

Cloud abstractions for AI workloads

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Abstract

AI workloads, often hosted in multi-tenant cloud environments, require vast computational resources but suffer inefficiencies due to limited tenant-provider coordination. Tenants lack infrastructure insights, while providers lack workload details to optimize tasks like partitioning, scheduling, and fault tolerance. We propose HARMONAlZE to redefine cloud abstractions, enabling cooperative optimization for improved performance, efficiency, resiliency, and sustainability. We outline key opportunities and challenges this vision faces.

CCS Concepts

- Computer systems organization → Cloud computing

Keywords

Cross-layer optimization, Tenant-provider cooperation, AI workloads

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1 Introduction

Modern AI workloads are widely compute-intensive, driven by the growing adoption of generative AI (GenAI), agentic applications, and large language models (LLMs). These workloads require large clusters of specialized hardware accelerators, such as GPUs and TPUs, to efficiently train, fine-tune

or serve models that contain billions or even trillions of parameters. Training and serving state-of-the-art AI models consumes substantial amounts of power, contributing to carbon emissions and raising sustainability challenges [54, 55]. Optimizing the efficiency of AI workloads is essential to mitigate their environmental impact. As these workloads scale to meet growing demands, their computational requirements outpace traditional hardware capabilities, necessitating not only energy-efficient algorithms [12, 60] but also innovative infrastructure designs that maximize resource utilization.

To maximize returns on costly hardware accelerators (e.g., GPUs costing tens of thousands of dollars), AI workloads are increasingly hosted in multi-tenant cloud environments. These environments enable resource sharing, offering tenants scalability, flexibility, and cost-efficiency while minimizing idle hardware and maximizing infrastructure utilization.

However, tenants operating in these environments face a fundamental challenge: they lack visibility into the infrastructure details (such as network topology, job placement, resource availability, etc.) that could be used to optimize their workloads. Providers often withhold such information to maintain commercial competitiveness or to preserve the flexibility to make changes to their infrastructure. This lack of awareness creates a barrier to fine-grained optimizations that could benefit both tenants and providers.

Providers are ideally placed to optimize infrastructure-level tasks critical to AI workloads, such as collectives, job scheduling and scaling, and fault tolerance [15, 23, 30, 56]. Yet, without insights into tenant workloads – such as communication patterns [32, 62] or hyperparameter adaptations [37, 43] – providers cannot optimize these tasks effectively.

The root cause of these inefficiencies lies in the lack of abstractions enabling cooperative optimization between tenants and providers (§ 2), a challenge shared across AI and other cloud applications [5, 10, 26]. Such abstractions would need to provide semantic information necessary for cross-layer control, allowing tenants and providers to jointly optimize performance, efficiency, availability and resilience, achieving outcomes that neither could accomplish alone.



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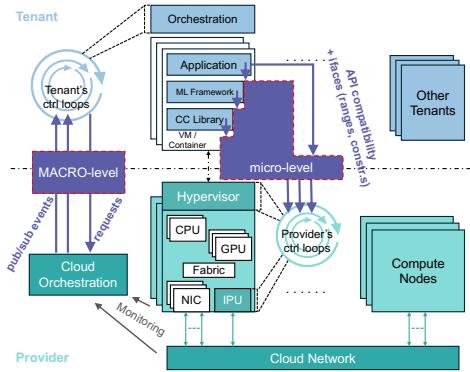


Figure 1: Architecture of HARMONAIIZE and overview of interactions between tenant and provider to realize cross-layer optimization opportunities via micro- and MACRO-level cloud abstractions. Dashed call-outs indicate potential realization loci (e.g., at IPUs [27]) of optimized control loops.

To address this gap, we propose widening traditional cloud abstractions to enable tenant-provider collaboration. Specifically, these abstractions expand cloud interface boundaries to provide tenants with additional information typically unavailable to them and enable providers to optimize workloads more effectively. Fig. 1 outlines the architecture of our proposal, HARMONAIIZE, and illustrates interactions between tenants and providers to enable cross-layer optimization opportunities (§ 4) via *micro-* and *macro*-level abstractions (§ 3). Compared to the status quo, HARMONAIIZE introduces two key innovations: (1) tenants' control loops are informed by infrastructure-level insights (e.g., a shift in network load), and (2) providers' control loops are guided by workload-specific requirements (e.g., required communication patterns), integrating optimizations that tenants could only achieve with perfect infrastructure visibility in an ideal scenario.

