

LiveTune: Dynamic Parameter Tuning for Feedback-Driven Optimization

Soheil Zibakhsh Shabgahi, Nojan Sheybani, Aiden Tabrizi, Farinaz Koushanfar

University of California, San Diego, USA

{szibakhshshabgahi, nsheybani, atabrizi, fkoushanfar}@ucsd.edu

ABSTRACT

Feedback-driven optimization, such as traditional machine learning training, is a static process that lacks real-time adaptability of hyperparameters. Tuning solutions for optimization require trial and error paired with checkpointing and schedulers, in many cases feedback from the algorithm is overlooked. Adjusting hyperparameters during optimization usually requires the program to be restarted, wasting utilization and time, while placing unnecessary strain on memory and processors. We present *LiveTune*, a novel framework allowing real-time parameter adjustment of optimization loops through *LiveVariables*. Live Variables allow for continuous feedback-driven optimization by storing parameters on designated ports on the system, allowing them to be dynamically adjusted. Extensive evaluations of our framework on standard machine learning training pipelines show saving up to 60 seconds and 5.4 Kilojoules of energy per hyperparameter change. We also show the feasibility and value of *LiveTune* in a reinforcement learning application where the users change the dynamics of the reward structure while the agent is learning showing 5 \times improvement over the baseline. Finally, we outline a fully automated workflow to provide end-to-end, unsupervised feedback-driven optimization.

CCS CONCEPTS

- Computing methodologies → Machine learning algorithms;
- Hardware → Impact on the environment.

KEYWORDS

Dynamic ML Training, Reinforcement Learning, Hyperparameter Tuning, ML Algorithms, Green Computing

ACM Reference Format:

Soheil Zibakhsh Shabgahi, Nojan Sheybani, Aiden Tabrizi, Farinaz Koushanfar. 2024. LiveTune: Dynamic Parameter Tuning for Feedback-Driven Optimization. In ., 9 pages. <https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

Arxiv, May 2024,

© 2024 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM

<https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

1 INTRODUCTION

The decade has seen a surge in feedback-driven optimization, most notably in machine learning paradigms. The increasing need for computational power for fine-tuned optimization in complex systems is pressing, calling for optimized utilization of computing resources. As one of the most prominent methods of feedback-driven optimization, deep learning's rise is attributed to two primary factors: the availability of vast data sets, and advancements in hardware which enhance computational capabilities. This also applies to several other learning paradigms, such as reinforcement learning.

Recent AI trends involve complex networks with billions of parameters, requiring extended training periods, some of which last months [30][28]. Training the contemporary sophisticated networks demands a careful selection of hyperparameters. Hyperparameters, distinct from model parameters updated during training, are often static or follow predetermined trajectories. They include structural elements like layer counts and per-layer parameters, as well as algorithmic settings such as learning rate, momentum, regularizations, and batch size [30]. The choice of hyperparameters significantly impacts model performance and training speed. Hence, selecting the right hyperparameters requires expertise and deliberate planning before training begins [17]. In common practice, researchers do extensive tests on a smaller subset of the data to determine the neighborhood of the best-performing hyperparameters. Often, this selection involves a thorough exploration of the hyperparameter space.

Existing methods for hyperparameter tuning, such as grid search [22] and Bayesian optimization [7], are impractical for ML development and rapid testing. In the experimentation phase of machine learning workflows, manual tuning and testing of different combinations of hyperparameters based on feedback, like the loss curve, is key. Manual tuning is a resource-intensive process that involves setting checkpoints, and then loading and remaking those checkpoints after every variable change. This is a repetitive task and often takes multiple attempts before the neighborhood of the right hyperparameter is found, wasting not only time but also exhausting hardware resources on every restart. After the range of correct hyperparameter values is found, an exhaustive search is done to find the best-performing set of hyperparameters in the specific problem.

The repetitive overhead of prominent learning paradigms is further characterized by the intense and iterative optimization workflow of reinforcement learning (RL). RL requires users to directly incorporate immediate feedback into the training workflow to achieve an optimal policy. In most scenarios, this requires complex algorithms that automate the integration of gathered feedback, or the user is required to stop training and start again with adjusted hyperparameters. In current workflows, users are not able to dynamically adjust RL parameters based on the performance of an agent's current policy, which drastically raises the amount of time and resources needed to find an optimal policy.

In response to the current inefficient workflows for feedback-driven optimization, we propose LiveTune, a novel framework designed for real-time dynamic adjustment of hyperparameters during runtime. This approach introduces unprecedented flexibility in optimization workflows, offering a new paradigm in continuous tuning while incorporating feedback. The framework contributes to reductions in execution time and power consumption across a wide range of optimization paradigms.

