Energy-Aware Benchmarking: A Case Study on Sampling Methods

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Abstract

Energy efficiency is increasingly recognized as an important dimension in machine learning research, yet systematic approaches to measuring and optimizing energy use remain underdeveloped. In this work, we provide a practical primer on energy measurements, highlighting key metrics, methodologies, and trade-offs. We introduce a methodology for energy benchmarking, aimed at enabling researchers to incorporate energy considerations into their algorithm evaluations and to design methods explicitly optimized for reduced energy demand. To demonstrate the value of energy-aware benchmarking, we focus on sampling, a fundamental and widely used operation in probabilistic machine learning that often incurs substantial computational cost. Guided by the insights gained from the analysis of algorithmic factors that affect energy efficiency, we introduce a novel sampling method that allows energy savings of up to $17\times$ compared to widely used approaches. Our results show how integrating energy considerations into the design and evaluation of algorithms can enable more sustainable machine learning practices.

1 Introduction

The continued deployment of machine learning (ML) methods in data centers, cloud devices, and user appliances alike is accompanied by increased concerns about the growing energy demand of the field [International Energy Agency, 2025, Gadepally, 2025]. Countermeasures include reducing the carbon-intensity of the electricity supply or shifting training and inference to times or physical locations with a higher share of renewable energy sources [Yang et al., 2023, Wiesner et al., 2023]. However, we argue that reducing the energy demand of the operations themselves is worthwhile.

Current work on efficiency in ML typically prioritizes performance metrics such as execution speed or floating-point operations per second (FLOPs). Yet these metrics are not necessarily correlated with actual energy consumption. Moreover, energy measurements in the field are often superficial, frequently capturing only system-level overhead rather than the true energy cost of algorithmic execution. Although a rich body of literature on energy measurement exists in other domains, the ML community remains comparatively underexposed to rigorous, high-quality energy evaluations [Chung et al., 2025, Różycki et al., 2025]. As a result, algorithms are still predominantly designed with speed and accuracy in mind, but rarely with explicit consideration of energy efficiency.

We argue that energy measurements, when performed correctly, are neither prohibitively difficult nor intrusive. Computing hardware vendors increasingly provision their platforms with power or energy meters. Given minimal methodological understanding, energy measurements can be hence integrated into algorithm evaluations with low overhead. Our goal is therefore to support broader adoption of

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energy-aware benchmarking and design in ML by: (i) raising awareness of the issue, (ii) providing a structured overview of relevant energy measurement methodologies, (iii) showcasing an exemplary, exhaustive energy evaluation, and (iv) demonstrating how integrating energy considerations into the design of algorithms can lead to more efficient algorithms. We present a holistic methodology for assessing the energy efficiency of algorithms, aimed at enabling researchers to incorporate energy considerations into their evaluations and to design methods explicitly optimized for reduced energy demand.

As an illustrative application, we focus on the task of *sampling*, a fundamental building block in ML and beyond. Sampling is at the core of numerous widely applied models and algorithms, ranging from Bayesian inference to generative modeling. Despite its conceptual simplicity, the process of generating random variates is often associated with significant computational costs and, consequently, high energy consumption. By introducing a novel sampling algorithm that outperforms state-of-the-art approaches in energy efficiency while demonstrating competitive sampling speed, we showcase how careful analysis of the algorithmic factors that affect the energy efficiency, combined with rigorous energy benchmarking, can lead to the design of novel, more energy-efficient algorithms.

2 Energy Efficiency

Energy efficiency in computing systems is shaped by hardware and algorithmic choices and expressed using various metrics emphasizing different optimization goals. In this work, we begin by defining the key concepts underlying energy-efficient computation (Section 2.1). We then introduce methodologies for measuring energy consumption (Section 2.2 and 2.3), followed by an analysis of common factors that influence the energy efficiency of algorithms (Section 2.4).

2.1 Concepts: What to Measure

Power is defined as the rate at which electricity is consumed, and *energy* is the cumulative amount of electricity required to perform a task. Therefore, energy is power integrated with respect to time $[t_0, t_1]$, as shown in Equation (1). Power ($\mathcal{P}$) is measured in Watts (W) or Joules per second, while energy ($\mathcal{E}$) is measured in Joules (J). In the context of computing, energy is often the more appropriate metric for optimization, as it directly relates to battery lifetime in mobile devices, operating costs in data centers, and environmental sustainability in terms of carbon dioxide emissions.

$$\mathcal{E}[\mathrm{J}] = \int_{t_0}^{t_1} \mathcal{P}[\mathrm{W}](t[\mathrm{s}])\,\mathrm{d}t\,. \tag{1}$$

However, optimizing only for energy may neglect power draw and performance requirements. Peak power draw is important to consider, given the hardware limitations on the power supply or availability in the electricity grid. The power demand is influenced by multiple factors [Kaxiras and Martonosi, 2008]:

$$\mathcal{P} \sim \underbrace{N \cdot C \cdot F \cdot V^2}_{\text{dynamic}} + \underbrace{N \cdot R_{\text{leak}}^{-1} \cdot V^2}_{\text{static}}. \tag{2}$$

Here, N denotes the number of actively switching transistors, which depends on both the circuit design and the program running. C denotes the capacitance, which is given by the circuit design. F denotes the clock frequency, which configurable (impacting performance) but limited by the circuit design. V denotes the supply coltage, which relates to the clock frequency C and configurable as well, but again limited by the circuit design. R_{leak} denotes the leak resistance and is is fixed by the circuit design. Therefore, reducing the power demand can be mainly achieved by adjusting the clock frequency or supply voltage, and through software design, by leveraging computations requiring a lesser number of active transistors.

