writes. This occurs only on machine A so we focus on it for these experiments. To avoid any writes, we repeat the experiment using FIO instead of HDFS. We configure FIO to use the read system call and evaluated both direct IO and buffered IO. The results were similar so we only show direct IO. We confirm that there are no writes performed during the experiments by checking the number of written sectors on the drive (from /proc/diskstats), before and after the experiments. In addition, we ensure that no writes have been performed in the system for at least one hour before the start of the experiments.

In Figure 9 we show the throughput timeline when using FIO with direct IO. FIO shows more variability in the common case compared to Hadoop because of context-switches between kernel and user space. The temporal slowdown is again visible despite the absence of writes. The slowdown appears every 130 min on average and last 5 min on average. The periodicity is almost identical to the HDFS case, suggesting that the HDFS metadata writes did not play a role in triggering temporal slowdown on machine A.

Figure 10 presents the IO request latency for FIO with direct IO. Again, tail latency increases during slowdown. The four different latency steps appear because direct IO sends, by default, four large requests (1 MB) to the drive.

Trigger of slowdown without writes. Next, we analyze whether temporal slowdown in the absence of writes is correlated with the number of reads performed or it is time-based. We introduce periods of inactivity using sleep periods between the reads. We make sure that these periods are much smaller than the duration of temporal slowdown so that we
do not miss slowdown events. We find that regardless of the inactivity period induced, the periodicity remains the same suggesting time-based triggers.

**Discussion on internal SSD root cause.** Since we do not have access to the proprietary SSD FTL design we can not directly search for the root cause internal to the drive. In theory, there are three known culprits for temporal slowdowns in SSDs yet our findings do not match any of them. The first one is write-induced GC \[27, 30\]. However, we show that temporal slowdown can appear in the absence of writes as well. The last two culprits are read disturbance and retention errors \[3\]. In the related work, in Section 8, we argue at length that these culprits appear on drives that are far more worn out (orders of magnitude more P/E cycles) than ours and after order of magnitude more reads have been performed. We hypothesize that temporal slowdown on our drives is triggered by periodic internal bookkeeping tasks unrelated to past drive usage or current workload.

### 5.3 Mitigation Strategies

We have found no simple way of masking temporal slowdown. It occurs for both buffered IO and direct IO. One could attempt to detect early signs of slowdown or estimate its start via profiling and then avoid performing reads during the period. This would yield more predictable performance at the expense of delays.

### 6 Permanent Slowdown

In this section, we introduce the permanent slowdown, an irreversible performance degradation that affects files at long timescales (days to weeks). Permanent slowdown occurs at a file level. It is not triggered by a single drive-wide event. Thus, at any point in time, a drive can contain both files affected by permanent slowdown and files unaffected by it. The exact amount of time it takes for a file to be affected by permanent slowdown varies from file to file and is not influenced by how many times a file was read. We only see permanent slowdown on machines of type A. Permanent slowdown causes a throughput drop of up to 15%.

We find that permanent slowdown is not specific to HDFS but affects all read system call that use bufferd IO. We link the slowdown to unexpected and permanent latency increases inside the drive for all IO requests.

For terminology, in the context of permanent slowdown, "before" means before the first signs of slowdown and "after" means after slowdown completely set in. The CDFs represent a single HDFS file composed of 8 blocks (i.e. 8 ext4 files). Figure [11] shows a different file where we caught the onset of the slowdown. Nevertheless, we have seen that all files affected by the slowdown show a similar degradation pattern and magnitude.

### 6.1 Performance Degradation at a Glance

Figure [11] shows the onset and impact of permanent slowdown. The plot shows a 10 hour interval centered around the onset of permanent slowdown. The file was created several days before this experiment was ran. For the first 4 hours, read throughput lies between 340 MB/s and 430 MB/s. This variation is explained by the intrinsic and the temporal slowdowns described in Sections 4 and 5. Around the fourth hour, the permanent slowdown appears and after less than one hour it completely sets in. From that point on, read throughput remains between 320 MB/s and 380 MB/s in this experiment and all future experiments involving this file.

Figure [12] compares the CDF of the read throughput of the same file before and after slowdown. At the median, throughput drops by 14.7% from 418 MB/s to 365 MB/s.