Recent work has introduced ad hoc approaches for optimizing AI workloads in specific cases [15, 37, 56]. In contrast, HARMONAIIZE advocates a general framework for cooperative optimization. Workload Intelligence (WI) [26] proposes dynamic, bi-directional communication for generic cloud cooperation. While HARMONAIIZE shares some goals with WI, it departs from preserving traditional VM abstractions and VM-oriented mechanisms. Instead, it elevates its abstractions closer to the workload and refactors functionality to leverage unique workloads characteristics, such as their accelerator-driven, iterative nature, performance predictability, proximity to the network, and tight synchronization.

This paper aims to spark discussion in the systems research community on rethinking cloud abstractions tailored to AI workloads and their potential benefits. We highlight cross-layer optimization opportunities these abstractions

could unlock. We also explore the challenges and trade-offs, such as standardization, privacy, and collaboration incentives, and propose a research agenda to bridge the tenant-provider gap, fostering efficient, sustainable, and scalable AI workloads in cloud environments.

2 Today’s Cloud Fails AI Workloads

Tenants today can choose from a range of cloud-based options to run AI workloads, including managed Machine Learning as a Service (MLaaS) platforms, Infrastructure as a Service (IaaS), or hybrid configurations. Each model presents trade-offs between abstraction and control, and current systems fall short in enabling effective cross-layer optimization.

MLaaS platforms (e.g., Google Vertex AI [17], AWS SageMaker [3]) offer convenient interfaces for launching and scaling training jobs. However, they provide little to no insight into low-level resource behavior or cluster conditions. For example, systems like Google’s Reduction Server [18] optimize communication, but tenants cannot influence or adapt those strategies at runtime. Furthermore, AutoML features limit control over model architecture and hyperparameters, while proprietary APIs restrict portability across clouds.

IaaS-based deployments, in contrast, grant tenants full control over infrastructure via virtual machines, Kubernetes clusters, and direct access to GPUs or TPUs. However, this control comes at the cost of responsibility. Tenants must manually manage aspects such as job placement, communication library selection, and failure recovery—tasks that are both complex and decoupled from provider-level information.

These limitations lead to three pervasive problems:

- **Jobs are static when they should be adaptive:** Most training jobs are configured statically, with fixed resource allocations and learning settings. This leads to inefficiencies when network conditions, cluster load, or hardware performance fluctuates mid-run. For instance, systems like KungFu [37] and Parcae [15] show that adapting batch sizes or optimizer settings dynamically can improve convergence and throughput. Today, such adaptations require extensive custom infrastructure.
- **Tenants and providers operate in the dark:** Tenants choose resources blindly, without visibility into current cluster utilization or topology. Communication libraries like NCCL [40] select algorithms (e.g., ring or tree) at initialization, based on assumptions that may no longer hold as the job progresses. Providers, on the other hand, lack hooks to influence job behavior in response to failures or congestion. This gap prevents runtime adaptation or efficient network-aware execution [8, 36, 56].
- **Resource allocation is clumsy and manual:** Cluster schedulers assign resources based on static tenant requests, even though ideal allocations vary over time. Advanced

scheduling systems like Pollux [43] and Gandiva [9] demonstrate the benefits of adaptive scaling, but require full control over both workload and infrastructure. Public clouds cannot offer this level of control without proper abstractions.

3 Coordinating AI Workloads with HARMONAIIZE

The lack of abstractions to enable cooperative optimization between tenants and providers significantly hinders the efficient execution of AI workloads in cloud environments. To address this challenge, we propose HARMONAIIZE, a set of abstractions designed to foster cooperative optimization between tenants and providers.

Broadly, AI workloads can be understood through two distinct timescales of control: *micro* and *macro*. This distinction highlights the varying nature of optimizations at each level and helps clarify the roles of tenants and providers in executing control loops and sharing information (c.f. Fig. 1). **Micro-level control:** The micro level focuses on fine-grained control of operations within a tenant’s workload. These operations typically occur within a single training iteration or an inference request. While workloads at this level exhibit predictable patterns across repeated cycles, their performance can still be influenced by the infrastructure and its dynamics.