Optimizing algorithms exclusively for speed can lead to excessive energy consumption, while optimizing only for energy may degrade performance; therefore, the *energy-delay product* (EDP) serves as a balanced optimization metric that accounts for both energy demand and computational speed in algorithm design. *Energy-delay-squared product* (ED^{2}P) prioritizes performance more strongly, as shown in the Equation (3):

$$\mathrm{EDP} = \mathcal{E}[\mathrm{J}] \cdot t[\mathrm{s}], \quad \mathrm{ED}^2\mathrm{P} = \mathcal{E}[\mathrm{J}] \cdot t^2[\mathrm{s}^2]\,. \tag{3}$$

This becomes more pronounced as even within the same system the power demand can change due to effects like dynamic voltage and frequency scaling, for which the ED^2P can be show to be better suited [Brooks et al., 2000].

2.2 Methodologies: How to Measure

Measuring power draw or energy consumption in computing systems can be approached from two complementary perspectives: direct physical measurement and indirect logical modeling.

Physical measurement Physical measurements rely on electrical sensors that directly or indirectly capture voltage and current in circuits. Examples include shunt resistors and Hall effect sensors [Ziegler et al., 2009]. Physical measurement methods provide high accuracy and fine temporal resolution, but require setup alterations in the form of hardware modifications, which may be impractical and sometimes even infeasible.

Logical modeling Alternatively, software power models can estimate power draw and energy consumption by multiplying hardware performance counters (cycles, instruction count, cache accesses etc.) or other software-level statistics with initial physical measurements of single operations [Bellosa, 2000]. For example, instead of measuring the energy consumption of a sampling routine on the circuit level using techniques described above, one counts the operations (lookup, addition, etc.) performed via software and then multiplies by separately taken physical measurements of the individual operations. While easier to integrate as no additional circuits are required, their accuracy depends heavily on the quality of the model (potentially disregarding side-effects such as cooling due to workload), thus making these methods ultimately more error-prone.

2.3 Hierarchy of Measurement Facilities

Another important dimension is granularity. One may analyze energy demand per instruction, per algorithm, or per system. At the instruction level, activity factors such as the number of transistor switches, the clock frequency, and supply voltage determine dynamic power [Kaxiras and Martonosi 2008, see Section 2.1]. At higher levels, interactions with the memory hierarchy, I/O, cooling, and communication can contribute substantially to overall consumption. Analyzing the energy demand at different levels requires different measurement facilities. Extending on existing classification Köhler et al. [2020], the measurement facilities can be categorized on where there are placed in relation to the computing system and how many components they measure at the same time.

External devices The most versatile but also coarse-grained instruments intercept the power supply between the power source and the device under test. Therefore, it yields a comprehensive description of the power draw and energy consumption of execution, but including the energy consumption of other processes going on in the device. Hence, it is advisable to control for confounders like storage activity, network connectivity and display brightness when performing measurements. In this study, we utilize the Microchip MCP39F511N, a dual-channel monitor that can measure the current power draw at up to 240 Hz and a 0.5% value error margin.

On-board monitors Modern mainboards contain power sensors, which are accessible through interfaces like the Intelligent Platform Management Interface (IPMI). Their resolution in time and value is typically not sufficient for machine learning applications. Without a dedicated power meter at the power supply of, e.g., for the GPU, the informative value is not higher than an external measurement device. However, hardware vendors offer development boards with dedicated power rails to report voltage, current, and power draw of different components of the system. For example, boards of the NVIDIA Jetson series integrate measurement facilities for CPU, GPU, the memory subsystem, WiFi, and the entire system. These devices can help with the analysis and optimization of machine learning algorithms, or the formulation of logical energy models. They provide moderate accuracy at little overhead and expose measurements through Linux kernel interfaces.

On-chip counters At the finest granularity, processors may integrate energy monitoring themselves. Intel's Running Average Power Limit [David et al. 2010, RAPL] interface is a well-known example. RAPL registers capture cumulative energy consumption (not power draw) at about 1 ms resolution. RAPL exposes the energy usage per domain (CPU cores, internal GPU, DRAM, full package).

RAPL-compatible interfaces exist in AMD processors since Ryzen Gen 3. Recent Apple Silicon processors (since M1) introduced their own set of hardware counters, including energy counters for the GPU and the Neural Engine. These mechanisms enable detailed energy accounting with negligible overhead, but are restricted to supported platforms.