The core of LiveTune is implemented through our novel “LiveVariables”. Each LiveVariable instance is initialized with a tag, an initial value, and a designated port on the host machine. Its internal value can be modified through this port. LiveVariables can replace normal variables in any code, such as those representing hyperparameters, allowing developers to update them and see the change immediately, without having to restart the process. Another component of LiveTune is the “LiveTriggers”. These are boolean flags that can be embedded in the program code or within loops. Leveraging LiveTune’s dynamic variable modification capability, LiveTriggers can activate or halt procedures based on developer commands, without needing to terminate the program. Upon activation, a LiveTrigger returns ‘True’ once before reverting to its default ‘False’ state.

Utilizing LiveTune has demonstrated a notable acceleration in optimization processes. This paper will detail the underlying mechanisms of LiveTune, its applications, and provide empirical evidence supporting its efficacy as a transformative tool in feedback-driven optimization.

In summary, our contributions are as follows:

- Introduction of LiveTune, an innovative end-to-end framework for feedback-driven optimization. It enables real-time, manual hyperparameter tuning in a manner that is energy-efficient and minimally disruptive to the optimization process.
- Versatile design of LiveTune so that it is applicable to any optimization pipeline regardless of objective or scale while inducing minimal overhead.

- Development of “LiveVariables” and “LiveTriggers”, allowing for dynamic variable updates and control over subprocesses without program termination.
- Devising an open source API for LiveTune¹ to facilitate automation and adaptation of the method in optimizing real-world systems.
- Extensive evaluations of LiveTune’s open-source API which demonstrates significant time and energy savings compared to conventional optimization in emerging learning paradigms.

2 PRELIMINARIES

2.1 Hyperparameter Tuning

Tuning hyperparameters has proven to be the most important task in ML training, as every model architecture and dataset has a unique set of hyperparameter configurations that enable optimal performance [2]. Rather than model parameters, which are learned during training, hyperparameters dictate the learning process and must be iteratively tuned to progressively enable better learning. Some fundamental hyperparameters include learning rate, regularization coefficients, number of epochs, and momentum.

Hyperparameter tuning involves systematically searching for an optimal combination of hyperparameters that results in the best performance of the model. A naive approach to this is a user performing a brute-force search across the entire hyperparameter space. Autonomous methods, such as grid search [22], allow users to specify a predefined range within the hyperparameter space that they believe will enable high performance. Random search algorithms [13] randomly sample the hyperparameter space and return the hyperparameters that showed the most promise. Search algorithms are often very resource-intensive and do not guarantee suitable results. More advanced methods, such as Bayesian optimization [7], use probabilistic models to predict how different hyperparameter configurations will perform. These methods are more efficient than search algorithms, however, they still may require fine-tuning by a user to achieve optimal results.

Even after sophisticated and resource-intensive algorithms are run to find suitable hyperparameter configurations, a human expert is often required to perform their own manual search to pinpoint the ideal hyperparameters for training. This takes a heavy toll on computing time and overhead, as training is in a constant cycle of starting to observe the effects of the hyperparameters and stopping if the hyperparameters are not suitable. LiveTune addresses this issue by allowing users to update hyperparameters without reloading the program instance. This enables a much more time and resource-efficient approach to training large ML models.

¹<https://github.com/soheilzi/LiveTune>

2.2 Reinforcement Learning

Reinforcement learning (RL) is a computational paradigm where a learner, called an agent, interacts with a dynamic environment to achieve certain goals by learning to make optimal decisions. The agent receives feedback in the form of rewards and modifies its strategy, termed as policy, to improve its performance over time.

In the RL context, the interaction between the agent and the environment is modeled as a Markov Decision Process (MDP). An MDP provides a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision maker. It is defined by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, r)$, where:

- \mathcal{S} represents the set of all possible states of the environment.
- \mathcal{A} denotes the set of all actions the agent can take.
- \mathcal{P} is the transition probability that determines the likelihood of moving from one state to another state given an action. Specifically, $\mathcal{P}(s'|s, a)$ is the probability of transitioning to state s' from state s after taking the action a .
- $r(s, a)$ is the reward function, which gives the immediate reward received after transitioning from state s to state s' due to action a .

The objective in RL is to learn a policy π , a mapping from states to actions, that maximizes the expected cumulative reward. The cumulative reward is often discounted by a factor $\gamma \in [0, 1]$, known as the discount factor, which represents the difference in importance between future rewards and immediate rewards. The expected return from a policy π , starting from state s , is given by:

$$J_\pi(s) = \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 = s \right]$$

where s_t and a_t denote the state and action at time t , respectively. S_0 is the initial state.

Deep reinforcement learning extends these concepts by using deep neural networks to approximate the policy π or the value functions associated with the states, which help in making decisions. This approach has been pivotal in solving complex decision-making tasks that require high-dimensional state and action spaces.

