A Framework for Network-Centric ML-Systems Datasets

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Abstract

The availability of high-fidelity systems datasets is key in designing machine learning (ML) approaches for solving systems problems. This paper is part of an effort to capture, understand, and model the energy and performance behavior of network-driven computation in a data-centric way. We present a multi-terabyte systems-level dataset and a general and extensible implementation of the data logging framework we used to produce it. Our dataset is parameterized by an exhaustive sweep of different software and hardware controls and captures system behavior in a fine-grain, low-level temporal signal that is agnostic to software semantics. We believe that these attributes enable defining ML tasks for systems problems without extensive knowledge of the underlying system.

1 Introduction

Modern hardware components and software stacks expose a large number of parameters that govern internal system operations and interactions. There is a lot of work on defining heuristics to control these parameters [6, 30, 50, 51, 20, 39]. In recent years, there has been an explosion in using ML-based techniques [71, 15] to uncover more subtle system heuristics for resource management [25, 5, 8, 12, 13, 21, 29, 34, 50, 51, 53, 57, 65, 77], hardware and system configuration [2, 7, 14, 21, 25, 43, 48, 68, 69, 72, 74, 76, 78], high-performance computing [44, 51, 34, 75, 2, 48, 60], and data-center-scale applications [12, 13, 74, 7, 69, 78, 67, 17, 16, 47, 70, 18].

Though ML is a natural solution for domains like image, video, and audio processing, the complexity of computer systems often requires extensive expertise to map systems problems to ML tasks. To our knowledge, there have been few publicly available systems datasets for ML [36, 37, 4, 11, 16]. *A goal of this work is to provide a representation of computer system behavior as a log-based data object amenable for use by different ML techniques.* We define a log as a multivariate time-series. Each log entry captures low-level, software agnostic metrics that reflect the behavior of the system at a moment of network interaction. Over the course of network-bound operation, a log becomes a rich data object that reflects local and global system behavior.

We present a parameterized and software-agnostic logging framework (figure 1*A*) that exposes how controlled changes can impact network-driven behavior. The framework can be parameterized by *1)* software for which execution is to be captured, *2)* metrics to be logged, and *3)* hardware settings. With this framework, we can identify a set of control parameters to study and exhaustively sweep through their values to generate comprehensive datasets of parameterized execution logs.

We used our framework to gather a dataset that captures the energy and performance behavior of different network servers. In the following sections, we describe our dataset and discuss the attributes of our logging framework. *Our goal is for this framework to be a template that enables gathering systems datasets, inviting a broader community of researchers to define and explore ML solutions for systems regardless of specialized domain knowledge.*

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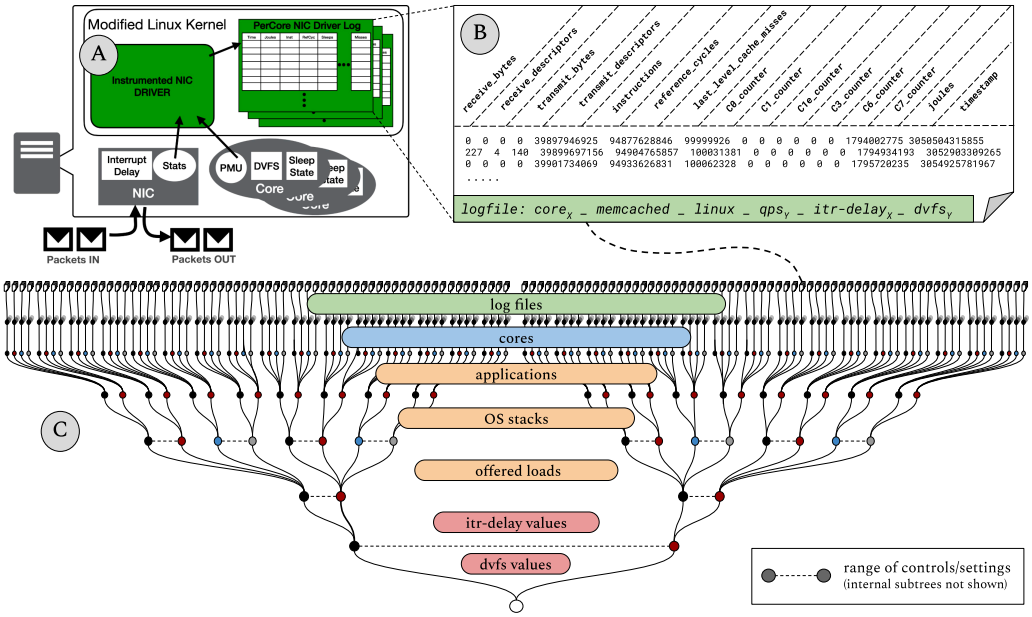


Figure 1: (A) Data logging framework. (B) Per-core log file. (C) An exhaustive parameter sweep.