Tenants have visibility into key workload-specific aspects such as communication patterns, task priorities, and fine-grained performance-cost trade-offs. However, the timeliness of control loops at the micro level is critical, as adaptation decisions require up-to-date infrastructure-level information. Consequently, we propose that providers should execute the control loop at the micro level, leveraging requirements specified by tenants. With their detailed knowledge of the underlying infrastructure, providers can make decisions such as selecting optimal communication algorithms, adjusting batch sizes or compression ratios to meet latency targets, or determining the best points for checkpointing the model.

Macro-level control: The macro level focuses on workload adaptation over coarser timescales, such as training epochs, multiple request batches, or in response to major trigger events (e.g., failures or resource availability changes). Examples of macro-level optimizations include scaling the number of workers, modifying parallelization strategies, or adjusting hyperparameters to improve training or inference efficiency.

These strategic optimizations require a broader view of workload objectives and system resources. Tenants are best positioned to execute control loops at the macro level, as they have detailed insights into workload requirements, such as expected training duration or desired accuracy targets. To enable effective macro-level decisions, providers should supply infrastructure-level updates, such as resource availability

| Opt. | Example benefits | Cross-layer approach | Scope |
|------|---|---|------------|
| O1 | ↓ 20% costs [37] | Joint hyperparameter tuning and resource allocation | Train |
| O2 | ↑ 2.4× comm. perf. [56] | Algorithm selection, collectives-as-a-service | Train, Inf |
| O3 | ↓ JCT by 37-50% [43] | Resource allocation | Train |
| O4 | ↑ 3.5× speedup [62] | Constraint-guided partitioning | Train, Inf |
| O5 | ↑ 1.9× efficiency [23] | Managed checkpointing | Train |
| O6 | ↑ 22.61× up time between failures [59] | Joint collection of observability data | Train |
| O7 | ↓ 53% energy, 38% operational carbon emissions [47] | Joint device-workload tuning | Train, Inf |

Table 1: Benefits of optimizations in literature and potential cross-layer approaches (§ 4), with primary workload scope.

changes or failure information. Importantly, these updates may be provided in aggregate or coarse-grained forms to safeguard sensitive infrastructure details.

By distinguishing between micro- and macro-level control and assigning responsibility accordingly, HARMONAIIZE enables a balanced approach to cross-layer optimization. Providers can leverage their expertise for real-time, fine-grained adaptations, while tenants retain control over strategic, workload-level decisions, creating a cooperative framework for optimizing AI workloads in multi-tenant cloud environments.

Given this high-level structuring of HARMONAIIZE, the next critical questions to address are: (1) what abstractions are necessary to enable these cooperative control loops, and (2) how can they be realized in practice while minimizing adoption overhead? We now present preliminary approaches to tackle these challenges.

3.1 Redefined cloud abstractions

We outline key principles and requirements these abstractions must satisfy. Following the division into micro- and macro-level control, we structure the design considerations for these abstractions accordingly.

Micro-level abstractions: Micro-level abstractions should prioritize well-defined APIs that align with existing AI workloads, enabling HARMONAIIZE to be adopted as a drop-in module with minimal code changes. These abstractions must support API compatibility while introducing additional interfaces for tenants to specify requirements and preferences (buy-in). Typically, these interfaces would allow tenants to define ranges or constraints to guide the provider’s decisions.

For instance, consider collective communication, where tenants often rely on popular libraries like NCCL. These libraries, however, lack adaptability and network awareness, which can result in suboptimal algorithm selection and degraded performance [56]. An abstraction for collective communication in HARMONAIIZE could offer a compatible API

that tenants already use while delegating underlying decisions – such as algorithm selection – and data path operations to providers. Providers, in turn, could leverage real-time network conditions to optimize performance dynamically. A similar approach has demonstrated promise in prior works [10, 56], which leverage network-aware abstractions to enhance communication performance in distributed ML workloads. The main challenge lies in ensuring these abstractions remain transparent to tenants, requiring minimal changes to existing codes while empowering providers to perform infrastructure-level optimizations effectively. Thus, micro-level abstractions must be lightweight, non-intrusive, and compatible with existing AI frameworks and libraries.

