**Abstract**

Operating systems include many heuristic algorithms designed to improve overall storage performance and throughput. Because such heuristics cannot work well for all conditions and workloads, system designers resorted to exposing numerous tunable parameters to users—thus burdening users with continually optimizing their own storage systems and applications. Storage systems are usually responsible for most latency in I/O-heavy applications, so even a small latency improvement can be significant. Machine learning (ML) techniques promise to learn patterns, generalize from them, and enable optimal solutions that adapt to changing workloads. We propose that ML solutions become a first-class component in OSs and replace manual heuristics to optimize storage systems dynamically. In this paper, we describe our proposed ML architecture, called KML. We developed a prototype KML architecture and applied it to two case studies: optimizing readahead and NFS read-size values. Our experiments show that KML consumes less than 4KB of dynamic kernel memory, has a CPU overhead smaller than 0.2%, and yet can learn patterns and improve I/O throughput by as much as 2.3× and 15× for two case studies—even for complex, never-seen-before, concurrently running mixed workloads on different storage devices.

**1 Introduction**

Computer hardware, software, storage, and workloads are constantly changing. Storage performance heavily depends on workloads and the precise system configuration [11, 76]. Storage systems and OSs include many parameters that can affect overall performance [10, 12, 97]. Yet, users often do not have the time or expertise to tune these parameters. Worse, the storage and OS communities are fairly conservative and resist making significant changes to systems to prevent instability or data loss. Thus, many techniques currently used were historically developed for database query optimization [47], improved caching [84], serving actual behavior and adapting on-the-fly, and hence may be more promising than fixed heuristics. ML techniques were recently used to predict index structures in KV stores [22, 48], for database query optimization [47], improved caching [84], cache eviction policies [90], I/O scheduling [38], and more.

In this paper, we describe our ML approach to improve storage performance by dynamically adapting to changing I/O workloads. We designed and developed a versatile, low-overhead, light-weight system called KML, for conducting ML training and prediction for storage systems. KML defines generic ML APIs that can be used for a variety of subsystems; we currently support several deep neural networks and decision tree models. We designed KML to be embeddable inside an OS or the critical path of the storage system: KML imposes low CPU and memory overheads. KML can run synchronously or asynchronously, giving users the ability to trade-off prediction accuracy vs. overhead.

Developing and tuning ML-based applications can be its own challenge. Therefore, we designed KML to run identically in user- or kernel-level. Users can develop and debug ML solutions easily in the user level, then upload the same model to run identically in the kernel.

We demonstrate KML’s usefulness with two case studies: (i) adapting readahead values dynamically and (ii) setting NFS rsize values automatically. In both cases, we aim to adapt these values within one second under changing and even mixed workloads. Overall, our approach to storage systems optimization using ML is a continuous observe-and-tune paradigm.

This paper makes five contributions:

1. We show that lightweight ML can indeed become a first-class citizen inside storage systems and OSs;
2. We offer flexibility through synchronous or asynchronous training and the ability to offload training to the user-level;
3. We introduce the idea of ML APIs that can be expanded to support additional and future ML techniques;
Figure 1: Two different operational modes that we built to achieve a high efficiency ML framework for tuning OS-level storage systems: (a) kernel space training and inference and (b) offline user space training and kernel space inference.

4. We apply KML to two important optimization problems (readahead and NFS rsize values); and

5. We evaluate our solutions using multiple, complex, and even mixed workloads, as well as two different storage devices. We demonstrate throughput improvements up to $2.3 \times$ for readahead and up to $15 \times$ for rsize. We show that ML models trained on a few workloads can generalize and optimize throughput for never-before-seen workloads or devices. And finally, we show that KML has small CPU overheads (< 0.2%) and dynamic memory footprint (4KB), well worth the overall I/O improvements.

Next, Section 2 describes KML’s design. Section 3 describes our two use cases (readahead and NFS rsize). Detailed evaluation of KML and two use cases are in Section 4. We survey related work in Section 5 and conclude in Section 6.

2 KML’s Architecture

Modern ML libraries are often general-purpose, rely on many large third-party libraries (e.g., in C++ or Python), and designed to process lots data using massive processing power (e.g., GPU clusters). Porting such ML systems to an OS kernel would be impractical, because an OS is a highly constrained and unforgiving environment. Thus, we chose to develop an ML framework from scratch—designed for low-overhead, light-weight, and highly tailored to OSs and storage systems and developers.

**KML high-level design choices.** Figure 1 demonstrates two different operating modes that we built. KML supports (a) in-kernel training and inference and (b) user space offline training and in-kernel inference. Once a model is built in user space, it can be loaded into the kernel as is. KML has a highly modular design: the core ML code base is shared by both user and kernel space. Operation mode (a) is designed for performance and accuracy, especially under high-I/O rates, because collecting and copying lots of I/O event data out of the kernel imposes high overheads. Operation mode (b) is designed to simplify ML model development for OS/storage developers. Users can develop and test an ML model design more easily in user space, testing different features, ML architectures, and hyper-parameters to reach a stable and accurate model.

2.1 Design Overview

Easy to develop and extend. In Figure 1(b), KML is compiled and linked with an application for both kernel and user space. u-MLib.a and k-MLib.ko are built using the same KML source code. We developed a wrapper layer for the KML development API: KML’s core code is uniform across both user and kernel APIs. This identical abstraction speeds up development, eases debugging, and facilitates extensibility (see Section 2.3). Nevertheless, we recognize that while we aim to make ML-based solutions easier to use, developers still require a good understanding of OS and storage system internals.

**Low overhead.** To make ML approaches practical for storage systems, they must have low computational and memory overheads. ML solutions have three phases that consume much memory/CPU resources: (i) inference (i.e., prediction), (ii) training, and (iii) data processing & normalization. We support asynchronous training and inference capabilities to reduce inference on the data path; KML also uses efficient communications between the data collection and model training & inference components, to help scalability and stability of ML-based designs. To reduce the data collection overheads, developers can facilitate subsampling techniques that are provided in KML. We detail our design choices to reduce these overheads in Section 2.4.