Tuning of hyperparameters such as the learning rate and the discount factor γ plays a critical role in the convergence and performance of RL algorithms. Prominent algorithms like Proximal Policy Optimization (PPO)[21], Double Deep Q-Network (DDQN)[15], and Advantage Actor-Critic (A2C)[14] have shown different sensitivities to these parameters. Recent advancements have demonstrated the efficacy of adapting these hyperparameters dynamically in response to ongoing learning progress, which can significantly enhance

learning efficiency and effectiveness in complex environments like the Hungry Thirsty Domain. LiveTune allows users to adjust hyperparameters and incorporate feedback to reduce the time to find an optimal policy without interrupting training. In section 5.2 we demonstrate the effectiveness of dynamic reward shaping and hyperparameter tuning to for teaching deep reinforcement learning agents.

2.3 Hungry Thirsty Domain

We assess our reinforcement learning strategies through reward shaping within the Hungry Thirsty domain [24]. This scenario involves a 4×4 grid, where obstacles block certain paths between adjacent blocks (see Fig ??). In randomly assigned corners of the grid, food and water are placed. Following Booth et al. [3], each episode is capped at 200 steps, using a modified environment to increase the challenge.

The agent possesses a simple set of actions: moving in cardinal directions, eating, or drinking. Its primary objectives are to avoid hunger by consuming food and managing thirst, which is compulsory for eating. The agent is classified as not hungry if it has consumed food in the preceding step and can only consume food if not thirsty. To quench its thirst, the agent must be situated on a water tile. Post-drinking, the agent faces a 10% chance of becoming thirsty again in every consequent step, necessitating a return to water. The agent's state at any time includes its grid location and boolean indicators for hunger H and thirst T .

Performance is evaluated by measuring the agent's fitness, defined as the number of steps spent not hungry, calculated as $F(\tau) = \sum_{t=1}^{200} \mathbb{I}(-H)$. The agent's optimal policy π directs it towards water when thirsty and towards food otherwise.

The reward function structure is designed to encourage the agent to manage its states effectively:

$$\begin{aligned} r(H \wedge T) &= R_4, & r(H \wedge \neg T) &= R_2, \\ r(\neg H \wedge T) &= R_3, & r(\neg H \wedge \neg T) &= R_1. \end{aligned}$$

Participants in our experiments adjust these rewards (R_1, R_2, R_3, R_4) within the range of $[-1, 1]$. The challenge is to create a reward scheme that accurately reflects the objective of minimizing hunger, a nontrivial task in reinforcement learning. Booth et al. demonstrate that suboptimal reward structures often result from incorrect assumptions about the spatial relationship between food and water.

Section 5.2 discusses how experiment participants utilize a heatmap of the most frequent states by the agent (see Fig 5) to dynamically adjust rewards to optimize fitness. LiveTune enables continuous, real-time monitoring and adjustment of parameters in training environments such as the Hungry Thirsty domain. This system allows for immediate and ongoing optimizations without the need to pause or restart the

training process, thereby enhancing learning efficiency and adaptiveness.

2.4 Green Computing

Green computing entails the eco-conscious utilization of computing resources, aiming to maximize energy efficiency while minimizing environmental impact [29]. This is crucial in AI where, for instance, training a natural language processing model can emit approximately 78,000 pounds of CO₂—more than double the annual carbon footprint of an individual in the US [26].

A primary strategy in green computing involves developing processor architectures that enhance performance per watt [32]. Such advancements ensure that CPUs and GPUs perform more efficiently, reducing both energy consumption and CO₂ emissions. Concurrently, optimizing software algorithms, particularly in deep neural network (DNN) training, can also yield significant efficiencies. By refining these algorithms to converge more rapidly and obviate the need for frequent restarts during training, programs like LiveTune further reduce energy use and resource waste, thereby shortening the lifecycle of model training.

These approaches collectively strive to sustain technological advancement without the accompanying environmental cost, aligning with the broader objectives of green computing to mitigate the ecological footprint of modern computing technologies.

3 RELATED WORK

Attempts at improving feedback-driven optimization workflows have been most prominent in the area of machine learning. Alongside this, improving reinforcement learning workflows has been recently proposed to allow for easier and faster training procedures. There are several approaches towards increasing efficiency in optimization workflows for these learning paradigms, each targeting different operations within learning workflows to achieve a singular goal: reducing training time. This section reviews key developments in this domain, highlighting their contributions and limitations. We examine the traditional approaches in auto hyperparameter tuning, the use of schedulers for adaptive parameter control, and checkpointing strategies for training robustness. Alongside this, we highlight seminal open problems brought forth in previous works regarding automating RL workflows. These methods, while instrumental in advancing learning workflows, also reveal the need for more dynamic and less resource-intensive solutions.

Auto Hyperparameter Tuning. Approaches to automate hyperparameter tuning include grid and randomized grid search. These methods can be expedited through prior knowledge or theoretical constraints [25]. AdaNS, an adaptive

genetic-based algorithm introduced by Javaherip et al., exemplifies this approach [6].

Schedulers. Certain hyperparameters, notably the learning rate, often need adjustment during training. For instance, Stochastic Gradient Descent (SGD) benefits from decaying learning rate schedules [19] [31] [5]. The Adam optimizer [8], though adaptively modifying the learning rate based on first and second-moment estimates, is commonly paired with a learning rate scheduler.