Likewise, GPU vendors integrate energy or power meters, accessible through their software stack. For example the NVIDIA System Management Interface (`nvidia-smi`) can report the current power draw at a point in time, which can be numerically integrated into the energy demand of an operation.

Best practices Even at fixed clock rates, switching between CPU architectures can significantly alter power demand but not necessarily energy demand. A low-power device (a microcontroller or efficient CPU core) can run for a longer time than a more power-intensive one, resulting in comparable energy integrals—or not, depending on the static power demand and thus energy proportionality (i.e., the degree of proportionality between energy consumption and workload) of the system [Barroso and Hölzle, 2007]. For a fixed problem size, the latter device can switch to idle mode after completion or process more elements for a given unit of energy. Consequently, to obtain more representative measurements, one should fix the CPU frequency and micro-architecture (cores) in experiments.

2.4 Energy-Efficient Design of Algorithms

The power draw and energy consumption of algorithms are shaped by multiple factors. A systematic analysis of these factors allows for a more comprehensive comparison of existing algorithms, provides insight into implementation trade-offs, and ultimately guides the development of novel energy-efficient methods.

Arithmetic operations The energy cost of an arithmetic operation depends on both the type of operation and the precision of the operands. In general, integer arithmetic is cheaper than floating-point arithmetic because floating-point operations require more complex circuitry, including normalization, rounding, and handling of exponents. Therefore, floating point operations require switching of more transistors, thus increasing power draw [Kaxiras and Martonosi 2008, see Equation (2)]. Among arithmetic operations, additions and subtractions are the least expensive, as they only require basic logic for carrying and summing bits. Multiplications are more costly because they involve repeated addition and shifting steps internally, and floating-point multipliers also require exponent and mantissa adjustments. Division and exponentiation are the most expensive operations, often requiring iterative algorithms or table lookups in hardware, which increase both latency and energy consumption [Knuth, 2014]. Reducing precision (e.g., using half-precision or single-precision floats instead of double) can further reduce energy usage while still maintaining acceptable numerical accuracy for many ML tasks [Micikevicius et al., 2018].

Conditional operations Branches dependent on unpredictable outcomes can lead to pipeline stalls and branch mispredictions, which waste energy. Branchless implementations, using arithmetic operations instead of conditionals, may improve both performance and energy efficiency.

Memory access There is a direct connection between the memory access behavior of modern computer systems and their electricity consumption [Horowitz, 2014]. Memory subsystems and CPU caches have long been overlooked in comparison to computational cores but constitute a large portion of active transistors in today's chip designs, leading to higher dynamic power demands. Memory hierarchy interactions are often more energy-intensive than arithmetic operations. This means that, for general-purpose computers, algorithms that trade computation for memory lookups may have slightly worse energy efficiency than plain recomputation. This effect is more pronounced with multiple, nested lookups (also known as *pointer chasing*) because it involves more active transistors, which increases power demand. It also breaks CPU cache locality and access prediction, resulting in prolonged CPU stalls (increased time demand) and thus non-linear increase in energy demand. Optimizing locality is thus crucial.

Overall, designing energy-efficient algorithms requires balancing these factors, often with application-specific trade-offs between quality, reproducibility, and computational constraints. Beyond these general factors, probabilistic ML adds a further source of energy demand: random number generation, which lies at the core of sampling algorithms.

Entropy source Many algorithms require (pseudo-)randomness, making random number generation an additional source of energy consumption. Hardware random number generators can provide high-quality entropy at low latency but often incur notable power costs. In contrast, software-based pseudo-random number generators (PRNGs) are lightweight, reproducible, and often sufficiently accurate for sampling-based algorithms. Nevertheless, the choice of generator matters: certain cryptographically secure or high-quality generators may introduce significant computational overhead. In extreme cases, the entropy source can become a dominant contributor to energy consumption.

3 Sampling

In the following, we first review classical methods for sampling from discrete probability distributions, along with recent state-of-the-art advances. We then introduce a novel sampling method explicitly designed for energy efficiency while maintaining competitive performance. Our approach leverages the factors discussed in Section 2 to systematically reduce energy demand. Finally, in Section 4, we present an experimental evaluation of these methods, illustrating how careful energy-aware analysis can drive algorithmic innovation.

Formally, by sampling from a discrete probability distribution we mean the task of generating random variates from any finite distribution over n outcomes. The distribution is characterized by probabilities $p_1, \ldots, p_n \in [0, 1]$ associated with outcomes $x_1, \ldots, x_n \in \mathcal{X}$, where $\sum_{i=1}^{n} p_i = 1$. We impose no restrictions on the structure of the outcome space $\mathcal{X}$: outcomes may be real numbers, categorical labels, strings, pointers to complex data structures, or any mixture thereof.