2.2 Fundamentals of Core ML library

KML provides primitives for building and extending ML models. This involves building algorithms for training ML models (e.g., back-propagation, decision-tree induction) and building the mathematical functions needed to implement them. The library design allows for seamless extensibility of library functionality. Additionally, our ML functionality is easily debugged in user space as it uses identical code and APIs in kernel space.

**Mathematical and matrix operations.** Most ML algorithms rely heavily on basic mathematical functions and matrix algebra. For example, a neural network classifier uses functions such as matrix multiplication/addition, softmax, and exponentiation. Hence, we implemented kernel versions of such common ML functions using well known approximation algorithms.

**Layer and loss-function implementations.** One can think of a neural network as a composition of layers and one or more loss functions. Many of these building blocks are used across many different neural network architectures. Layers like a fully connected layer, ReLU [63], or sigmoid are essential building blocks of many neural networks; loss functions are also fairly common across many applications. Both layers and loss functions implement two main functionalities, one during the inference (forward) phase and another during the back-propagation (training) phase.
We implemented these common components and their forward and back-propagation functionality from scratch in KML: layer/loss functions, data structures related to the layer/loss, etc.

**Inference and training.** When stacked together, the elements of a conventional neural network can form a DAG. Thus, a neural network inference means traversing the DAG starting from the initial node(s) (where the inputs are provided), toward the resulting nodes (where the neural output network is produced). KML implements a standard training method used in neural networks—back-propagation [73]. KML also includes Stochastic Gradient Descent (SGD) which uses the gradients computed using back-propagation to optimize the network weights.

### 2.3 KML’s Modular Design

We now elaborate on KML’s operation modes: (i) in-kernel training and inference (see Figure 1(a)), and (ii) user space training and inference (see Figure 1(b)).

**Training in kernel space.** We use the readahead use case to describe how KML works in kernel training and inference mode. Figure 2 shows KML’s framework (k-MLib.ko), a KML application (readahead.ko), and target storage components (Block device and Memory Management subsystems). The yellow background denotes KML related components. The blue background depicts the target storage components, which are specific to the readahead case. The green line represents execution and data flow. Numbered boxes refer to transitions happening between the components.

As we mentioned in Section 1, we designed our use cases based on a continuous *observe-and-tune* principle. In its first stage, the readahead module observes and collects data. Since our target component is the memory management (e.g., page cache) system, the readahead module starts collecting data from this component (Figure 2 ①). The readahead module then extracts features and transfers them to the KML framework to be normalized (Figure 2 ②). After the data processing and normalization stage is done, if the readahead module is operating in training mode, it trains on the normalized data, and the execution flow ends here. However, if the readahead module is operating in inference mode, it feeds the normalized data to the readahead neural network model and tunes the target components based on the model’s prediction (Figure 2 ③).

How a KML application optimizes a target component depends on the problem and its solution. Here, the readahead module updates readahead sizes on a per-file basis (Figure 2 ④) or a per-device basis (Figure 2 ⑤). When the readahead module is inferencing, execution flow forms a closed-circuit. After the readahead module changes readahead sizes, OS memory state changes; thereafter, new inputs go to the readahead neural network model, leading to updated predictions. Therefore, ML is particularly suitable to solve problems that require an ongoing cycle of observing and tuning.

In the ML ecosystem, data collection is a crucial part. One reason we offer kernel training is to train on data collected with a high sampling rate. Tracing OSs and storage systems with high accuracy and sampling rates is challenging [5]. Nevertheless, tracing tools like LTTng [60] can bring overhead down to as little as 5%. Additionally, traces may still be inaccurate due to data loss. LTTng collects trace data in shared user/kernel lockless circular buffers; under heavy sampling loads, some trace events can be dropped if LTTng’s user-level processing threads do not consume the samples fast enough. However, operating in kernel space gives KML more control over thread scheduling to reduce loss of sampled events. Since our use cases may require high sampling rates for I/O events, placing data processing and normalization in user space would lose too much valuable data than in the kernel. Still, we believe a user-kernel co-operated design may be beneficial in some cases (part of our future work).

**Training in user space.** Building ML solutions is an iterative process. To find the essential features and build accurate models, we need to run multiple data analyses, train, then test an ML model with different architectures and hyper-parameters. To speed up model development and debugging, KML offers offline user-space training and kernel inferencing mode (see Figure 1(b)). As KML’s user- and kernel-space libraries use the same APIs and code base, models trained in user space can be loaded into the kernel as is.

Figure 3 shows how the readahead model works in operation mode. Components highlighted in yellow represent KML-specific implementations. The red arrows denote the offline data collection and training paths.

We started by collecting training data using in-kernel tracing of the target storage components [5]. Next was feature-extraction; this is where user-space training was useful, because we could run various analyses, test different features, and implement...
many data-normalization techniques without re-running I/O experiments. After we finalized the feature selection, we trained and tested the readahead ML model in user space, varying several hyper-parameters; we used Tune [57] to optimize our hyper-parameters. When the readahead ML model was ready for real-time testing, the only remaining step was to save the trained model to a KML-specific file and load it into the readahead kernel module. KML APIs facilitate all the functionality necessary for building, training, saving, and deploying ML models in-kernel.

To ensure identical kernel and user APIs, we use wrappers to abstract external functionality. KML’s development API provides 30 functions that fall into five categories: (i) memory management, (ii) threading, (iii) logging, (iv) atomic operations, and (v) file operations. For example, we have a simple wrapper called kmalloc that calls malloc in user-level and kmalloc in kernel space. For brevity, API details and prototypes are omitted, but part of our released code (see Section 2.6).

### 2.4 Computational & Memory Overheads

OSs and storage systems are susceptible to performance degradation and increased latency if computational and memory resources are not carefully managed. Therefore, we designed KML with efficient CPU and memory usage in mind. There is often a positive correlation between the computational and memory footprint of an ML model and its training and inference accuracy. Hence, KML is highly configurable, letting users trade-off overheads vs. prediction accuracy to best suit the problem at hand.

