Underutilization in Research GPU Clusters: SE Challenges

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Abstract

GPU clusters underpin modern deep learning, yet studies across industry and academia consistently report widespread GPU underutilization. Prior work and our own analysis indicate that inefficiency often stems from recurring patterns in code, job scripts, and runtime behaviour that users rarely detect. We argue that addressing this issue is a MSR challenge: it requires mining inefficiency patterns, combining static and dynamic signals for actionable feedback, validating job-submission artefacts, and developing privacy-aware datasets linking code, configuration, and runtime metrics.

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1 Motivation and Findings

Utilization of GPU resources in a cluster environment is returning topic of research. Hardware access patterns must evolve with more GPU devices, more users per node [26] and bigger jobs [25]. Understanding of users' behavior is crucial to improve resource utilization and plan future investments. Administrators monitor computational jobs with profilers [5]: for hardware [2], provided by vendors like *NSight* [16], framework-based like *PyTorch* profiler [8, 21], or for job schedulers like *SLURM* [9, 26]. These solutions usually focus only on one of the aspects of the problem, not considering the environment as a multilevel system containing users, processes defined in particular programming languages, job schedulers, nodes with different hardware configurations and GPU devices. Only a few tools provide a holistic view of the system performance [7, 19, 28] but users still do not know how to improve their code performance by locating processing bottlenecks. User surveys showed that even if users measure processing time [26], which is on a bill, they do not consider GPU utilization can be improved.

Inspired by industrial [6] and academic [14, 18, 26] studies showing that up to half of deep-learning jobs in production have $< 50\%$ utilization [13], we explored whether similar inefficiencies appear in small research-centric, user-driven environments. We analyzed GPU utilization logs from the WUT Eden cluster [11]. We identified several users whose long-running jobs repeatedly showed sustained GPU utilization below 40%. From this group, two users agreed to take part in exploratory interviews. Insights from these interviews informed a 41-item questionnaire sent to 50 active cluster users, yielding 33 valid responses [12] (66% response rate).

Ad-hoc and individualized workloads. Only 24% users *often* run replication packages, while 46% *rarely or never* do. This highlights the need for adaptive SE tools—such as environment introspection, configuration linting, and lightweight profilers that can analyze arbitrary user scripts without prior setup. *Semgrep* static analysis [17, 24] can be only a part of this process [6].

Awareness gap. Although queues are often congested, only 29% of users *often* monitor GPU utilization, and 47% do so *rarely or never*. Many assume "the scheduler ensures efficiency", or lack convenient metrics during long runs. Thus, inefficiency persists unnoticed — not from unwillingness, but from missing feedback.

Conditional readiness. Users express motivation to improve: 88% would adjust configurations if inefficiency was detected, 76% rated dashboards as *useful*, and 82% valued training materials. The issue is therefore not resistance but the absence of mechanisms.

2 Implications for MSR Research

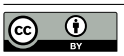
Low GPU utilization often stems from recurring, detectable patterns in code, configuration, and runtime behaviour [6, 26]. For the SE and MSR communities, the challenge is to build preventive, evidence-driven tools despite limited visibility into real cluster workloads.

(1) *Mining inefficiency patterns from code, scripts, and logs.* Gao et al. [6] show that $\approx$ 85% of inefficiencies correspond to identifiable static patterns (e.g., data-loader bottlenecks, remote reads, oversubscription). Pattern mining, commit-history analysis, and correlating edits with runtime traces—can extract such patterns from existing DL repositories and cluster logs. These mined motifs form the empirical backbone for static checks, underutilization predictors, and libraries of common fixes.

(2) *Combining static and dynamic signals for actionable feedback.* Users want explanations and concrete fixes [4, 20, 23]. Combining mined patterns with lightweight profiling enables concise guidance—e.g., "GPU idle → host-device transfer bottleneck; use async loading"—delivering explainable, actionable feedback.

(3) *Validating job scripts and configuration artefacts.* Misconfigured SLURM scripts remain a major cause of wasted GPU time [10, 22, 27]. Mining historical submissions [22] can reveal recurring mistakes and their impacts.

(4) *Need for datasets.* Several HPC datasets now include GPU metrics-and some even expose SLURM scripts or limited links to source code—but they still emphasize system-level resource traces over full code–job–runtime integration [1, 3, 8, 15]. These datasets offer a useful starting point, yet remain incomplete due to privacy and institutional constraints. Further progress requires privacy-preserving logging, synthetic or anonymized corpora, and closer collaboration with HPC centres to produce richer, code-linked workload data.



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