Checkpointing. Checkpointing is a standard practice in machine learning to safeguard against progress loss due to unexpected performance issues. This approach involves regularly saving model updates. Typically, human experts monitor the training process to determine the optimal time for restarting the model with updated hyperparameters, using a previously saved checkpoint. Recent years have seen a growing interest in researching checkpointing strategies. One of the early contributions in this area was by Vinay et al., who explored the use of MPI (Message Passing Interface) in creating fault-tolerant deep learning (DL) applications, with a focus on checkpoint-restart mechanisms [1]. Another significant study by Rojas et al. examined checkpointing in deep neural networks on a large scale. They highlighted a notable overhead issue, identifying significant idle time for GPUs during the checkpointing process [18].

Automating RL. AutoRL is an emerging field of research that aims to enable more efficient optimization workflows for RL [16]. This work highlights open problems that exist in this space, emphasizing that classical automated hyperparameter tuning in RL is extremely challenging due to the huge hyperparameter search space. The authors list this as an open problem that has not yet been solved.

LiveTune brings forth a new paradigm to the field of feedback-driven optimization, especially in ML and RL environments. LiveTune eliminates the need for expensive restarts by providing a framework allowing the change of parameters from outside the running algorithm. Alongside this, LiveTune can even be used at a higher level to allow a developer to continuously test parameters in learning settings and manually shrink the hyperparameter search space based on feedback, thus lowering the computational complexity of automating optimization for learning tasks.

4 METHODOLOGY

4.1 The LiveTune Framework

This section details the LiveTune framework, focusing on its innovative approach to enabling continuous training through the use of LiveVariables.

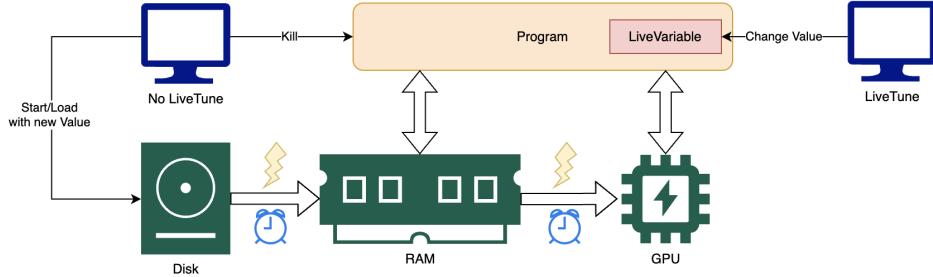


Figure 1: Variable change procedure for LiveTune and conventional method.

LiveVariables: LiveVariables are a specialized class of variables designed for dynamic adjustments during runtime without restarting the training process. Upon creation, each LiveVariable allocates a port on the host machine, replacing static variables, such as learning rates, with a dynamic counterpart. These variables are managed by initiating a dedicated listener thread per instance, which monitors and updates the variable’s value safely using TCP and semaphore mechanisms. The internal state of a LiveVariable is composed of the current value, a unique tag, and the assigned port, which can be queried through its instance.

Value Modification: Modification of a LiveVariable’s value during runtime is performed by sending a new value to its listener port via TCP. This is managed safely with semaphores to prevent conflicts. The `is_changed()` method is crucial for determining if updates to the variable are necessary, facilitating efficient continuous training.

Dictionary Thread: The management of multiple LiveVariable ports is streamlined through a dictionary thread. Employing the singleton pattern [4], this thread maintains a unique instance that logs each LiveVariable’s tag and port, ensuring system-wide consistency. Communication with this central dictionary is essential for coordinating updates and maintaining system integrity.

Tuning Interface: The user interface of the LiveTune system, referred to as the “tune” program, simplifies the process of variable adjustment. It requires the dictionary port, a tag, and a new value for the operation, establishing a secure communication link with the dictionary thread to verify and update values as depicted in Figure 2. This process ensures that adjustments are applied correctly without type mismatches or disruptions to the main program.

By integrating these components, the LiveTune framework supports real-time hyperparameter tuning, significantly enhancing the flexibility and efficiency of machine learning training processes.

4.2 The LiveTune Workflow

LiveTune is a versatile framework designed to accommodate a variety of workflows across different domains. It does not prescribe a specific workflow but instead provides tools that enhance interaction with program variables dynamically through Live Variables. By design, Live Variables are engineered to return their most recent values upon being called, making them ideally suited for use within repetitive loop structures.

In typical use cases, each iteration within a loop provides feedback to the user in the form of log files, output data, or visual plots. An example of this feedback mechanism in action is detailed in Section 5.2. Based on this feedback, users can make informed decisions about necessary adjustments to the program’s variables. Through the provided API, these changes can be implemented instantly, affecting the subsequent iteration. For instance, in a supervised learning scenario, the learning rate could be set as a Live Variable. As the training progresses, the program outputs the current training and test losses at each iteration. Analyzing these loss curves enables the expert to adjust the learning rate dynamically, optimizing the training process in real time.