**Reducing computational overheads.** Matrix manipulation is a computationally intensive ML building block that relies on floating-point (FP) operations. OSs often disable the floating-point unit (FPU) in the kernel to reduce context-switching overheads. To address this, we considered three approaches: (1) quantization, (2) fixed-point representations, and (3) temporarily enabling the FPU unit in kernel space. Quantization provides compact representation, allows developers to compute matrix manipulation operations, and does not require an FPU [19,23,35,38,74]. Quantization can help reduce computational and memory overheads, but it reduces accuracy [41]. Fixed-point representation computes FP operations using integer registers. Since all FP operations are emulated, integration of fixed-point representation is fairly easy and even faster in certain cases [17,58]. However, fixed-point representation works within fixed ranges which can result in numerical instability [51]. Since both accuracy and stability are vital KML design goals, we chose a third alternative: KML temporarily enable the FPU in the Linux kernel using kernel_fpu_begin and kernel_fpu_end. To avoid context-switch overheads, we minimize the number of code blocks that use FPs and keep these blocks small.

**Reducing memory overheads.** Three factors affect KML’s dynamic memory consumption: (1) ML model-specific data, (2) KML’s internal memory allocations at training and inference, and (3) data collection for both training and inference. ML model-specific data and KML’s internal memory usage depend on the number of layers, layer sizes, and layer types. KML uses dynamic memory allocation for all internal usage purposes (e.g., layer gradients); this helps reduce interference and memory pressure. KML gathers input data in a lock-free circular buffer; then, an asynchronous training thread trains on gathered data. When collecting data with a high sampling rate, the size of the lock-free circular buffer is important to the ML model’s performance and accuracy. Users need to configure the size of the circular buffer to account for the data sampling rate such that the asynchronous training thread can catch up with processing. If the size of the circular buffer is misconfigured, KML may lose useful training data, which can reduce the resulting ML model’s accuracy.

**Operating under resource-constrained conditions.** KML exposes a memory allocation and reservation API for ML internals. The primary motivation behind KML’s memory reservation capabilities is to ensure predictable performance and accuracy, even under memory pressure. This allows KML to operate without worry of memory allocation lagging or failing, which would hurt performance and accuracy.

**Data processing & asynchronous training.** To make ML solutions generalizable, data normalization is often utilized. KML supports data normalization functionalities such as moving average, standard deviation, and Z-score calculation. However, data normalization often requires heavy FP computation. Thus, KML supports offloading training, inference, and data normalization to a separate asynchronous thread—away from the data path itself. This thread communicates with other KML components (e.g., data collection) using a lock-free circular buffer. By default, we let Linux schedule this kthread as needed; KML also supports pinning the kthread to a CPU core, to ensure it gets higher scheduling priority when high sampling rates are required.

Subsampling is another viable solution to reduce data collection overheads, which KML supports. However, subsampling can reduce prediction accuracy, so care is needed to select a suitable sampling rate. In Section 4.3 we evaluate the impact of subsampling windows on overheads, prediction accuracy, and overall I/O performance.

### 2.5 Stability & Explainability

Both the training and inference phases for ML solutions can be computationally intensive. Except for model initialization and saving models to files, KML APIs involve no other I/Os. KML’s impact on the stability of storage performance is limited to memory-allocation latency and concurrency. Memory allocations in both user and kernel space can use locking mechanisms, which could incur unexpected latencies. To minimize these problems, KML allocates memory only in the asynchronous training thread. KML uses a lock-free circular buffer for data communication and reserves 512 bytes of additional memory to further ensure stability under memory-pressure conditions. Lastly, we applied standard k-fold cross validation techniques to ensure the stability of our ML solutions.

ML solutions can suffer from unexpected behavior and
are harder to explain. Conversely, traditional heuristics have well-defined behaviors often expressed as closed-form formulas. An ML algorithm may behave erratically when used in new, unforeseen settings, which could hurt system performance where ML is deployed. This type of issue is difficult to troubleshoot due to the long-standing explainability problems that affect ML models [3]. KML currently supports two ML models: neural networks and decision trees. Decision tree predictions are more explainable because they are represented as a tree of successive IF-THEN statements, bisecting the range of the features considered. Deep neural networks, however, are more challenging to explain and verify. Nevertheless, recent work focuses on explainability in ML [3, 42, 70, 75]. While we plan to improve KML model stability using feedback-based control algorithms in the future, we currently focus on demonstrating that ML can tune storage system parameters better than existing heuristics.

2.6 Implementation
KML contains 12,213 lines of C/C++ code (LoC). KML’s core ML part has 5,539 LoC, which can be compiled in both user and kernel space. Our readahead neural network model code is nearly 1K LoC long: 486 LoC for collecting data, initializing the model, creating an inference thread, and changing block-level and file-level readahead sizes; and another 351 LoC for model definition, data processing, and normalization. Our NFS neural network model also includes nearly 1K LoC: 435 LoC for data collection, model initialization, and running inference to predict workload type; and 338 LoC for creating the model and manipulating data. All of our code has been released on github (https://github.com/sbu-fsl/kernel-ml [4]), which includes examples, sample data, models, and full API documentation (all 30 methods).

3 Use Cases
We now detail our two use cases: (1) readahead neural network and decision tree models and (2) NFS neural network model. We describe the following for each: (i) problem definition, (ii) data collection for training, (iii) data preprocessing and feature extraction, and (iv) building the ML model.

3.1 Use Case: Readahead

Problem definition. Readahead is a technique to prefetch an additional amount of storage data into the OS caches in anticipation of its use in the near term. Determining how much to read ahead has always been challenging: too little readahead necessitates more disk reads later and too much readahead pollutes caches with useless data—both hurt performance. The readahead value is a typical example of a storage system parameter: while tunable, it is often fixed and left at its default. Some OSs let users pass hints via fadvise and madvise to help the OS recognize files that will be used purely sequentially or randomly, but these often fail to find optimal values for varied, mixed, or changing workloads. Next, we detail our readahead neural network design (following Figure 3). Our goal is to predict optimal readahead sizes while running under dynamic I/O workloads.