3.1 Common Sampling Methods

We chose three discrete sampling methods to benchmark their energy efficiency and compare our own algorithm against: the inversion method, the alias method, and the Fast Loaded Dice Roller (FLDR). The inversion method [Devroye, 2006] is one of the the most widely used sampling method and is integrated into many commonly used libraries. The Alias method [Walker, 1974b] is a more efficient approach to random variate generation, though less commonly employed in standard libraries. FLDR [Saad et al., 2020] is a recently developed method for discrete sampling that is claimed to be faster than the Alias method and other state-of-the-art competitors. Due to space constraints, the details are provided in the Appendix A. Next, we shortly revisit the idea of lookup table-based sampling in order to then introduce our discrete sampling method.

3.2 Lookup Table based Sampling

Naive lookup table sampling constructs a lookup table containing duplicates of each outcome x_i proportional to its probability p_i:

$$\frac{\text{occurrences of } x_i \text{ in table}}{\text{table size}} = p_i. \tag{4}$$

Sampling a random variate then reduces to uniformly selecting a random table index $I \sim \text{Uniform}\{1, \ldots, N\}$ and returning $S = \text{Table}[I]$, where N is the table size, see Figure 1a ("Classic Lookup Table") for an example lookup table.

In practice, memory constraints bound the table size N, limiting representable probabilities to multiples of $1/N$. Approximating probabilities to precision b bits requires quantizing each p_i to $\hat{p}_i = \text{round}(p_i \cdot 2^b)/2^b$, yielding a table of size $N = 2^b$. While approximation error decreases logarithmically with b, memory requirements grow exponentially, making high-precision sampling prohibitive.

3.3 Our Sampling Method

Our approach, which we call *cLUT*, is based on the idea of lookup tables, reusing precomputed results, while conserving memory requirements and memory accesses. Sampling using lookup tables offers multiple benefits (single lookup, no arithmetics, no branching) that enable energy efficiency as detailed above, but suffers from huge memory requirements even for reasonable precision. Sampling from a distribution with 32-bit precision requires storing $2^{32} \approx 4.3$ billion entries (17GB for values

Distribution

x_i	$p(x_i)$
x_1	7/16
x_2	5/16
x_3	3/16
x_4	1/16

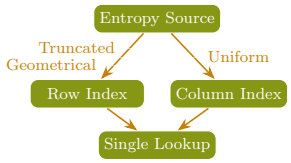
Classic Lookup Table

1/4	x_1	x_1	x_1	x_1
1/4	x_1	x_1	x_1	x_2
1/4	x_2	x_2	x_2	x_2
1/4	x_3	x_3	x_3	x_4
p	1/4	1/4	1/4	1/4

Compressed Table

1/2	x_1	x_2
1/4	x_1	x_3
1/8	x_1	x_2
1/8	x_3	x_4
p	1/2	1/2

(a) Classic and compressed lookup table for example distribution.



(b) Schematic.

Figure 1: (a) The classic and compressed lookup table for an example distribution on given by p (left). The classic lookup table (middle) contains each value according to its probability p at a precision of $b = 4$ bits. The compressed lookup table (right) stores the same distribution. For example, the probability of x_1 is given by the compressed lookup table as $\frac{1}{2} \cdot \frac{1}{2} + \frac{1}{4} \cdot \frac{1}{2} + \frac{1}{8} \cdot \frac{1}{2} = \frac{7}{16}$. (b) Schematic of our sampling algorithm: A row index is sampled geometrically and a column index uniformly. The sample is generated by a single lookup.

stored in a 32-bit format). The impractical memory requirements (that scale exponentially) motivate our approach to decrease the memory requirements by losslessly compressing the lookup tables strategy, then sampling using the compressed tables with a tailored sampling scheme.

Compression scheme Intuitively, our compressed lookup table can be viewed as a two-dimensional array consisting of $r + 1$ rows and 2^c columns, with $r, c \in \{0, \dots, b\}$ satisfying $2^{r+c} = 2^b = N$. Each row i of the first r rows corresponds to a frequency of 2^{r-i}, where row indices run from 1 to r. The r+1-th row corresponds to the same frequency as the r-th row, namely $2^{r-r} = 1$. For an exemplary compression, see Figure 1a.

This lossless compression scheme preserves the total frequencies while drastically decreasing the size of the lookup table. Compressing a naive lookup table with $N = 2^{r+c}$ entries to a compressed lookup table with $(r + 1) \cdot 2^c$ entries yields a compression ratio of $\rho = 2^r/(r + 1)$.

Sampling step To generate a sample $S \in \mathcal{X}$ using a compressed lookup table, we generate two indices independently: a row index $I \in \{1, \dots, r{+}1\}$ and a column index $J \in \{1, \dots, 2^c\}$. We sample the index I according to a truncated geometric distribution, and the column index J uniformly:

$$\mathbb{P}(I = i) = \max(2^{-i}, 2^{-r}) \quad \text{for } i = 1, \dots, r{+}1, \quad \text{and } \mathbb{P}(J = j) = 2^{-c} \quad \text{for } j = 1, \dots, 2^c.$$