### 6.2 Analysis

**Generality.** We start by analyzing the generality of the permanent slowdown. HDFS uses the sendfile system call to transfer data. Using the `perf` tool we find that sendfile shares most of its IO path in the Linux kernel with the read system
We next analyze IO request latency. Figure 13 presents a throughput comparison between HDFS (sendfile system call) and FIO (read system call). The two rightmost CDFs show the throughput for HDFS and FIO before permanent slowdown. HDFS and FIO behave similarly. The same applies after permanent slowdown sets in (leftmost CDFs). Similar results were obtained using libaio as an IO engine for FIO. This result shows that permanent slowdown does not affect a particular system call (sendfile) but the group of read system calls that use buffered IO.

We use FIO to generate reads using buffered IO. We configure FIO to use the read system call (i.e. sync io engine as a FIO parameter). Figure 13 presents a throughput comparison between HDFS (sendfile system call) and FIO (read system call). The two rightmost CDFs show the throughput for HDFS and FIO before permanent slowdown. HDFS and FIO behave similarly. The same applies after permanent slowdown sets in (leftmost CDFs). Similar results were obtained using libaio as an IO engine for FIO. This result shows that permanent slowdown does not affect a particular system call (sendfile) but the group of read system calls that use buffered IO.

**Correlations.** We next analyze IO request latency. Figure 14 compares the CDFs of request latency in HDFS on one file before and after permanent slowdown. Permanent slowdown induced an increase in latency at almost every percentile. Thus, most requests are treated slower. At the median, the latency increases by 25%. The latencies in the tail of the CDF are explained by the inherent and the temporary slowdowns. We re-run the experiment using FIO and saw similar results.

We also measure latency when sending one request at a time. We vary request size between 128KB and 1MB. We find that single request latency also increases after permanent slowdown and for all sizes. The increase in latency is constant in absolute terms and is thus not correlated to request size. The latency for the default request size of 256 KB increased by 33%. These findings show that latency increases are due to the drive and not due to the software layers.

**Discussion on internal SSD root cause.** The read disturbance and retention errors discussed as potential culprits for temporary slowdown could conceivably lead to permanent slowdown [3] if left uncorrected by the drive. However, the same argument we made for temporal slowdown applies. Read disturbance and retention occur on drives much more worn out (orders of magnitude more P/E cycles) than ours and after performing orders of magnitude more reads. We hypothesize that the reason for permanent slowdown lies with error correction algorithms being triggered inside the drive after enough time has passed since file creation.

**6.3 Mitigation Strategies**

We consider mitigation strategies that are more aggressive in generating request level parallelism in the hope that they could compensate for the throughput loss. We find that both direct IO as well as increasing the number of requests sent in parallel with buffered IO can mask permanent slowdown.

First, we look at the behavior of permanent slowdown when reading with direct IO. It is known that direct IO issues more and larger requests to the block layer, when compared to buffered IO [13]. In our experiments it issues four 1MB in parallel. Figure 15 presents a throughput comparison between HDFS and FIO with direct IO. The two rightmost CDFs correspond to the throughput of FIO with direct IO before and after permanent slowdown. The difference between the two is minimal. We repeated the experiment using a smaller, 256KB direct IO request size (by tuning `/sys/block/<device>/queue/max_sectors_kb`). The results remained the same suggesting that having a larger number of parallel requests is key for best performance.

We also analyzed making buffered IO more aggressive. We increase the request size from 256KB to 2MB by modifying the read ahead value. This change automatically brings...
about a change in the number of request sent in parallel to the drive. When request size is 256KB, two requests execute in parallel. For a 2MB request, four parallel execute in parallel.

Figure 16 presents four CDFs representing the throughput after permanent slowdown with HDFS reads and FIO buffered reads. The leftmost CDFs correspond to the default request size of 256KB and show the impact of permanent slowdown. The rightmost CDFs are for a request size of 2MB. The modified buffered IO is able to mask the permanent slowdown with increased parallelism.

Figure 16: HDFS read vs Buffered FIO. CDFs of file throughput. Before permanent slowdown with IO requests of 256KB, and after permanent slowdown with large IO requests of 2MB.