Studying the problem. We experimented with running 4 different RocksDB [32] benchmarks, each with 20 different readahead sizes (8–1024), and attempted to determine the readahead sizes that yield the best performance (in ops/sec) for each workload. This became our training data, which can help predict readahead values for other workloads and environments. This investigation revealed that each workload has a unique behavior and requires a different readahead size to reach optimal performance. We further investigated the correlations between file access patterns, RocksDB workload labels, and performance. This helped us determine the information and features needed to build a good model, as described below.

Data collection. We used LTITng [60] to collect trace data, which we then used for finding useful features for the readahead problem. We captured most page cache tracepoints [26] (e.g., add_to_page_cache, writeback_dirty_page). We collected and processed over 20 GB of traces by running multiple 10-minute RocksDB benchmarks on an NVMe-SSD device. Ten minutes was sufficient for RocksDB to reach a steady state. After examining these traces, we selected a set of candidate features based on our domain expertise. We then picked the features of interest and decided where to call hook functions which are responsible for gathering necessary information (e.g., struct page) for inference. Our hook functions provide three important raw values: (1) time difference from the beginning of execution, (2) inode number, and (3) page offsets of the files that were accessed in locations where the hooks were called.

Data preprocessing & normalization. We summarize the input data at one-second intervals to ensure we can quickly adapt to changing I/O workloads while ensuring stability under short-term activity spikes. Based on our domain expertise, and through model experimentation, we selected the following five features for our model: the number of transactions taking place each second, the calculated cumulative moving mean and the cumulative moving standard deviation of page offsets, the mean absolute page offset differences for successive transactions, and the inode number (to ensure we process only RocksDB file accesses). Before we fed these features to our readahead neural network, we applied Z-score normalization to each feature.

Why we chose machine learning for this use case. After studying the readahead problem, we wanted to explore whether machine learning would be suitable for solving this problem or whether more traditional heuristics could still work. Therefore, while extracting features from collected traces, we visualized the features to investigate what type of patterns and clusters the data has. Figure 4 shows a t-SNE [89] visualization of normalized features that are generated from both NVMe-SSD and SATA-SSD traces. t-SNE is a visualization technique that applies dimension reduction and is often used for representing high-dimensional data and looking for clusters. We can observe that sequential and random workloads are somewhat separated; alas, data points from the same workload type are distributed over multiple clusters, overlapping clusters of other types. Worse,
even random workloads’ clusters overlap with some sequential workloads’ clusters, because RocksDB’s warm-up phases involve mostly sequential accesses—another source of dynamism. All these findings strongly suggest that workload classification for the readahead problem would be fairly challenging using traditional heuristics. Hence, we felt motivated to explore ML solutions to solving the readahead problem.

Building neural network model. We modeled the readahead problem as a classification problem and designed a neural network with three linear layers (with hidden layer sizes of 5 and 15), using sigmoid non-linearities in between layers, and with a cross-entropy loss method as the loss function. We used an SGD optimizer [45,72], and set a learning rate of 0.01 and a momentum of 0.99 after trying different values; all these values are common in the literature [8]. We also used Tune [57] to optimize the learning rate and momentum. Our readahead neural network trains on the aforementioned input data and predicts the workload type. We trained on the following four types of RocksDB workloads on NVMe-SSD because they provide a diverse combination of random and sequential operations: (i) readrandom, (ii) readseq, (iii) readrandomwriterandom, and (iv) readreverse. Class frequencies were close, suggesting that classification accuracy is a good metric to evaluate the performance, with the least frequent class being 21.4% and most frequent class being 28.8%.

We tested the neural network’s performance with the aforementioned data via k-fold cross validation with k = 10, and found out that it achieved an average accuracy of 95.5%. We also analyzed the contribution of each feature to the classification performance; we randomized the order of a feature of interest across samples in the validation dataset, and then calculated the 10-fold validation performance [9]. Using Pearson correlation analysis [68], we found that two features were highly correlated: the cumulative moving standard deviation and the cumulative moving mean of page offsets. Including both would have over-emphasized their importance in this analysis, so we excluded the cumulative standard deviation of page offsets. Cross validation results were 69.6%, 76.4%, 42.6%, and 89.1% for number of transactions, cumulative moving mean of page offsets, mean absolute page offset differences, and current readahead value, respectively. This shows that mean absolute page offset differences is the most important feature, because randomizing its order reduced the validation results the most (down to 42.6%)—followed by number of transactions, cumulative moving mean of page offsets, and finally the currently used readahead value.

After obtaining classification predictions, we set the empirically determined optimal readahead sizes according to the predicted workload type. In Section 4.4, we evaluate the readahead neural network not only on workloads we trained on but also on workloads that were not included in the training data and workloads running on different devices (NVMe vs. SATA SSDs).

Figure 4 shows that the same type of workloads for SATA-SSD vs. NVMe-SSD are not placed in the same clusters all the time. We use neural network input data that is generated only from an NVMe-SSD to train readahead neural network; nevertheless, we still get significant performance improvement even for SATA-SSDs (see Section 4.4). This indicates that our readahead neural network is indeed learning higher-level abstractions about the workloads, one that traditional heuristics would struggle with.

Finally, we also experimented with the readahead neural network using TPC-H [87] queries running on MySQL [66] to show how our readahead neural network behaves on completely different types of workloads and applications and how generalizable the models are.

Decision-tree models. We also built a decision-tree (DT) model for workload type classification based on the same features and training data. The readahead DT model contains 59 nodes with a maximum depth of 9. We omit the full DT figure for brevity (available as part of our source/data release), but for example, the decision at the root node is whether the Z-score of the mean absolute page offset was less than −0.549. We tested the prediction accuracy of this DT using the same procedure with the readahead neural network (10-fold cross-validation), and observed that it results in an average prediction accuracy of only 75.4%. As mentioned in Section 2.5, KML supports DTs because DTs trees are more explainable than neural networks and run considerably faster. We evaluated the readahead DT using the same procedure as the neural networks (Section 4.4).