Another example is model checkpointing, a critical component of large-scale model training [33, 39, 50]. UCP [33] demonstrates an API that enables efficient and flexible checkpointing across a range of parallelization strategies. With HARMONAIZE, tenants could use abstractions to specify desired checkpointing frequencies, the importance of individual checkpoints, and trade-offs between overhead and fault tolerance. Providers could then optimize checkpointing [21, 52] based on tenant preferences and real-time infrastructure conditions, while ensuring compatibility with UCP’s data format.

Macro-level abstractions: While maximizing API compatibility is critical for micro-level abstractions, macro-level abstractions allow for a more flexible, clean-slate approach to interface design. The primary goal of macro-level abstractions is to provide tenants with an interface that is both expressive enough to convey meaningful information and narrow enough to protect sensitive infrastructure details. One potential design is for providers to expose a pub/sub interface, enabling tenants to subscribe to infrastructure-level events and updates. For example, if a provider frees up a GPU, it could send a notification to all subscribed tenants. To prevent contention when multiple tenants attempt to allocate the same resource, the system could implement mechanisms such as priority-based allocation, reservation windows, or price-based auctioning [9]. To ensure broad applicability, this interface should be standardized across providers.

Importantly, tenants are not restricted to reacting solely to provider-generated events. They can also initiate adaptations based on workload conditions, such as training progress, accuracy milestones, or monitoring metrics, as per current practice [37]. HARMONAIZE’s abstractions simply enhance their decision-making capabilities by providing richer infrastructure information, to adapt workloads more strategically.

Given the coarser nature of macro-level adaptations, some scenarios may require tenants and providers to engage several rounds of negotiation to align on strategic decisions, as

in [9, 24]. This process could involve tenants specifying high-level goals, constraints, and preferences, while providers suggest optimizations that address these requirements.

3.2 Control loops

Control loops are not a novel concept introduced by HARMONAIZE; both tenants and providers already execute control loops independently. However, these loops often operate in isolation, limiting their potential for optimization. Instead, the key contribution of HARMONAIZE lies in restructuring existing control logic and introducing interfaces that enable new opportunities for cooperation. We now elaborate on how tenants and providers can execute control loops cooperatively, sketching a plausible realization of HARMONAIZE’s abstractions.

Provider side: To meet the requirement for fast, data-path-like execution, the provider’s control loops could be implemented within the worker’s hypervisor or a provider-managed container. A proven reference model for such an approach is Google’s Andromeda [14]. Additionally, recent advancements in Infrastructure Processing Units (IPUs) [27] open new possibilities. IPUs are isolated compute units that operate as a separate trusted domain. This isolation allows providers to execute control loops securely and efficiently, offering a fast path for infrastructure-level optimizations while maintaining isolation from tenants. In either case, we must avoid exposing sensitive infrastructure details to tenants.

In restructuring control loops, some burden may shift to providers, as certain data-path routines previously executed by tenants may now be handled by the provider. For instance, in the case of collective communication, the provider becomes responsible for algorithm selection, as discussed earlier. But simply executing algorithm selection within the provider’s control loop and feeding the results back to the tenant would be both cumbersome and potentially leaky. Instead, as demonstrated by [56], the provider initiates collective communication operations directly through the API compatibility layer envisioned in HARMONAIZE. Encouragingly, offloading collectives to IPUs (or DPUs) has already shown significant performance benefits in existing systems [4, 19, 20].

Tenant side: Control loops executed by the tenant retain their existing flexibility and remain within the tenant’s own orchestration layer. HARMONAIZE does not impose restrictions on how tenants manage their workloads. Instead, it enhances the tenant’s control logic by enabling them to subscribe to and act upon relevant provider-supplied events. This additional context enriches the tenant’s decision-making process, allowing infrastructure updates into their optimizations.

4 Cross-Layer Benefits of HARMONAIZE

We now illustrate how HARMONAIZE enables a range of cross-layer optimizations that are difficult or impossible to realize in today's cloud environments. In each case, HARMONAIZE acts as the missing link between tenant-level logic and provider-level infrastructure, enabling both sides to make more informed, coordinated decisions.