7 Discussion

We showed that intrinsic and permanent slowdowns occur because software cannot adapt its strategy for extracting the maximum performance and parallelism from the device in the face of changes in SSD behavior. In the common case, software can extract the maximum performance and parallelism from the SSD using a set strategy of generating IO requests. When SSD performance drops due to internal causes, the same set strategy cannot continue to extract the same performance level. A more aggressive strategy is needed. Yet, HDFS cannot adapt. This points to the need to consider more adaptable software designs that readjust according to perceived performance drops and instabilities in hardware.

The more aggressive approaches that we evaluated were switching to direct IO and increasing the size and number of parallel IO requests in buffered IO. Unfortunately, for existing applications, especially those with large code bases like HDFS, these more aggressive approach may not always be easy to leverage. Switching to direct IO may require extensive changes to application code. Increasing the aggressiveness of buffered IO may lead to wasted disk reads if turned on at machine level. If turned on per application, aggressive buffered IO may influence fairness in the co-existence with colocated workloads. In addition, from an operational perspective, increasing the aggressiveness of buffered IO is not straight-forward. First, it is not intuitive because under the common case the default strategy for buffered IO is enough to extract maximum performance from SSDs. Moreover, in Linux, the settings required to increase aggressiveness are controlled by a seemingly unrelated configuration that controls read-ahead size.

Our findings have an impact on the way systems are benchmarked on SSDs. If two systems are tested on copies of the exact same file, 10-20% of the performance difference may come from intrinsic slowdown (a copy is more fragmented) and/or permanent slowdown (a copy is older). Even if the same input file is used but at different points in time, 10% of the performance difference may come from permanent slowdown. Finally, if systems are tested for short periods of time, 10% of the difference can come from temporary slowdown if one of the systems is unlucky to run during one slowdown episode. In the extreme case, one system may be affected by all three slowdowns at the same time while another may only be slightly affected by intrinsic slowdown. In this case, almost 30% of the performance difference may come from the slowdowns and not the systems under test.

8 Related Work

Related to sources of performance variation internal to SSDs. Garbage collection (GC) in SSDs is known to trigger temporary slowdowns but it is write induced [27, 30]. Flash on Rails [27] reports no GC-like effects in read-only workloads. Since our paper focus solely on read-only workloads we do not discuss further GC.

There are two types of errors that can appear in read-only workloads, retention errors and read errors. Retention errors occur when data stored in a cell changes as time passes and are caused by the charge in a cell dissipating over time through the leakage current [3, 5]. Read (disturbance) errors occur when the data in a cell is modified over time as a neighboring cell is read repeatedly and are caused by the repeated reads shifting the threshold voltages of unread cells and switching them to a different logical state [3, 4]. In practice, retention errors happen much more frequently than read disturbance errors [20].

The temporary slowdowns we encountered show a different pattern compared to the two read errors described above. Related work shows that read errors are highly correlated with the number of P/E cycles that the drive went through [3]. Our drives have a very low P/E cycle. At the end of our experiments, the amount of data written to the drives over their entire lifetime was just 1TB, double their capacity. In contrast, related work uses drives with thousands of P/E cycles to show a noticeable increase in error rates [3]. Similarly, to obtain read errors, related work [4] perform hundreds of thousands of reads on a single page in order to see noticeable effects. Our experiments perform at most a few thousand reads. In addition, the read-errors results from related work [4] are on drives that already under-
went thousands of P/E cycles.

Gunawi et al. [10] study 101 reports of fail-slow hardware (some of which SSD-related) incidents, collected from large-scale cluster deployments. One the SSD front, they find firmware bugs that cause latency spikes or stalls and slow reads due to read retries or parity-based read reconstruction. The study finds that slow reads occurs mostly on worn out SSDs or SSDs that approach end of life. We show that similar problems can occur on very lightly used SSDs. Moreover, we analyze the impact that these hardware issues have at the application level.