This capability is particularly valuable during initial experimentation phases when the optimal settings of hyperparameters are unknown, and rapid iteration is necessary to approximate the best parameters. Once a suitable range of hyperparameter values is identified, it is advisable to transition to more traditional optimization methods, such as grid search or checkpointing, to fine-tune the values and achieve the best performance.

4.3 Continuous Training

Compatibility with Training Loops. LiveTune can be integrated with established ML and RL frameworks such as PyTorch and TensorFlow seamlessly. These frameworks typically manage data processing through a loop that iterates over datasets in epochs. LiveTune facilitates this by enabling checks and resets of the optimizer and other hyperparameters, like batch size, at the start of each epoch. An

example of this integration strategy is illustrated in Algorithm 1, showing how LiveTune enhances typical training procedures without disrupting existing workflows.

Efficient Hyperparameter Adjustment. To minimize unnecessary computational overhead during training, LiveTune employs the `is_changed()` method for each `LiveVariable`. This method efficiently assesses whether adjustments to hyperparameters are required, optimizing resource utilization and system performance. Our experimental results indicate that, while the impact on performance varies, the optimizer resets generally introduce negligible overhead.

In conventional machine learning workflows, any adjustment to a hyperparameter necessitates halting the current program instance and loading a new instance with the updated settings from disk—a process that significantly wastes computational resources [18]. In contrast, LiveTune implements hyperparameter updates directly within the existing program instance, eliminating the need for reloads and thereby reducing the overhead associated with such changes. This method not only saves on computational resources but also reduces the time spent in non-productive setups.

Figure 1 contrasts the workflow of traditional hyperparameter adjustment with that of LiveTune, highlighting the efficiency improvements by eliminating the need for program restarts and reducing the operational overhead associated with typical hyperparameter adjustments.

ALGORITHM 1: Continuous Training Loop with Dynamic Learning Rate Adjustment

```

while True do
    train(model, dataloader, optimizer)
    if LR.is_changed() then
        | optimizer ← Optimizer(LR())
    end
end

```

5 EXPERIMENTAL EVALUATION

In this section, we evaluate our method on both usability and energy consumption. Initially, we explore the energy and time required for restarting a program. We show the effect of model and dataset size in the resources required for a typical machine learning algorithms setup procedure. Subsequently, we conduct two in-depth user studies on LiveTune’s efficiency: 1) two groups compete to train a neural network given limited resources and 2) individual users aim to train an optimal policy in a reinforcement learning task.

5.1 Energy and Time Consumption

Setup. Our experiments use a well-known image classification algorithm in the PyTorch framework [12]. We examine

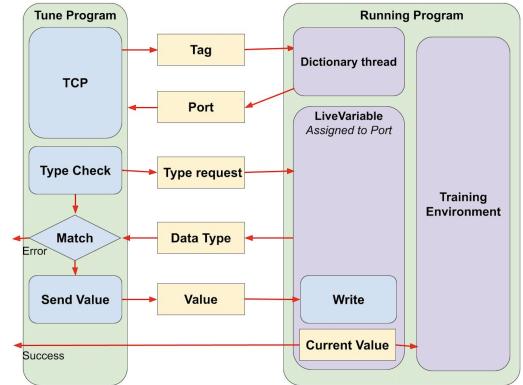


Figure 2: LiveTune variable change procedure.

the impact of model size by employing various versions of the VGG architecture [23]. Three datasets are used: ImageNet-1k [20], TinyImageNet [11], and CIFAR100 [10]. These are popular choices for image classification tasks.

- ImageNet contains large 224x224 pixel images.
- TinyImageNet has medium-sized 64x64 pixel images.
- CIFAR100 includes small 32x32 pixel images.
- Each dataset’s size affects how long it takes to load it into the program.

We conducted our tests on a powerful computer setup. This includes a single Nvidia A6000 GPU and an AMD Ryzen Threadripper 3990X 64-Core Processor. The memory operates at a speed of 3200 megatransfers per second. We track the execution time of each part of the algorithm, reporting the warmup time when the model starts iterating through batches with a stable flow. To ensure reliability, we repeated each experiment six times and calculated the average results. **Discussion.** Figures 3 and 4 show the average GPU power consumption and loading time, respectively. These figures reveal a consistent pattern: larger datasets and models tend to take longer to load and consume more power. We divide the basic classification algorithm into four main stages:

- (1) Python and Library Loading: Starting a Python program requires loading the Python interpreter into memory, which takes time.
- (2) Setting Up the Model: This involves defining the model, the data loader, and the optimizer.
- (3) Loading Model Parameters and Data: This step reads the model parameters and data batch from the disk.
- (4) Moving to the Hardware Accelerator: The most demanding stage in terms of time and energy. Here, we transfer the code, data, and parameters to the GPU.