2 Dataset

Our dataset *(A.1)* is motivated by interest in developing a network-centric and software-agnostic ML controller that can improve system energy-use while maintaining desired performance. For such a controller to be viable, it must *1)* be exposed to software-agnostic controls that have a net effect on energy and performance and *2)* understand system behavior across different modes of operation in order to affect desired change using available controls. Below, we describe our log-level representation of system behavior, two hardware-level controls that we chose to explore, and the different network and software configurations we used to capture a range of system behaviors. The dataset consists of per-core logs for every parameterized run of our exhaustive sweep of controls.

2.1 Log Data

Figure 1 illustrates an individual log file (1*B*) within a tree of experiments (1*C*) that produced our dataset. A timestamped log entry is generated every time the network interacts with the system and resides in a log file parameterized by the core for which logging was triggered. Every entry captures hardware metrics that are largely agnostic to the overarching software: number of instructions, cache misses, energy-use *(A.2.1)*, received and transmitted bytes, etc. *A full log is analogous to a video that describes overall system behavior, composed of frames that each individually describe execution at a single instant of the video.*

2.2 Hardware Controls

We explored two generic hardware controls whose values can be easily adjusted: processor dynamic-voltage-frequency-scaling (DVFS [19, 3]) and NIC interrupt-delay (ITR-delay) [33, 49]. DVFS is used to control core speed [27, 42, 61, 23, 46, 10, 35, 48, 45, 40, 26, 66, 41, 24, 22], and ITR-delay is used to control the rate at which a NIC fires interrupts signalling new work [73, 56, 54, 9, 22]. While there are many other controls to choose from, we use these two because of their simplicity and because preliminary logs revealed their clear impact on system behavior. We explored up to 340 unique combinations of ITR-delay and DVFS, producing a multi-terabyte dataset of log files parameterized by these two hardware controls and the different software and network configurations used. We will publish our dataset and logging framework at `https://github.com/SESA/intlog`.

OS	Application	Network Loads	Client-Server Loop	CPU/App	CPU/OS
Linux, EbbRT	NetPIPE	64B, 8KB, 64KB, 512KB	Closed	Low	High
	NodeJS	N/A	Closed	High	Low
	Memcached	200K, 400K, 600K QPS	Open	Low	High
	Memcached-Silo	50K, 100K, 200K QPS	Open	High	Low

Table 1: Operating system (OS), application, and network configurations. Network loads reflect mean values: our framework's benchmark tool generates distributions of offered loads (requests-per-second *(QPS)* or packet load sizes *(KB)*).

2.3 Software and Network Configurations

We ran our experiments with a matrix of configurations (*Table 1*) that populate our dataset with a versatile list of interactions between network demand and software processing efficiency:

Applications We divide the space of applications into the cross product of closed-versus-open-loop and high-versus-low CPU demand. Closed-loop performance, *throughput*, depends on the ability of server and client components to conduct synchronous packet exchange. Open-loop performance, *tail-latency*, depends on the ability of a server to satisfy a service-level-agreement (SLA, e.g. 500μs 99% tail-latency) for client-generated loads [63].

Operating Systems Our framework is designed to integrate naturally with different operating systems (OSes) that present varying local and global behavior worth capturing. Our integration with Linux and EbbRT [62] introduced 400 lines of new code. Including EbbRT as an alternative dataset parameter to Linux captures the performance and energy behaviors of a specialized library OS. To minimize general-purpose system noise in our Linux experiments, we built and used a set of application-specific high-performance Linux appliances [64, 28] *(A.3)*.

3 Attributes of a Data Logging Framework

Our framework adopts three main approaches:

1. **Software agnostic implementation**, to work effectively with no change to software.
2. **Fine-grain epoch-based logging**, to expose local events that explain global behavior.
3. **Noise-aware logging**, to produce logs that require minimal cleanup.

3.1 Software Agnostic Implementation

Our framework collects data transparently across different network applications and OSes [1]. We place its logic as far from the software stack and as close to the underlying hardware as possible. We implement logging in the NIC device driver - the first piece of logic to run after packets are received and the last to run before they are transmitted. This further enables seamless logging of network metrics to provide a more comprehensive context around network-induced system behavior *(A.2.3)*.