Readahead in per-file basis. So far, we have shown how we approach the readahead problem when a single I/O workload is accessing one device. Storage system developers recognize the challenge of handling mixed storage workloads running on the same system—a common occurrence [7]. In that case, readahead values cannot be set at the device level, as that would be suboptimal in mixed workloads. Instead, readahead values should be set at a higher abstraction level, on a per-file basis. To show our neural network’s versatility, we use the same model to tune readahead sizes not only on a per-disk basis but also on a per-file basis. Whereas before we ran inference every second and set one readahead value for an entire device, here we ran
inference every second on each open file and set a readahead value directly in Linux’s struct file. We evaluated the per-file basis approach and found that it could predict and improve I/O throughput for mixed workloads better than both the vanilla and per-disk approaches (see Section 4.4).

3.2 Use Case: NFS rsize

Problem definition. Networked storage systems such as NFS are popular and heavily used. NFS is used for storing virtual machine disks [62], hosting NoSQL databases [83], and more. A misconfiguration of NFS can hurt performance. We experimented with different applications using NFS and found out that one critical NFS configuration parameter is the rsize—default network read-unit size. Hence, we focus predicting an optimal NFS rsize value based on workload characteristics.

Studying the problem. We tested NFS using the same methodology as for readahead. The only difference here is tuning rsize instead of readahead. We used NFSv4 for all of our tests. The NFSv4 implementation we used supports only seven different rsize values (4K–256K). However, in the NFS use case, there are additional external factors not present in the readahead problem that can affect I/O performance (e.g., NFS server configuration, network speed, and number of clients connected to the same server). We experimented with four different RocksDB benchmarks under different NFS server configurations and network conditions. We configured our server with two different NFS mount point options—one backed by NVMe-SSD and one backed by SATA-SSD. We injected artificial network delays to simulate slower networks. Our experiments revealed that random and sequential workloads require different rsize values to achieve optimal performance.

Data collection. We enabled NFS and page-cache related kernel tracepoints to collect training data (e.g., nfs4_read, nfs4_readpage_done, vmscan_lru_shrink_inactive, and add_to_page_cache). Unlike the readahead neural network model, we collected data from traces not only to model page cache behavior, but also network conditions. Similarly studying these traces, we chose our feature set and placed our hook functions. Our feature set includes eight features (described below) which are calculated using the following five data points: (i) time difference from the beginning of execution for each tracepoint transaction, (ii) NFS file handles, (iii) file offsets in NFS requests, (iv) page offsets of the files that were accessed, and (v) number of reclaimed pages during LRU scans.

Data preprocessing & normalization. We applied the same data preprocessing and normalization techniques that we used for the readahead neural network. The NFS neural network model consists of eight features which are computed every second: (1) number of tracepoint transactions, (2) average time difference between each nfs4_read and nfs_readpage_done matching pair, (3) average time difference between each consecutive nfs4_read request, (4) average time difference between each consecutive nfs4_readpage_done request, (5) mean absolute requested offset difference between each consecutive nfs4_read request, (6) mean absolute page offset difference between each consecutive add_to_page_cache, (7) average number of reclaimed pages, and (8) current rsize.

Neural network model. We trained and tested our NFS neural network model using exactly the same methodology as the readahead problem; for brevity, we detail only the differences between the neural network models. We approached the NFS problem as a workload characterization problem and constructed our NFS neural network model with four linear layers (with hidden layer sizes of 25, 10, and 5) with sigmoid activation functions in between. Similar to the readahead neural network, we used cross entropy as the loss function and SGD as the optimizer. We evaluated the NFS neural network model and found out that it results in a prediction accuracy of 98.6% (using 10-fold cross-validation).

4 Evaluation

Our evaluation proceeds as follows: First, we explain our evaluation goals in Section 4.1. We then describe the testbed design and benchmarks that we used to evaluate the readahead and NFS rsize neural networks in Section 4.2. In Section 4.3 we provide performance details regarding KML’s training and inference. Section 4.4 shows how the readahead ML models improve performance. Finally, in Section 4.5, we present our evaluation of the rsize neural network model for NFS.

4.1 Evaluation Goals

Our primary evaluation goal is to show that using ML techniques inside the OS can be used to tune parameters dynamically and improve storage systems’ performance.

We start by showing the practicality of using ML in kernel space. We evaluate KML’s system overheads in terms of (i) data collection overhead, (ii) training cost, (iii) inference cost, and (iv) memory usage. Then, we evaluate both readahead and NFS neural network models to show how they improve the I/O performance and quickly adapt the system in the presence of changing workloads and conditions. To show that our models can learn abstract workload patterns, we first present the generalization power of our models by testing it on workloads not included in the training dataset. Next, we present benchmarks on a device type that was not used in the data collection phase or training. We also built a decision tree model for the readahead problem to have comparable results since decision trees are more explainable, still popular, and closer in operation to traditional heuristics.

Furthermore, we evaluate KML’s versatility by applying the readahead neural network model on a per-file basis. This demonstrates KML’s ability to optimize individual I/Os in a mixed workload. Lastly, we evaluate our readahead ML models’ behavior when they mispredict and how quickly they recover.

4.2 Testbed

We ran the benchmarks on two identical Dell R-710 servers, each with two Intel Xeon quad-core CPUs (2.4GHz, 8 hyper-threads),
24GB of RAM and an Intel 10GbE NIC. In some experiments, we intentionally configured the system with only 1GB of memory to force more memory pressure on the I/O system; but we also show experiments with the full 24GB of system RAM. We used the CentOS 7.6 Linux distribution. We developed KML for Linux kernel version 4.19.51, the long-term support stable kernel; we added our readahead ML models to this kernel and used it in all experiments. Because HDDs are becoming less popular in servers, especially when I/O performance is a concern, we focused all of our experiments on SATA and NVMe SSDs. We used Intel SSDSC2BA200G3 200GB as our SATA-SSD device and a Samsung MZILV960HCJH-000MU 960GB as our NVMe-SSD device, both formatted with Ext4. These two devices were used exclusively for RocksDB databases. To avoid interference with the installed CentOS, the two servers have a dedicated Seagate ST9146852SS 148GB SAS boot drive for CentOS, utilities, and RocksDB benchmark software. We used 10GbE switches to connect the machines (useful for NFS experiments). We observed an average RTT time of 0.2 milliseconds.