O1-Runtime adaptation: In cloud environments, system conditions and workload requirements evolve continuously. Traditional AI workloads, particularly training, operate with fixed configurations set at initialization, making them inflexible to changes in resource availability or workload dynamics during execution. Approaches such as those described in [15, 37] enable dynamic adjustments to key training parameters (e.g., learning rate, batch size, gradient accumulation) and system configurations (e.g., communication protocols, resource usage). This allows tenants to respond to shifts in cluster load, network congestion, or performance variability, optimizing training efficiency and convergence speed.

O2-Collective communication: Collective communication libraries suffer from inefficiencies due to a lack of network awareness and adaptability [8, 36, 56]. For instance, selecting the best communication algorithm (e.g., ring- vs. tree-based) relies on knowledge of network topology and utilization, which tenants cannot access. Consequently, sub-optimal choices are common, and libraries such as NCCL [40] that decide on strategies at initialization may make choices that become less effective as conditions change. Additionally, common strategies often rely on assumptions about network paths that may not align with the actual physical configuration, resulting in unexploited optimization potential.

O3-Cluster scheduling: Another issue lies with scheduling, where tenants must configure resources manually. Suboptimal and static configurations can lead to queuing delays or inefficient resource usage. The optimal resource allocation varies dynamically [9, 43], yet tenants lack adaptive scheduling tools that could adjust resource allocation based on real-time cluster load, or resource availability.

O4-Parallelization and partitioning: For large models, effective distributed execution depends on complex combinations of data, operator, and pipeline parallelism [25, 46]. While automation of parallelization through planning tools could greatly accelerate model execution, these tools expect access to the underlying cluster topology [7, 28, 32, 34, 48, 51, 62]. Planning optimal partitions also depends on dynamic conditions like workload composition, network load, and resource availability, requiring tenant monitoring combined with provider-accessible infrastructure-level information.

O5-Reliability: Resilience in large-scale training is a critical challenge [49]. Failures cause delays and often require manual intervention, as tenants lack infrastructure visibility.

Tenant-led systems, relying on redundancy, can incur unsustainable overheads [23]. This highlights the need for efficient checkpointing [6, 21, 39, 50, 52], which could benefit from deeper infrastructure visibility. Providers are well-positioned to manage fault tolerance holistically, avoiding the inefficiencies of treating training tasks as isolated black-boxes.

O6-Availability: Recovery techniques, e.g., check pointing, mitigate the impact of failures, but such failures still cause a significant loss in revenue, e.g., as much as a \$30K [42]. Recent work [59] shows that the mean time between failures can be increased by 22.61% if defective components are detected proactively and removed quickly. However, such approaches require knowledge of a tenant's workloads and events coupled with the provider's ability to perform proactive measurements using information about their infrastructure. Tenant and provider cooperation ensures that diagnostics framework have access to the application level events and signals needed to disambiguate problems and the infrastructure level observability data needed to triage and identify the root cause of these problems.

O7-Energy management: Energy consumption is a critical concern for AI workloads [54]. Achieving efficiency requires aligning workload characteristics with infrastructure capabilities [12, 60]. For example, dynamic inference cluster reconfiguration can optimize energy and cost while meeting performance SLOs [47]. However, such optimizations demand insights into workload needs and infrastructure (e.g., assessing carbon intensity), which are often siloed. Cooperative optimization bridges this gap, enabling better strategies.

Recent works (Table 1) show gains in these areas (O1-7), with cross-layer cooperation expected to amplify the benefits. Beyond these examples, other potential areas for tenant-provider cooperation include profiling and troubleshooting tools, adaptive workload management [41], and adaptive communication compression [1, 11, 38, 58].

5 Discussion

Adoption. The adoption of HARMONAIZE is underpinned by a natural alignment of incentives between tenants and providers. Tenants gain improved performance, efficiency, availability and resilience for their workloads, while providers benefit from better infrastructure utilization and the ability to offer differentiated, value-added services. Moreover, a buy-in approach affords incremental deployability. Tenants can adopt HARMONAIZE's abstractions at their own pace, without disrupting existing workloads. Providers, in turn, can continue handling workloads from non-adopting tenants using current practices while leveraging the additional insights provided by HARMONAIZE tenants. This gradual deployment model ensures a smooth transition toward cooperative optimization.