Therefore, we sample a table-index $(I, J) = (i, j)$ with probability $2^{-\min(i,r)-c}$. The column index J can be efficiently sampled using any uniform sampler. The row index I can also be sampled extremely efficiently using, for example, the procedure detailed in Algorithm 1 in lines 2-5. A sample is then generated by returning the value stored in the compressed lookup table at that index:

$$S = \mathcal{T}[I, J].$$

Algorithm 1 Our approach: Sampling using compressed lookup tables

Require: number of samples n, compressed lookup table $\mathcal{T}$ of size $(r + 1) \times 2^c$
Ensure: array of samples $\mathcal{S}$ of size n

1: **for** $k = 1$ **to** n **do**
2: *// Generate a row index geometrically:*
3: $I \leftarrow 1$
4: **while** $I < r + 1$ & `randomBit()` $= 1$ **do**
5: $I \leftarrow I + 1$
6: *// Generate a column index uniformly:*
7: $J \leftarrow \text{Uniform}\{1, \dots, 2^c\}$
8: *// Look up sample at generated index:*
9: $\mathcal{S}[k] \leftarrow \mathcal{T}[I, J]$
10: **return** $\mathcal{S}$

Preprocessing step We construct the compressed lookup table directly from the binary expansion of the probabilities $\hat{p}_i$ rounded to precision of 2^{-b}. A value x_i appears in row j if and only if the

j-th bit of $\hat{p}_i$ is one. The rounded probabilites $\hat{p}_i$ can be adjusted to sum to exactly 1 by using a sum-preserving rounding scheme, making our sampling procedure rejection-free. The number of active bits across the binary representations of the $\hat{p}_i$ may differ, which results in rows of unequal width in the initial construction of the compressed lookup table. To improve the sampling speed, we ensure that all rows have uniform width by moving entries to rows below while doubling them (to ensure correct frequencies).

4 Evaluation

Evaluation setup Our experiments were conducted on a conventional laptop powered by an Intel i7-1255U processor and 16 GiB of DDR4 RAM, running Ubuntu Linux. To ensure accurate measurements, as to prevent inaccuracies from *Dynamic Frequency and Voltage Scaling* [Le Sueur and Heiser, 2010] and thread movement across cores, we fixed the CPU's clock rate at its maximum of 4.7 GHz and bound single-thread workloads to a single core. As our particular Intel *Hybrid* CPU architecture comprises of larger **p**erformance cores and limited **e**fficiency cores, we opted for the P-cores for consistent measurements. We test state-of-the-art approaches and our cLUT method in Python and C. We compare all algorithms on a set of synthetically generated distributions (with the number of unique outcomes n spanning the range $[10^4, 10^7]$), randomly sampled from Dirichlet priors to ensure a wide range of entropy values. We measure energy usage, average power, EDP, and execution time.

Evaluation of Python implementations We benchmark our cLUT algorithm and discrete samplers from popular Python ML libraries, namely, `RandomGenerator.choice()` from NumPy, `multinomial()` from PyTorch, and `random.choice()` from JAX [Harris et al., 2020, Paszke et al., 2019, Bradbury et al., 2018]. The discrete samplers from NumPy, PyTorch and JAX all use (optimized) versions of the inversion method (see Appendix A). To simulate a real-world sampling application, time and energy measurements account for the entire pipeline, including preprocessing, 10^8 sampling iterations, and the execution overhead. To comply with a realistic and user-friendly evaluation scenario, we perform measurements via logical modeling as opposed to direct physical measurements, as described in Section 2.2. For robustness, energy consumption is measured by two sources: RAPL interface as an on-chip counter and Microchip MCP39F511N (MCP) as an external source (see Section 2.3). Average power and EDP values are computed with respect to RAPL data (see Section 2.1). Due to the space restrictions, we provide results only on the package domain of RAPL as the most representative.

Figure 2 shows the mean and standard deviation of energy consumption and execution time for each distribution size. The discrete sampler from NumPy is shown to be the least efficient overall, while JAX and PyTorch exhibit varying relative performance depending on the size of the distribution. The proposed cLUT sampler demonstrates efficiency in all dimensions: the energy demand of cLUT is up to 17$\times$ lower for larger distributions ($n \in (10^6, 10^7]$) and up to 6$\times$ lower for smaller distributions ($n \in [10^4, 10^6]$), as shown in Table 1. One may notice that energy consumption is not always correlated with the execution time. E.g., in the group of larger distributions, JAX exhibits longer runtimes than PyTorch yet consumes less energy. In such scenarios, the Energy-Delay Product (EDP, see Section 2.1) offers a more balanced metric, revealing that PyTorch achieves greater overall efficiency (Table 1).

Evaluation of C implementations As the C implementation allows for low-level energy measurements, we distinguish between the preprocessing and sampling stages and measure them separately. We run 10^3 warm-up sampling iterations before doing actual measurements for 10^7 sampling iterations. As in the previous group of experiments, we measure the package domain from RAPL for energy consumption. MCP measurements are not applicable because the runtime is too short for capturing accurate energy readings. We compare cLUT to C implementations of classic methods and recent state-of-the-art advances for discrete sampling.