**Benchmarks.** We chose RocksDB’s `db_bench` tool to generate diverse workloads for evaluating the readahead and NFS `rsize` neural networks. RocksDB [32] is a popular key-value store and covers an important segment of realistic storage systems; `db_bench` is a versatile benchmarking tool that includes a diverse set of realistic workloads. Workloads can be run individually or in series, and the working set size can be easily configured to generate more I/O pressure on a system. On the 1GB RAM systems, we configured a RocksDB of twice the size (2GB).

To demonstrate that our ML models can learn from and optimize for different types of real-world workloads, we chose the following six popular yet different `db_bench` workloads: (1) readrandom, (2) readseq, (3) readrandomwriterandom (alternating random reads and writes), (4) readdereverse, (5) updaterandom (read-modify-write in random offsets), and (6) mixgraph (a complex mix of sequential and random accesses, based on Facebook’s realistic data that follow certain Pareto and power-law distributions [14]).

We trained our readahead neural network on traces that contain only four of these workloads: readrandom, readseq, readdereverse, readrandomwriterandom—all running only on the NVMe-SSD. These four tend to be the simpler workloads, because we wanted to see whether KML can train on simpler workloads yet accurately predict on more complex workloads not trained on. This also ensures a balanced representation of randomness and sequentiality in the training dataset.

After the training phase completed, we tested our models on all six workloads as well as different devices. This was done to show that our models not only perform accurate predictions on the training set samples, but they also generalize to two new and complex workloads (updaterandom and mixgraph as well as a different device (SATA-SSD)—which were excluded from the training data. We evaluated mixed workloads by running two concurrent `db_bench` instances, each on a separate RocksDB database and using a different workload profile, both stored on the same device. We kept the hardware configuration the same as before (1GB RAM) to increase system and page-cache pressure.

We also experimented with our readahead network model using TPC-H [87] queries running on MySQL [66], to evaluate how generalizable and effective the readahead neural network is to an entirely different workload. In this paper we do not claim that our readahead neural network model will work universally to optimize readahead values for all possible workloads. Rather, these use cases are meant to demonstrate the KML framework’s versatility. With more workloads and datasets, one can build a wide range of ML models to optimize many storage problems.

### 4.3 KML’s Overheads

An ML model’s overhead depends on its architecture. Generally, deeper or higher-dimensional neural networks consume more memory and CPU than, say, decision-tree models. It is vital that an ML component, especially one that may run inside the kernel, consume as little CPU and memory as possible. Next, we evaluate the readahead neural network overheads.

**Data gathering overheads.** The only inline operations that readahead neural network inserts directly in the data path are data collection probes. Hence it is vital for these probes to be optimized. Figure 5(C) shows how the data collection CPU overheads (percentage) change with subsampling window sizes. When there is no subsampling in the system \((X = 1)\), the CPU overheads of data collection probes is as high as 0.18%. Although this is a fairly low overhead considering the multiplicative I/O benefits we report, this overhead can be reduced further by increasing the subsampling window. However, increasing the subsampling windows size can hurt prediction accuracy and performance improvements, as less data is available to make rapid predictions. See Figure 5(A) and (B). Figure 5(B) shows that workloads with a lot of randomness

**Figure 5:** Performance (A), prediction accuracy (B) and CPU overheads (C) in seven different subsampling window sizes for the per-disk read-ahead neural network. Upward green arrows denote that higher is better.
1.7 ms on average. We measured that the readahead decision window size from one to five or ten actually improved both prediction accuracy and normalized performance worsen. However, we noticed an unexpected behavior for the readseq workload. Increasing the subsampling window size from one to five or ten actually improved both prediction accuracy and normalized performance; this is because readseq keeps the I/O subsystem busy at near maximum bandwidth, and increasing subsampling window size reduced short-term noise that resulted in more frequent mispredictions.

We can also observe that the data collection overheads depend on the workload type. For example, readseq workload’s average data sampling frequency per-second is around 30K but its data collection overhead is still lower than mixgraph workload which has 20K average data sampling frequency per-second. The reason that data collection overheads change based on the workload type, is due to the sudden I/O bursts resulting in some cache misses (bi-modal histograms omitted for brevity).

**Inference/training overheads.** The readahead neural network performs inference (prediction) and changes the block-layer readahead value in 21 µs on average (std. dev. < 10%). This action executes in a separate, asynchronous kernel thread, once in every second. Hence, it has negligible impact on the overall OS performance. When the readahead neural network runs in per-file mode, KML runs inferences an average 135 times a second (i.e., one per open file); inferencing for all open files consumes 1.7 ms on average. We measured that the readahead decision tree inference takes only 8 µs (using the same feature vector). The readahead neural network and decision tree have the same data pre-processing and normalization implementation—the only difference between them is in the inference part. Overall, these overheads are fairly small and acceptable, considering the multiplicative I/O performance benefits they enable.

As discussed in Section 3.1, our readahead neural network prototype offloads training to the user level. We measured the time to perform one training iteration in user level at 51 µs on average; this training iteration includes the forward pass, back-propagation, and weight update stages.

**Memory overheads.** The readahead neural network allocates 3,916 bytes of dynamic memory during the model’s initialization phase. While inferencing, KML temporarily allocates 676 bytes before returning the inference results. This overall memory footprint is negligible in today’s multi-GB systems. The readahead decision tree occupies only 2,432 bytes of dynamic memory during initialization. The decision tree model does not allocate dynamic memory during inference. Lastly, the kernel module readhead.ko has a binary memory footprint of 432 KB and the kernel module nfs.ko is 636 KB, while the KML framework itself (k-Mlib.ko) has a memory footprint of 5.5 MB.

**Practicality and scalability.** Our vision is KML could enable a future where traditional heuristics are gradually replaced with ML-based approaches to improve storage and network I/O performance. In Section 4.4 we demonstrate, for example, that our readahead neural network model improves I/O performance by as much as 2.3x, but consumes less than 0.2% additional CPU cycles: we believe this is a fairly acceptable trade-off for most users. Nevertheless, we tested this model with 100 concurrent inferences and found that both overheads and I/O improvements have scaled linearly; hence KML’s benefits still outweigh its overheads.