Timing and enablers. The timing of HARMONAIZE’s introduction is critical. If introduced too early, it risks stifling innovation by imposing abstractions on a still-evolving ecosystem. Conversely, if introduced too late, the accumulated technical debt – an issue particularly pronounced in ML systems [45] – and the complexity of standardizing entrenched systems may diminish its impact. In recent years, the pace of innovation in AI and workload deployment has been relentless. However, the ecosystem has begun to coalesce around pre-canned recipes and best practices, with systems and libraries like vLLM [31], DeepSpeed [44], Megatron-LM [46], NCCL, and Huggingface’s Transformers [53] becoming de-facto standards. This growing stability signals that the ecosystem is now ripe for a new layer of abstraction, as we envision.

Why not generalize beyond AI? One might critique that the issues HARMONAIIZE addresses apply to general large-scale distributed systems, not just AI workloads. While true, these challenges are particularly acute for AI workloads due to their tightly synchronous nature and the high infrastructure costs associated with them. Additionally, AI workloads are typically iterative, accelerator-driven, and less control-flow oriented, making them more predictable. This predictability suggests that the optimization problem is more tractable compared to general distributed systems [26], offering substantial potential gains. For AI, even marginal improvements can translate into significant cost savings and performance enhancements, justifying a focused approach.

Attempting to generalize beyond AI risks overwhelming complexity. Crafting one-size-fits-all solutions while maintaining narrow, meaningful interfaces for cooperative optimization is a significant challenge [26]. To achieve practicality, prior work has often narrowed its focus, as seen in collectives [56], network awareness in DCs [10] and P2P applications [57], or in domains like virtualized congestion control [13, 22], ISP-CDN-content provider cooperation [16, 29], and serverless-cloud cooperation [5, 61]. Our work applies a similar philosophy in the AI workloads domain.

Could tenants do it all themselves? Some argue that tenants, particularly those operating thousands of GPUs in the cloud, already experience a “bare metal”-like environment with access to provider-specific interfaces for managing placement, network locality, and maintenance. While this may hold true for the largest cloud customers, these interfaces are often proprietary, non-standardized, and inaccessible to the broader tenant base. HARMONAIIZE aims to democratize access to advanced optimizations by providing a standardized framework, making such capabilities available to a wider range of tenants and use cases. This democratization is a necessary step toward a shared responsibility for better sustainability of AI workloads [54].

Immediate roadmap for HARMONAIIZE. Beyond the discussion this paper aims to inspire, the immediate roadmap for HARMONAIIZE is grounded in several foundational building blocks already produced by the research community. A first proof-of-concept prototype for HARMONAIIZE can leverage recently open-sourced tools and frameworks. These include tools for simulating AI job schedulers [2], emulating the behavior of distributed jobs [35], and systems realizing collective communication as a service [56] and runtime adaptations [37]. By integrating these components, an initial prototype could demonstrate the feasibility of HARMONAIIZE’s cooperative optimization vision and showcase the tangible benefits of cross-layer control loops for AI workloads.

Early efforts could then focus on the opportunities identified in § 4 and establish a framework for evaluating the impact of HARMONAIIZE’s abstractions on representative AI workloads. Such a framework would enable systematic assessment of the performance, efficiency, availability and resilience gains achievable through cooperative optimization. Using published results, Table 1 illustrates select benefits that are representative of cooperative optimizations that we expect from HARMONAIIZE.

Several open avenues for exploration remain. Beyond the identified opportunities, further research could uncover additional potential for cooperative optimization. Another intriguing direction is the automation of control loop logic based on high-level intents, allowing tenants to specify their goals without needing to define intricate control mechanisms. Finally, addressing the privacy implications of sharing infrastructure information with tenants is a concern. HARMONAIIZE abstractions must balance the need for transparency with the imperative to safeguard sensitive provider details.

By fostering cooperative optimization, HARMONAIIZE can create a virtuous cycle of innovation and efficiency in multi-tenant cloud environments.

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