3.2 Fine-Grain Epoch-Based Logging

Per-Interrupt Logging An interrupt is the hardware event used by the NIC to signal to software that a network packet has been successfully sent or received. We exploit the lowest level of software that runs in response to NIC interrupts in order to log our metrics. This ensures that we capture log entries that reflect critical moments of system interaction with the network. While this approach can be supplemented with periodic sampling, we believe that it sufficiently captures highly salient events of network-driven execution (see figure 2).

[1] We integrated our platform with Apache Flink, an application streaming platform. We found our framework easy to integrate in this new domain without application or runtime changes.

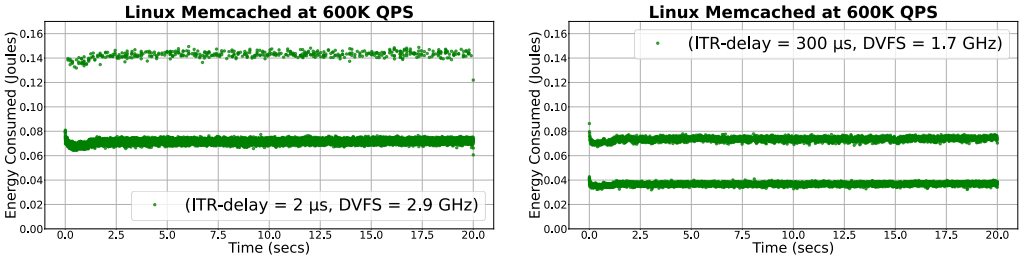


Figure 2: Per-interrupt measurements of a Memcached server processing 600K requests-per-second for 20 seconds. Interrupt-based logging defines epochs across timestamped log entries that reflect real values of elapsed time regardless of experimentally-induced frequency changes *(A.2.2)*. The logs that produced these plots are parameterized by two different ITR-delay and DVFS pairs that yield best *(right)* and worst *(left)* energy-use. All other log parameters are identical. The banding of energy-measurements reflects bimodal system behavior that was captured by our framework's interrupt-level logging. This banding reflects local system events which partition execution into idle (bottom band) and busy (top band) moments and explain net system energy-use.

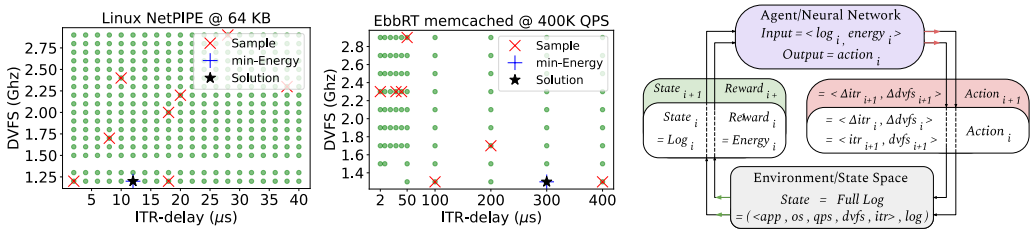
3.3 Noise-Aware Logging

We ensure that *logs reflect relevant system behavior by minimizing general system noise* in our experiments. For example, we maintain core affinity through application/core pinning and NIC-queue/core mapping to avoid run-time scheduling and memory allocation/de-allocation perturbations.

We ensure that *data logging has minimal impact on the system behavior that we want to capture*. For example, we use x86_64 non-temporal store instructions to read our log data. They are optimized for write-once-read-later data access, minimizing cache-coherency effects and the eviction of performance-critical application cache-lines.

4 Concluding Statements

Using our dataset, we posed a systems optimization problem as an ML task: when and to what values should we set our two hardware controls to yield optimal energy-use and performance. We demonstrated that a simple Bayesian optimization algorithm [1, 18, 52, 55] can effectively exploit structure in our dataset and converge to an optimal ITR-delay and DVFS setting for each of our permutations of software and network configurations (figures 3a and 3b). This result motivates us to pursue more complex ML tasks, such as developing a software and network agnostic reinforcement learning (RL) agent that can dynamically adjust ITR-delay and DVFS controls (figure 3c).



(a) (b) (c)

Figure 3: Current *(a, b)* and future *(c)* work on solving an energy and performance problems using ML.

We hope that our work can provide a motivational and extensible approach for capturing representative system-level datasets and using them to address issues of high priority, from datacenter energy efficiency to the general global minimization of computational resource footprint.