### 4.4 Readahead Evaluation

**Readahead background.** There are two places in the Linux kernel where readahead is defined: the block layer and the file system level. When a file is opened, the VFS initializes an open struct file and copies the readahead value for that file from the corresponding block layer. Upon a page fault for that file, the page-cache layer uses the value stored in the file to initiate reading-ahead the desired number of sectors of that file. However, the readahead value in the file structure is initialized only once when the file is opened. So when KML changes the block layer readahead value, the Linux kernel does not copy the new value to any file already opened. This means that open files may continue to use a sub-optimal readahead value, even if better values are available (e.g., due to workload changes). That is why we implemented a mechanism that changes the readahead size for open files when KML changes the disk-level readahead value. This propagates newer readahead values to each open file, improving our adaptability. Conversely, if KML mispredicts the
workload type and changes the readahead size to a suboptimal value, short-term performance degradation can happen, which might hurt overall performance.

**Back-to-back workloads on NVMe.** Figure 6 shows four workloads running back to back with each subfigure comparing a vanilla run (colored orange) to our KML-enabled readahead run (colored blue). The readahead value was left at the default value (i.e., 256) at the start of both vanilla and KML-enabled runs, but when the next workload started, it used the last readahead value from the previous workload’s run (e.g., the readahead value at the end of the leftmost subfigure is the same at the start of the subfigure immediately to its right). This experiment evaluates KML’s ability to optimize the readahead values when the I/O workload may change every few minutes. The X axes indicate the run time in minutes. The Y axes indicate throughput in thousands of ops/sec (higher is better), and have different scales for each experiment. The Y2 axes show the readahead values used or predicted by KML over time in terms of number of sectors (denoted with a green line and using the same scale). Each workload ran 15–50 times in a row, so it ran long enough to observe mis/predictions patterns. As seen in Figure 6, KML adapts quickly to changing workloads by tuning the readahead value in about one second.

Although we observe some mis/prediction patterns, seen as sudden spikes, overall throughput still improved across all four runs, averaging 63.25% improvement: 140% improvement for readrandom, 2% for readsequential, 109% for mixgraph, and 12% for readreverse. We note that even a small improvement in throughput can yield significant cumulative energy and economic cost savings for long-running servers [54].

**Read-sequential workloads.** Out of the six workloads we ran, Figure 9 shows the one where KML performed the worst: read-sequential. Reading data sequentially directly from the raw SATA-SSD is nearly 1,000× faster than the mixgraph workload, and nearly 400× faster with the NVMe-SSD. Here, there is little opportunity for KML to improve throughput for a sequential workload that reads at speeds near the maximum throughput of the physical device.

**Read-reverse workloads.** As we can see from the fluctuating green line (readahead values in Figure 6) KML mispredicts readreverse as readseq and changes the readahead value to something suboptimal. These two workloads both access files sequentially—one reading forward and one backward. Interestingly, readseq and readreverse are quite close from a feature representation perspective, which explains the mispredictions. But since both of these workloads access files sequentially, their optimal readahead values are also quite close to each other. Thus, even when KML mispredicts readreverse as readseq or vice versa, this had a small overall impact on performance.

**Summary of readahead neural network results.** We summarize all readahead neural network results in Figure 9. We observe that the average throughput improvement for NVMe-SSD is ranging from 0% to 65%. We saw greater improvements in the SATA-SSD case, ranging from 2% to 130% (2.3×). Lastly, we ran the complex mixgraph workload on NVMe-SSD with the system memory set to the maximum (i.e., 24GB) and the database size set to be relatively large, 65GB (compared to a 2GB baseline database size). This experiment ran for nearly an hour (48.5 minutes) and resulted in an average throughput improvement of 38%.
Mixed workloads. Mixed workloads are considered a challenging optimization problem [7]. In Figure 8, we present a timeline performance comparison using the readahead neural network model running on a per-disk vs. per-file basis. The per-file mode performs better overall because readahead values are set for each open file independently. Conversely, in the per-disk mode, a single readahead value is set at the disk level and hence uniformly on all open files: a readahead value good for one workload is likely to be suboptimal for other open files. One reason why the per-disk mode cannot predict workload types correctly is that when different workloads are mixed—even sequential ones or ones with regular patterns—the mix looks more like a purely random workload at the disk level. Figure 7 shows overall mixed workloads performance comparisons. Per-file mode performed overall better in every combination of mixed workloads. If we compare only the sequential parts of the mixed workload combination (orange bars in Figure 7), in per-disk mode, we observe significant performance degradation. However, in per-file mode, we can observe performance improvements for both the sequential and random (blue bars in Figure 7) parts of the mixed workload combination. The reason why per-disk mode performs better for the random parts of the mixed workload combinations is for the same reason: mixing workloads looks more random-like at the disk level. KML predicts these as readrandom or readrandomwriterandom which coincidentally fits this part of the workload, but significantly hurts non-random workloads.

Decision tree evaluation. In addition to the neural network model, we implemented a decision tree model for the readahead problem to compare the two ML approaches on the same problem. We tested the readahead decision tree the same way. Figure 10 shows that there is a performance improvement for workloads with a random component. For the readahead decision tree, we measure average throughput improvement for random workloads on NVMe-SSD as ranging from 48% to 59%; and in the SATA-SSD case, ranging from 99% to 119% (2.19×). While good, the neural network model yielded greater improvements, as discussed above.

The DT model, however, degraded performance for sequential workloads. it degraded performance for sequential workloads on NVMe-SSD by 15–40%; and in the SATA-SSD case, by 36–73% worse. We investigated this performance degradation. Figure 11 shows the readseq workload running on a RocksDB instance stored on an NVMe-SSD. Here, the readahead decision tree predicts the workload correctly in the first three minutes, despite some fluctuations. Afterwards, the decision tree model’s predictions fluctuate wildly, and at around minute 10 it consistently makes wrong predictions. Overall, this was somewhat expected for our I/O optimization problem: neural network models, while more complex to train and use, are more adaptable than decision-trees [36]. Specifically, when the DT model mispredicts, and system conditions change (i.e., I/O activity), the DT model continues to mispredict, and it cannot recover as quickly as the more adaptable neural network model.