Jung et al. [13] find at least 5x increased latency on reads when enabling reliability management on reads (RMR). RMR refers collectively to handling read disturbance management, runtime bad block management, and ECC. The latency differences causing the slowdown we uncover are much less pronounced. Moreover, our slowdowns illustrate dynamics in read latency over time whereas this work focuses on read-related insights from parameter sweeps.

Hao et al. [11] perform a large-scale study analysis of tail latency in production HDDs and SSDs. Their study presents a series of slowdowns and shows that drive internal characteristics are most likely responsible form them. They characterize long slowdown periods that (may) last hours and affect the whole drive, without any particular correlation to IO rate. Like them, we find that the drive is most likely responsible for most of the slowdowns. We did not experience large period of slowdowns across the whole drive, probably due to the fact that our drives are more lightly used.

Related to fragmentation in SSDs. Conway et al. [7] show that certain workloads cause file systems to age (become fragmented) and this causes performance loss even on SSDs. Their workloads involve many small files (<1MB). Kadekodi et al. [16] also exposes the impact of aging in SSD across a variation of workloads and file sizes. They focus on replicating fragmentation to improve benchmarking quality. Similarly, Chopper [14] studies tail latencies introduced by block allocation in ext4 in files of maximum 256 KB. In contrast, we study intrinsic slowdown in much larger files (256 MB) and we quantify the impact on HDFS.

Related to extracting best performance out of SSDs. He et al. [13] focus on five unwritten rules that applications should abide by to get the most performance out of the SSDs and analyze how a number of popular applications abide by those rules. These rules boil down to specific ways of creating and writing files: write aligned, group writes by death time, create data with similar lifetimes, etc. These findings are all complementary to our work. The authors also point to small IO request sizes and argue that they are unlikely to use the SSD parallelism well. In contrast we see that in the common case, the default IO request sizes can extract the maximum SSD performance but fall short when hardware behavior changes as exemplified by the permanent slowdown.

Related to storage-influenced HDFS performance

Shafer et al. [24] analyze the performance of HDFS v1 on HDDs using Hadoop jobs. They show three main findings. First, architectural bottlenecks exist in Hadoop that result in inefficient HDFS usage. Second, portability limitations prevent Java from exploiting features of the native platform. Third, HDFS makes assumptions about how native platforms manage storage resources even though these vary widely in design and behavior. Our findings complement this past work by looking at SSDs instead of HDDs. Moreover, we look at the influence that internal drive characteristics have on HDFS performance while this past work focuses on software-level interactions. Harter et al. [12] study HDFS behavior under HBase workload constraints: store small files (<15MB) and random IO. In contrast, we study HDFS under regular conditions, with large files and sequential IO.

Related to performance variability of storage stacks

Cao et al. [6] study the performance variation of modern storage stacks, on both SSDs and HDDs. For the workloads they analyzed they find ext4-SSD performance to be stable even across different configurations, with less than 5% relative range. In contrast we show variations of up to 30% over time, for one single configuration for HDFS. Maricq et al. [18] conduct a large-scale variability study. Storage wise, they focus on understanding performance variability between HDDs and SSDs. Similar to us, they find that sending large number of requests to the SSDs reduces performance variability. However, they focus on workloads with direct IO and small request sizes (4KB). In contrast, we study SSD variability both under direct IO and buffered IO. We delve deeper into the importance on the number and size of requests. Vangoor et al. [29] analyze the performance overheads of FUSE versus native ext4. Their analysis shows that in some cases FUSE overhead is negligible, while in some others it can heavily degrade performance. HDFS is also a user space file system, however it has a different architecture and functionality, and use cases than FUSE. In this work, we analyze the interaction between HDFS and lower layers of the storage stack, under HDFS main use case, sequential IO in large files.

9 Conclusion

In this paper we introduced and analyzed three surprising performance problems (inherent, temporal and permanent slowdowns) that stop HDFS from extracting maximum performance from some SSDs. These problems are introduced by the layers sitting beneath HDFS (file system, SSDs). The lower layers also hold the key to masking two of the three problems by increasing IO request parallelism during the problems. Unfortunately, HDFS does not have the ability to adapt. Its access pattern successfully extracts maximum performance from SSDs in the common case but it is not aggressive enough to mask the performance problems we found. Our results point to a need for adaptability in storage stacks.
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