In our tests, setting up the GPU and transferring data consumed up to 50 seconds and used about 5.4 kJ of energy.

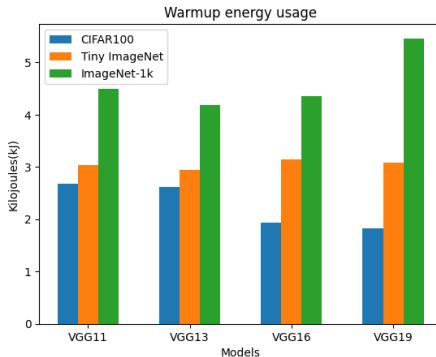


Figure 3: GPU energy consumption of each warmup of our algorithm on different model sizes.

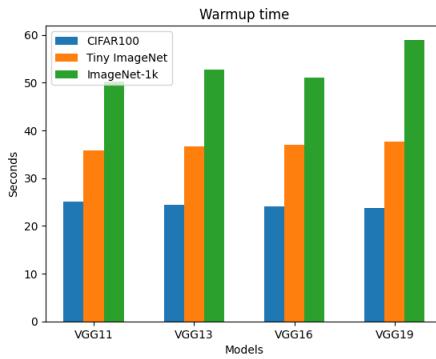


Figure 4: Warmup time of our base algorithm on different model sizes.

5.2 Reward Shaping Using LiveTune

Sutton and Barto [27] emphasize that the reward signal should directly reflect the task goals rather than the methods to achieve them. This principle underlines that a reward function must encode the actual performance metrics of the task. Sparse rewards, which are challenging to learn from, are thus infrequently utilized as highlighted by Knox *et al.* [9]. The complexity of selecting an appropriate reward function is well-documented by Booth *et al.* [3] through their experiments in the Hungry Thirsty Domain [24]. They gathered 30 experts from top-tier US universities who either actively use reinforcement learning (RL) in their research or have substantial academic exposure to it. For participant details, refer to Appendix A in [3]. In their experiments, these experts spent an hour developing optimal reward functions and choosing between algorithms like DDQN [15], PPO [21], and A2C [14], along with setting parameters such as gamma, learning rate, and exploration strategies.

Setup. Our experimental setup mirrored that of Booth *et al.* [3], involving 7 participants with diverse backgrounds,

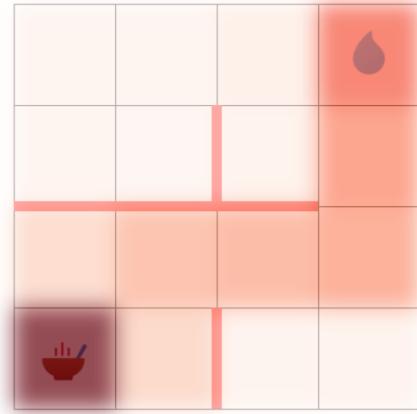


Figure 5: Live heatmap of agent's position on the map. Experts make judgments on how to tune the parameters based on visual feedback.

three of whom met the original study's expertise criteria. The remaining participants, less familiar with RL, received a preliminary tutorial. Utilizing the same algorithms and parameters as the original study, participants aimed to train the most effective RL agent, incorporating LiveTune for dynamic adjustment of reward functions and algorithm parameters. When running the experiment LiveTune generates a web user interface for users to interact with the program. As the baseline users have access to a live plot of the fitness of their agent and a heat map of how the agent is moving inside the gridworld, shown in figures 5 and 6. Using feedback from the algorithm, the users can change the reward function structure and hyperparameters of the algorithm. All users are evaluated on the time it takes them to teach the agent and the final score they achieved.

Discussion. We utilized the anonymized dataset from Booth *et al.* for evaluating LiveTune, comparing it against the traditional method used by [3]. Although our participants did not share the same reinforcement learning background as those in the baseline study, the fitness score for agents they trained averaged 86.51. This contrasts with a baseline average of 5.08 using the same DDQN algorithm. Our participants reached their final submissions in an average of 35 minutes, compared to the one hour allowed in [3]. In conclusion, the outcomes of this study illustrate the efficacy of LiveTune in enhancing the performance of reinforcement learning tasks even when participants lack specialized training in this domain. This improvement in agent fitness scores under constrained time conditions, compared to traditional methods, underscores the potential of LiveTune to facilitate more efficient and effective learning processes.

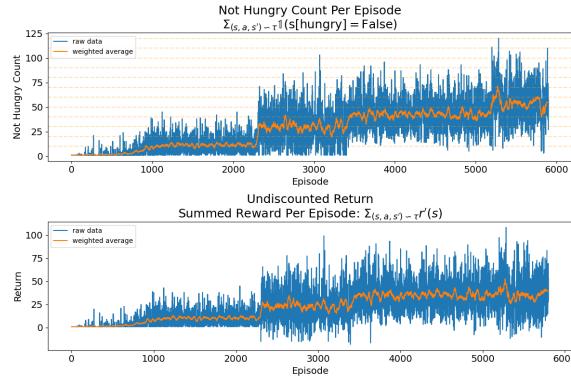


Figure 6: Live plot of the agent’s fitness and discounted reward based on the reward function. The jumps observed in the discounted rewards correspond to a LiveTune-enabled change to the reward function structure by the user.