Figure 3 illustrates the energy efficiency of the evaluated methods and highlights the systematic advantage of the cLUT sampler in reducing energy consumption. This advantage arises not only from acceleration but also from the elimination of computationally expensive operations; figures are shown in Table 2. The polarity of the power data is explained by the different behavior of the methods on different entropy ranges: distributions with high entropy are more likely to belong to the

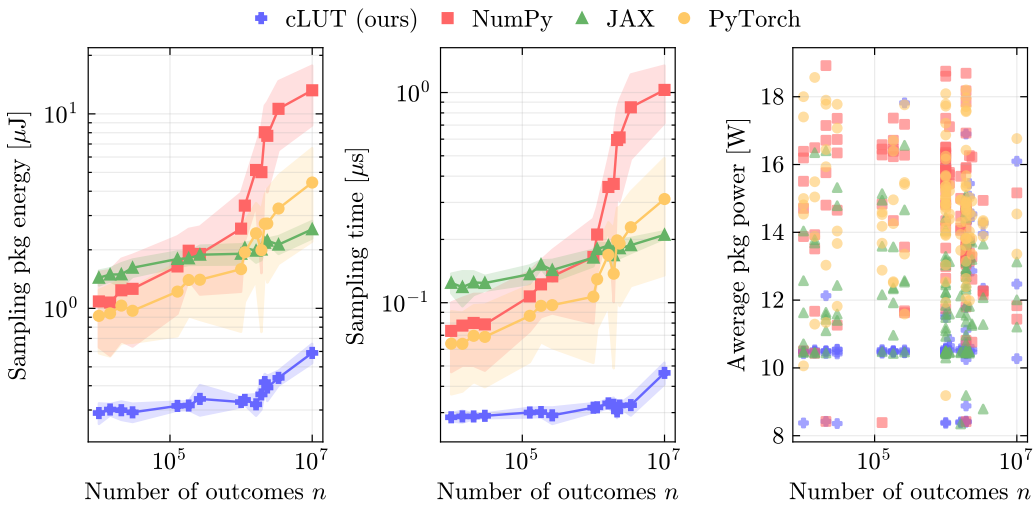


Figure 2: Energy efficiency of built-in discrete samplers from widely used libraries (NumPy, JAX, PyTorch) and our approach (cLUT). Shown are (1) average energy consumption (RAPL:pkg, mean and standard deviation microjoules), (2) the overall execution time (mean and standard deviation in microseconds), and (3) average power draw (each point denotes a result for a distribution, in Watts) per one single sample from distributions of varying sizes n. The plots are shown on a log-log scale.

	Sampler	RAPL:pkg [μJ]	MCP [μJ]	Time [μs]	Average power [W]	EDP [$\mu J \cdot \mu s$]
$n \in [10^4, 10^6]$	JAX	1.76 ± 0.26	3.45 ± 0.47	0.15 ± 0.02	12.17 ± 1.69	0.26 ± 0.07
	NumPy	1.95 ± 1.15	3.34 ± 1.92	0.13 ± 0.07	15.12 ± 2.18	0.33 ± 0.33
	PyTorch	1.33 ± 0.67	2.33 ± 1.17	0.09 ± 0.05	14.86 ± 1.99	0.15 ± 0.14
	cLUT (ours)	$\mathbf{0.32 \pm 0.03}$	$\mathbf{0.62 \pm 0.05}$	$\mathbf{0.03 \pm 0.00}$	$\mathbf{10.50 \pm 1.09}$	$\mathbf{0.01 \pm 0.00}$
$n \in (10^6, 10^7]$	JAX	2.08 ± 0.25	4.09 ± 0.46	0.18 ± 0.02	11.80 ± 1.52	0.37 ± 0.08
	NumPy	6.30 ± 4.00	11.70 ± 7.77	0.47 ± 0.32	14.07 ± 1.93	4.23 ± 4.58
	PyTorch	2.40 ± 1.36	4.29 ± 2.51	0.17 ± 0.10	14.68 ± 1.38	0.53 ± 0.54
	cLUT (ours)	$\mathbf{0.38 \pm 0.08}$	$\mathbf{0.72 \pm 0.13}$	$\mathbf{0.03 \pm 0.00}$	$\mathbf{11.53 \pm 2.20}$	$\mathbf{0.01 \pm 0.00}$

Table 1: Benchmark of discrete samplers from popular Python libraries relevant to machine learning (JAX, NumPy, PyTorch) and our cLUT method. Measured are energy consumption of the sampling procedure (RAPL:pkg, in microjoules), energy consumption of the whole system during execution (MCP, in microjoules), execution time (in microseconds), average power draw (in Watts), and Energy-Delay Product (EDP, see Section 2.1), grouped by the distribution size n (number of unique outcomes). RAPL energy consumption is additionally supplemented by the energy consumption of the overall system measured by MCP. Execution of 10^8 samples was repeated and measured five times, and then averaged to a single iteration.