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A Appendix

A.1 Dataset Details

1. Our dataset of logs resides in four folders labeled by our chosen network applications: `mcd`, `mcdsilo`, `node`, and `netpipe`. Each folder contains two sets of log files, one set of Linux logs and one set of EbbRT logs. Each log file contains raw timestamped log entries, and each entry lists: *log_identifier, receive_bytes, receive_descriptors, transmit_bytes, transmit_descriptors, instructions, reference_cycles, last-level_cache_misses, C1_counter, C3_counter, C6_counter, C7_counter, joules, rdtsc_timestamp*.
2. Each log file name is parameterized by the control values of the experiment that created it: `*.i_Core_ITR_DVFS_RAPL`, where `*` is the OS/application configuration, `i` is the experimental run number, `Core` is the processor core that the data is collected from, ITR is the interrupt-delay value used, `DVFS` is the frequency value that the processor core is set to, and `RAPL` is the RAPL power-limiting value that the package is set to.
3. Our dataset also contains non-log-based output files that were collected by our framework. One such file is created by the different client workload generators and shows the overall performance of the server. Others are per-experiment timestamp files that each contain two timestamps, the beginning and end of the experiment. We use these files to clean up logs and discard noisy entries generated during the initialization and clean-up of a server.

A.2 Framework Implementation Details

1. Energy is read from the MSR_PKG_ENERGY_STATUS register. While we validated results for per-application energy savings with respect to global rack energy numbers, we chose to use MSR_PKG_ENERGY_STATUS instead, because it allows reading at a finer granularity of one millisecond. In contrast, the per-second granularity of rack-level measurements could complicate the ability to attribute detailed energy-use to specific system events.
2. The `rdtsc` instruction [31] exists on every core and simplifies multi-core data logging by avoiding the use of global clock sources and synchronization. We invoke `rdtsc` to count the number of CPU ticks since the processor was reset. We then divide this value by the processor frequency imposed by the DVFS setting of our experiment to timestamp logs at a fixed-rate.
3. Typically, log data can be mapped to userspace memory. However, it is then the application's responsibility to handle storage, violating software agnostic properties. Instead, TCP protocols allow sending specific packet request data over the network to a storage server as an approach for log retrieval. In contrast to implementing custom network protocols for log data retrieval at the level of the OS, our implementation in the NIC device driver results in a more efficient process of transmission by avoiding the need to run the entire OS network stack. Another property of our NIC-level data logging is the use of fixed mapping between network queues and physical cores to create pre-allocated, per-core data structures sized appropriately for a target application and its offered load. This pre-allocation eliminates run-time OS overheads of dynamically allocating and freeing memory.

A.3 OS Stacks Studied

1. We integrated our logging framework into the NIC device drivers of two OSes, Linux and EbbRT [62]. Linux and EbbRT kernel images are setup similarly by configuring IA-32 architectural MSRs, processor specific MSRs (Tables 35-2 and 35-18 in [32]), and NIC features - disabling direct-cache injection, enabling receive-side scaling (RSS), and enabling hardware checksum offloading. We match the numbers of NIC transmit and receive descriptors and write-back thresholds for packet transmissions. We disable hyperthreads and TurboBoost on all processors. Prior work enables TurboBoost [9, 38, 27, 58], but energy-use anomalies have been reported upon use with different sleep states [42].
2. To reduce system noise in Linux logs, we built a set of application-specific Linux appliances that run a custom high-performance 5.5.17 kernel. We followed suggestions from prior work on reducing Linux core-operation costs [59] to create a modified high-performance

configuration of the 5.5.17 kernel. Linux appliances are constructed to run a RAM-based filesystem and contain only a small set of system libraries and kernel modules needed to run their constituent applications [28]. During Linux experiments, we pin applications to physical cores, avoiding system scheduling overheads and noise in the logs. We also disable Linux *irqbalance* in order to map packet receive interrupts to their respective cores. This ensures the affinity of log entries to the core for which logging has been triggered by a NIC interrupt.

3. We used EbbRT's library OS framework to construct custom binaries for the applications we consider. EbbRT consists of specialized, multi-core library OS components that are optimized to aggressively use per-core memory and fine-grain locking. These include the 82599 NIC driver, a custom TCP/IP stack, virtual and physical memory allocators that exploit large pages and pinned memory to avoid page-faults, and generic I/O buffers that enable zero-copy application data processing. It originally only ran within a virtualized environment through its custom `virtio` device driver. We ported it to run baremetal by developing a device driver for the Intel 82599 family of NICs. This driver interfaces with a multi-core TCP/IP stack and programs the NIC with per-core queues and interrupts, maintaining the affinity of TCP connections to their respective cores. Our logging framework was prototyped on this driver.