TPC-H benchmarks. As we mentioned in Section 4.2, we evaluated our readahead neural network model—trained on RocksDB workloads—on TPC-H queries (both with NVMe-SSD). This intends to show the model’s accuracy limitations when presented with vastly different workload and application combinations. Figure 12 shows performance improvements as much as 39% for most query types. For query 11, however, the readahead neural network failed to characterize the workload correctly and resulted in a 53% performance reduction. Nevertheless, overall TPC-H performance still improved by 6%. We expect that neural network models trained on more traditional SQL database workloads would likely yield even better predictions across most similar databases.
4.5 NFS Evaluation

Figure 13 shows the NFS rsize neural network performance improvements using the same evaluation techniques of readahead. Throughout these experiments, we ran multiple iterations of the same workloads. Since rsize is a mount point parameter for NFS, our NFS neural network can tune rsize values only in the beginning of the iteration. (We plan to fix the Linux kernel to permit rsize to change dynamically.) Hence, in sequential workloads, if the NFS neural network makes even one misprediction, it will affect the entire iteration, leading to performance degradation. Nevertheless, in random workload cases, we still measured around 15× performance improvement; in separate experiments (not shown for brevity), performance improvements for random workloads reached up to 20×. This demonstrates the significant potential of KML.

5 Related Work

Machine learning in systems and storage. In follow-up work to Mittois [37], a custom neural network was built that makes inferences inside the OS’s I/O scheduler queue. The neural network decides synchronously whether to submit requests to the device using binary classification [38]. There are notable differences between that system and our KML. That system was trained offline using TensorFlow and exclusively trained in user space. Additionally, each of their two layers were custom built. Conversely, KML provides a more flexible architecture. KML training, retraining, normalization, repeated inference—all are possible and accomplished with ease in any combination of online, offline, synchronous, or asynchronous settings. Lastly, KML easily supports an arbitrary number of generalizable neural network layers; our experiments demonstrate more expressive classification abilities on a more diverse set of devices.

Laga et al. [50] improved readahead performance in the Linux Kernel with Markov chain models, netting a 50% I/O performance improvement in TPC-H [87] queries on SATA-SSDs. In contrast, our experiments ran on a wider selection of storage media (NVMe-SSD and SATA-SSD) and workloads. In TPC-H, we show improvements up to 39% despite TPC-H being a completely new workload for our readahead model. Moreover, our results illustrate that our readahead model can improve I/O throughput by as much as 2.4×—all while keeping memory consumption under 4KB, in comparison to Laga et al.’s much larger 94MB Markov chain model.

Parameter tuning for storage and operating systems has been a challenge and researchers approached this problem using control theory [80] and data distribution analysis for storage clusters [2]. Some research has attempted to apply ML techniques to OS task scheduling [17, 65], with small reported performance improvements (0.1–6%). Nevertheless, it is becoming increasingly popular to apply ML techniques to storage and OS problems including: tuning SSD configurations [53], memory allocation [61], TCP congestion [30], building smart NICs [79], predicting index structures in key-value stores [22, 48], offline black-box storage parameter optimization [13], reconfigurable kernel datapaths [69], local and distributed caching [84, 90], database query optimization [47], and cloud resource management [21, 24, 25, 82].

Adapting readahead and prefetching. Readahead and prefetching methods are both well-studied problems [27, 49, 77, 78] and see use in distributed systems [16, 18, 29, 52, 55, 56, 64, 86]. Many have attempted to build statistical models to optimize and tune systems [33, 77, 78]. However, the main limitation of statistical models is their inability to adapt to novel new workloads and devices. We have shown that our model can adapt to never-before-seen workloads and devices. Another way to improve a readahead system is to predict individual I/O requests and file accesses by observing workload patterns [6, 27, 40, 49, 88, 91, 94, 96]. Predicting file accesses using hand-crafted algorithms is a reasonable first approach. However, such manual labor simply cannot keep up with the diversity and complexity of ever-changing modern workloads. Conversely, as long as we have training data, ML models can adapt, retrained as needed, and optimize much faster. Simulations are also viable solutions for readahead and prefetching problems [15, 34, 71, 95, 99]. However, simulations are computationally expensive and are limited to the datasets that the models are trained and tested with. Additionally, the models produced in simulations are not designed for resource-constrained environments, making it non-trivial to migrate such models to the kernel. It is possible to use a user-space library to intercept file accesses [93] or to require application-level changes [98]. In contrast, KML requires no application changes and is capable of intercepting mmap-based file accesses.

Finally, while techniques exist to improve NFS performance, we are unaware of automated ones that use ML [43].
6 Conclusion

Operating systems and storage systems have to support many ever-changing workloads and devices. To provide the best performance, we have to configure storage system knobs based on workloads’ needs and device characteristics. Unfortunately, current heuristics cannot adapt to workload changes quickly enough and require constant development efforts to support new devices. We propose KML to solve these problems—an ML framework inside the OS that adapts quickly to optimize storage performance. KML enables finer granularity optimizations for individual files in even mixed workloads—a challenging problem. Our preliminary results show that, for a readahead problem, we can boost I/O throughput by up to 2.3× without imposing significant CPU/memory overheads. For the NFS `rsize` problem, the improvement was up to 15×. These I/O throughput improvements far outweigh the small memory and CPU consumption of KML.

Future work. We plan on using KML to tune knobs for other OS subsystems: e.g., packet and I/O schedulers, and networking. We are adding ML techniques to KML, such as reinforcement learning [44], which can be a better fit for solving certain OS problems. To support more advanced ML approaches (e.g., Recurrent Neural Networks (RNNs) [92]) and Long Short-Term Memory (LSTM) [39]), we are extending KML to support arbitrary computation DAGs. We also plan to integrate user-kernel co-operated design into KML. Finally, loading an unverified ML model into a running kernel opens up new attack surfaces. We are exploring known techniques to digitally sign and certify loadable models [46, 59].

7 Acknowledgments

This work was made possible in part thanks to Dell-EMC, NetApp, and IBM support; and NSF awards CCF-1918225, CNS-1900706, CNS-1729939, and CNS-1730726.

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