	Sampler	RAPL:pkg [nJ]	Time [ns]	Average power [W]	EDP [$\mu J \cdot s$]
$n \in [10^4, 10^6]$	Inversion method	728.21 ± 73.56	43.22 ± 2.69	16.99 ± 2.33	31.3 ± 2.16
	Alias method	264.06 ± 118.05	17.39 ± 7.02	15.41 ± 3.66	5.25 ± 4.33
	FLDR	256.22 ± 88.76	16.59 ± 5.0	15.62 ± 2.75	4.61 ± 3.24
	cLUT (ours)	$\mathbf{175.21 \pm 47.32}$	$\mathbf{14.32 \pm 2.48}$	$\mathbf{12.58 \pm 4.05}$	$\mathbf{2.52 \pm 0.92}$
$n \in (10^6, 10^7]$	Inversion method	676.31 ± 110.39	45.07 ± 4.39	15.34 ± 3.52	30.04 ± 3.0
	Alias method	422.41 ± 104.72	34.04 ± 8.12	12.81 ± 3.46	14.75 ± 7.2
	FLDR	278.66 ± 176.24	19.49 ± 10.9	14.37 ± 3.55	7.15 ± 11.7
	cLUT (ours)	$\mathbf{179.41 \pm 64.68}$	$\mathbf{15.53 \pm 4.29}$	$\mathbf{11.7 \pm 3.33}$	$\mathbf{2.97 \pm 2.14}$

Table 2: Benchmark of C implementations of classic methods and recent state-of-the-art advances for discrete sampling, and our proposed cLUT method (see Section 3.3). Measured are average energy consumption (RAPL:pkg, in nanojoules), execution time (in nanoseconds), power draw (in Watts), and Energy-Delay Product (EDP, see Section 2.1) per single iteration of sampling, grouped by the distribution size n (number of unique outcomes). Execution of 10^7 samples was repeated and measured five times, and then averaged to a single iteration.

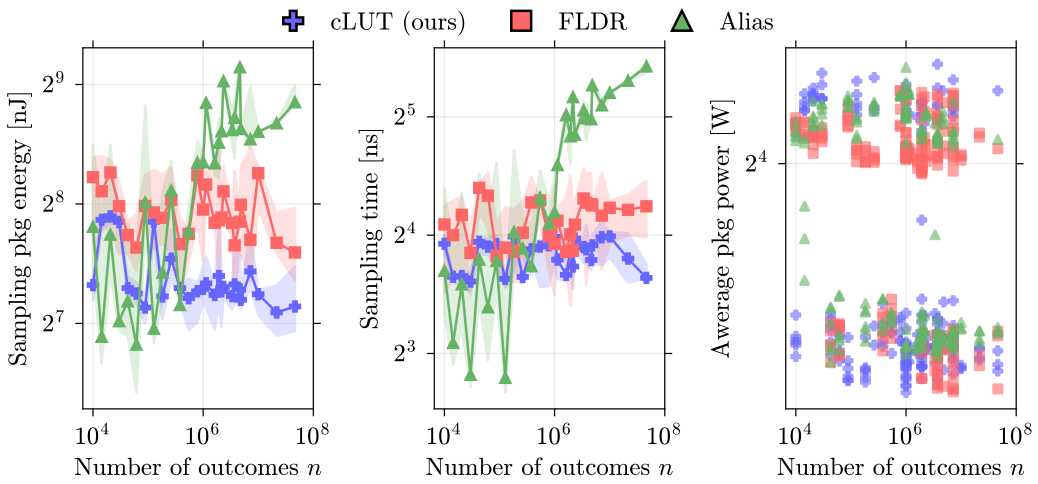


Figure 3: Energy efficiency of C implementation for classic methods and recent state-of-the-art advances for discrete sampling, and our proposed cLUT method. Shown are (1) average energy consumption (RAPL:pkg, mean and the interval between the 1st and 3rd quartiles in nanojoules), (2) execution time (mean and the interval between the 1st and 3rd quartiles in nanoseconds), and (3) average power draw (each point denotes a result for a distribution, in Watts) per one single sample from distributions of varying sizes n. Preprocessing time was measured separately and subtracted to isolate the pure sampling time. The plots are shown on a log-log scale.

upper cluster. The inversion method is shown to be less scalable with respect to the distribution size n, and the inversion method is found to be entirely uncompetitive (Table 2).

5 Conclusion

In this work, we provided a comprehensive primer and framework for incorporating energy awareness into algorithmic research, outlining fundamental concepts, metrics, and methodologies for assessing power draw and energy efficiency. We demonstrated how such analyses can reveal previously hidden trade-offs and guide the design of more sustainable computational methods.

As an illustrative case study, we examined discrete sampling, a fundamental operation in probabilistic machine learning and beyond. Based on rigorous analysis of the energy dynamics of sampling algorithms, we derived our own energy efficient sampling method *cLUT*. Through extensive benchmarking across multiple software frameworks and implementation levels, we showed that cLUT substantially reduces both execution time and energy demand. In Python-level evaluations, cLUT achieved up to a 17$\times$ reduction in energy consumption for large distributions ($n > 10^6$) and up to a 6$\times$ reduction for smaller ones, while maintaining or exceeding the speed of competing implementations in NumPy, PyTorch, and JAX. In low-level C benchmarks, cLUT consistently demonstrated the lowest average power consumption and energy-delay product, confirming that its efficiency stems from the elimination of energy-intensive operations.