5.3 In-Person Competition

Setup. In our investigation of LiveTune’s applicability for real-time hyperparameter tuning, we organized an in-person competition designed specifically for ML model developers. Eighteen graduate students of varied ML backgrounds participated, grouped into control and experiment groups based on random assignment. Participants faced the challenge of training a deep neural network (DNN) on a subset of the Fashion-MNIST dataset, under constraints that obscured the real hyperparameters by mapping them to four adjustable, but non-linearly correlated, variables. The hyperparameters are learning rate, weight decay, momentum, and dropout rate. The control group managed hyperparameter tuning via a traditional command line interface, necessitating program restarts for each change. Conversely, the experiment group used the LiveTune framework, facilitating dynamic adjustments through a web interface without needing restarts.

Each participant’s machine environment was standardized using Docker, limiting each to 2 processors and 8GB of RAM, thereby negating hardware performance variances. The competition setup also included a Tensorboard interface for immediate feedback on training modifications, emphasizing how changes in hyperparameters impacted model loss and accuracy. The participants were given 1.5 hours to complete their training.

Results and Discussion. The outcome of the competition provided insightful data on LiveTune’s efficiency. The experiment group, using LiveTune, achieved an average test accuracy of 85% by running 135 epochs over the 1.5-hour session. In contrast, the control group reached an 83% accuracy with 103 epochs. Notably, LiveTune users conducted on average 33 additional epochs, highlighting the time saved

that would otherwise be spent on program restarts and hyperparameter reconfiguration. This efficiency is critical as it suggests a significant reduction in the non-productive overhead associated with traditional hyperparameter tuning.

Furthermore, the experiment underscores LiveTune’s potential to facilitate more environmentally sustainable ML practices by lessening computational waste through efficient resource use. Our findings advocate for broader adoption of LiveTune in diverse ML training scenarios, potentially revolutionizing hyperparameter tuning practices by significantly curtailing the ecological footprint of ML projects.

6 CONCLUSION

In conclusion, LiveTune introduces a significant advancement in feedback-driven optimization, particularly in the context of machine learning training and online reward design. This framework allows for real-time dynamic adjustment of parameters, offering a novel approach that enhances machine learning workflows by notably improving efficiency and reducing both time and computational resource consumption. Through the implementation of "LiveVariables" and "LiveTriggers," LiveTune provides flexible, on-the-fly tuning capabilities without the need for restarting training processes. Our evaluations demonstrate considerable savings, reducing time and energy usage by up to 60 seconds and 5.4 Kilojoules per hyperparameter adjustment, respectively. Furthermore, the application of LiveTune in reward shaping within reinforcement learning workflows has demonstrated a transformative impact, achieving up to a 5 \times improvement in efficiency over traditional methods. This enhancement is particularly crucial in domains such as robotics and human-computer interaction, where adaptive learning and quick responsiveness to environmental feedback are essential. By enabling more dynamic and responsive tuning of reinforcement models, LiveTune not only optimizes learning outcomes but also significantly accelerates the development of more intuitive and interactive robotic systems and HCI interfaces. These advancements promise to drive forward the capabilities of autonomous systems and improve the synergy between humans and technology, underscoring the broad and versatile applicability of LiveTune in cutting-edge technology sectors. While this work focuses primarily on prominent learning paradigms, LiveTune can serve as a very valuable tool for any continuous feedback-driven optimization workflow. In future work, we aim to explore the integration of LiveTune into broader types of computational workflows and further optimization of its core components to support an even wider range of applications, such as CAD optimization, and machine learning paradigms.