These findings emphasize that energy consumption is not necessarily correlated with runtime or throughput alone. Metrics such as the Energy–Delay Product (EDP) provide a more holistic view of efficiency, capturing both computational performance and energy demand. Our experiments highlight that even well-optimized libraries can vary substantially in energy efficiency, underscoring the importance of integrating energy metrics into benchmarking and model evaluation workflows.

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A Details on sampling algorithms

Alias method The alias method [Walker, 1974a, Vose, 1991] preprocesses a probability distribution over n outcomes into two tables: a probability table and an alias table. Each of the n outcome is represented by an integer between 1 and n (e.g. through the mapping $x_i \mapsto i$) and assigned a "bucket" in with equal weight $1/n$. The probabilities $p_1, \ldots, p_n$ are redistributed so that each bucket contains either a single outcome with probability $p_i \geq 1/n$, or a mixture of two outcomes. Two tables are constructed: the probability table and the alias table. The probability table stores the proportion at which bucket i is "filled" with outcome i. The alias table stores the second outcome, if any, that is distributes to the bucket.

During sampling, one first selects a bucket uniformly at random, and then performs a biased coin flip to decide between the primary and alias outcome stored in that bucket. Sampling occurs therefore in two steps. First, a "bucket" is randomly selected among $\{1, \ldots, n\}$ with equal probability $(1/n)$. Second, the value stored in the probability table in that bucket is read out and a biased coin is flipped according the read probability, e.g., by generating a uniform random variate on the unit interval $[0, 1]$ and checking wether it is bigger than the specified probability. If heads, the bucket index is returned; if tails, the value stored at the Alias table is returned. This has the time complexity of generating a single sample at $O(1)$ after $O(n)$ preprocessing, at $O(n)$ memory. See Figure 4 for an illustration. Figure 4 contains one possible implementation of the alias method for a distribution with $n = 5$ outcomes given by the probabilities $(7/25, 6/25, 1/25, 6/25, 1/5)$. Generation of a single sample could look like this: (i) a random bucket index is drawn equiprobable and turns out to be 4, (ii) a biased coin is flipped with $4/5$ probability to land heads. It lands heads and 4 is returned. If it would have landed tails, 2 would have been returned, since 2 is stored in the alias table at bucket 4.

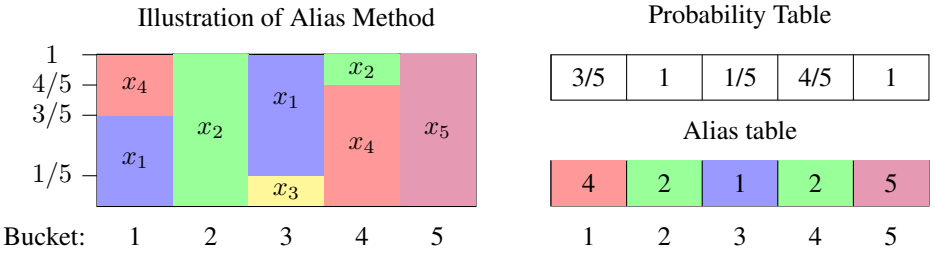

Figure 4: The Alias method for sampling from a discrete distribution. Each bucket has equal probability $1/n$. A coin flip decides between the primary and alias outcome. Example of a distribution with $n = 5$ outcomes given by the probabilities $(7/25, 6/25, 1/25, 6/25, 1/5)$.

Inversion method The inversion method relies on the cumulative distribution function (CDF) $F(x)$ associated with the distribution. Given a uniform random variate $U \sim \mathrm{Unif}(0, 1)$, one obtains a sample from the distribution by computing (see Figure 5 for an illustration):

$$S = F^{-1}(U)\,.$$

This construction works because the CDF transforms the probability space into the unit interval, and applying the inverse recovers the correct distribution of outcomes. The method is conceptually simple, but requires efficient computation of the inverse CDF, which is only analytically available for certain distributions (e.g., exponential, geometric). For more complex distributions, numerical approximation or interpolation of the inverse CDF may be used, at the expense of computational and energy cost.

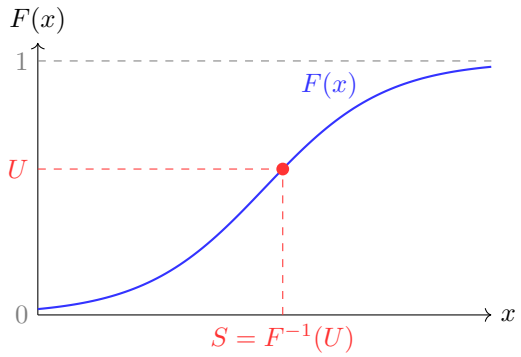

Figure 5: Illustration of the inversion method. A uniform variate $U \sim \mathrm{Unif}[0, 1]$ is drawn, then mapped through the inverse CDF F^{-1} to obtain a sample S that is distributed according to F.

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- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.