REFERENCES

- [1] Vinay Amatya, Abhinav Vishnu, Charles Siegel, and Jeff Daily. 2017. What does fault tolerant deep learning need from mpi?. In *Proceedings of the 24th European MPI Users' Group Meeting*. 1–11.
- [2] Rémi Bardenet, Mátyás Brendel, Balázs Kégl, and Michele Sebag. 2013. Collaborative hyperparameter tuning. In *International conference on machine learning*. PMLR, 199–207.
- [3] Serena Booth, W Bradley Knox, Julie Shah, Scott Niekum, Peter Stone, and Alessandro Allievi. 2023. The perils of trial-and-error reward design: misdesign through overfitting and invalid task specifications. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 5920–5929.
- [4] Erich Gamma, Richard Helm, Ralph Johnson, and John Vlissides. 1993. Design patterns: Abstraction and reuse of object-oriented design. In *ECCOP'93—Object-Oriented Programming: 7th European Conference Kaiserslautern, Germany, July 26–30, 1993 Proceedings* 7. Springer, 406–431.
- [5] Bo Yang Hsueh, Wei Li, and I-Chen Wu. 2018. Stochastic gradient descent with hyperbolic-tangent decay. *Corr abs/1806.01593* (2018).
- [6] Mojtaba Javaheripi, Mohammad Samraghi, Tara Javidi, and Farinaz Koushanfar. 2020. AdaNS: Adaptive non-uniform sampling for automated design of compact DNNs. *IEEE Journal of Selected Topics in Signal Processing* 14, 4 (2020), 750–764.
- [7] Tinu Theckell Joy, Santu Rana, Sunil Gupta, and Svetha Venkatesh. 2016. Hyperparameter tuning for big data using Bayesian optimisation. In *2016 23rd International Conference on Pattern Recognition (ICPR)*. IEEE, 2574–2579.
- [8] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).
- [9] W Bradley Knox, Alessandro Allievi, Holger Banzhaf, Felix Schmitt, and Peter Stone. 2023. Reward (mis) design for autonomous driving. *Artificial Intelligence* 316 (2023), 103829.
- [10] Alex Krizhevsky, Geoffrey Hinton, et al. 2009. Learning multiple layers of features from tiny images. (2009).
- [11] Ya Le and Xuan Yang. 2015. Tiny imagenet visual recognition challenge. *CS 231N* 7, 7 (2015), 3.
- [12] TorchVision maintainers and contributors. 2016. *TorchVision: PyTorch's Computer Vision library*.
- [13] Rafael G Mantovani, André LD Rossi, Joaquin Vanschoren, Berndt Bischl, and André CPLF De Carvalho. 2015. Effectiveness of random search in SVM hyper-parameter tuning. In *2015 international joint conference on neural networks (IJCNN)*. Ieee, 1–8.
- [14] Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous methods for deep reinforcement learning. In *International conference on machine learning*. PMLR, 1928–1937.
- [15] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. 2015. Human-level control through deep reinforcement learning. *nature* 518, 7540 (2015), 529–533.
- [16] Jack Parker-Holder, Raghu Rajan, Xingyou Song, André Biedenkapp, Yingjie Miao, Theresa Eimer, Baohe Zhang, Vu Nguyen, Roberto Calandra, Aleksandra Faust, et al. 2022. Automated reinforcement learning (autorl): A survey and open problems. *Journal of Artificial Intelligence Research* 74 (2022), 517–568.
- [17] Jesus Rodriguez. 2018. Understanding hyperparameters optimization in deep learning models: concepts and tools. *LinkedIn Pulse* (2018).
- [18] Elvis Rojas, Albert Njoroge Kahira, Esteban Meneses, Leonardo Bautista Gomez, and Rosa M Badia. 2020. A study of checkpointing in large scale training of deep neural networks. *arXiv preprint arXiv:2012.00825* (2020).
- [19] Sebastian Ruder. 2016. An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747* (2016).
- [20] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. 2015. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)* 115, 3 (2015), 211–252. <https://doi.org/10.1007/s11263-015-0816-y>
- [21] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347* (2017).
- [22] BH Shekar and Guesh Dagnew. 2019. Grid search-based hyperparameter tuning and classification of microarray cancer data. In *2019 second international conference on advanced computational and communication paradigms (ICACCP)*. IEEE, 1–8.
- [23] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).
- [24] Satinder Singh, Richard L Lewis, and Andrew G Barto. 2009. Where do rewards come from. In *Proceedings of the annual conference of the cognitive science society*. Cognitive Science Society, 2601–2606.
- [25] Leslie N Smith. 2018. A disciplined approach to neural network hyperparameters: Part 1—learning rate, batch size, momentum, and weight decay. *arXiv preprint arXiv:1803.09820* (2018).
- [26] Emma Strubell, Ananya Ganesh, and Andrew McCallum. 2019. Energy and policy considerations for deep learning in NLP. *arXiv preprint arXiv:1906.02243* (2019).
- [27] Richard S Sutton and Andrew G Barto. 2018. *Reinforcement learning: An introduction*. MIT press.
- [28] Mingxing Tan and Quoc Le. 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*. PMLR, 6105–6114.
- [29] David Wang. 2008. Meeting green computing challenges. In *2008 10th Electronics Packaging Technology Conference*. IEEE, 121–126.
- [30] Tong Yu and Hong Zhu. 2020. Hyper-parameter optimization: A review of algorithms and applications. *arXiv preprint arXiv:2003.05689* (2020).
- [31] Tao Zhang and Wei Li. 2020. kDecay: Just adding k-decay items on Learning-Rate Schedule to improve Neural Networks. *arXiv preprint arXiv:2004.05909* (2020).
- [32] Benjamin Zhong, Ming Feng, and Chung-Horng Lung. 2010. A green computing based architecture comparison and analysis. In *2010 IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Physical and Social Computing*. IEEE, 386–391.