Towards Autonomous Infrastructure Learning: Behavioral Pattern-Driven Optimization for Sustainable and Socially Responsible ML Infrastructure

Andrew Espira

Saint Peter's University

Research Assistant Proposal – Data Science Institute

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# 1. Introduction

Modern machine learning training clusters frequently experience resource underutilization due to inflexible reservation policies, excessive GPU (graphics processing unit) allocation for long-running jobs, and inefficient job scheduling. These inefficiencies increase operational costs, reduce system performance, and limit accessibility for research groups with constrained resources.

While prior systems such as Gandiva, Tiresias, Optimus, and Pollux have introduced innovations in scheduling and fairness, they operate reactively without leveraging behavioral patterns for predictive optimization (Xiao et al., 2018; Gu et al., 2019; Peng et al., 2018; Qiao et al., 2021).

This proposal examines the feasibility of autonomous infrastructure learning using behavioral pattern recognition to optimize machine learning clusters. It investigates the application of event-sequence analysis methods to identify and predict resource inefficiencies, with the goal of advancing sustainability and social responsibility objectives.

# 2. Problem Statement

Large-scale ML training environments suffer from three interrelated issues:

* Resource Hoarding – Jobs often reserve more computer resources, such as GPUs, than they actually need. This results in unused GPU time and lowers how efficiently the whole cluster works.
* Queue Spiraling – When job scheduling does not prioritize workloads well, jobs can block each other and make wait times longer for everyone. This reduces the number of jobs that finish and can make the system seem unfair.
* Accessibility Barriers – When resources are not allocated efficiently, the cost of computation goes up. This makes it harder for smaller organizations or those with limited budgets to use the cluster.

Grounded in these challenges, the key research questions are:

1. How can behavioral pattern recognition identify resource waste patterns in ML cluster environments?
2. What event-sequence analysis methods (including but not limited to CRE-inspired approaches) can predict resource inefficiencies?
3. Can proof-of-concept autonomous recommendations improve resource allocation without manual intervention?
4. How might such improvements translate to sustainability and social responsibility outcomes?

# 3. Proposed Approach

The framework will investigate three integrated components:

Behavioral Pattern Detection Module

* Explore event-sequence analysis methods for identifying resource waste patterns
* Investigate multiple approaches including CRE-inspired techniques, time-series anomaly detection, and statistical pattern recognition
* Evaluate Graph Neural Networks for topology-aware cluster analysis (Hamilton et al., 2017)
* Analyze historical traces from production clusters to validate pattern detection feasibility

Proof-of-Concept Optimization Engine

* Develop basic autonomous recommendation system based on detected patterns
* Implement simple pattern-to-action mapping for scheduling suggestions
* Test feasibility of real-time pattern recognition using eBPF instrumentation
* Validate concept with controlled experiments on resource allocation improvements

Impact Assessment Framework

* Quantify potential resource efficiency improvements through pattern-based optimization
* Analyze cost reduction implications for resource-constrained institutions
* Develop methodology for measuring sustainability and social impact outcomes
* Create reproducible evaluation framework for community validation

# 4. Related Work

Existing ML Schedulers:

* Gandiva (OSDI’18): GPU sharing and context-switching for efficiency improvement (Xiao et al., 2018).
* Tiresias (NSDI’19): Fair scheduling policies for distributed deep learning (Gu et al., 2019).
* Optimus (EuroSys’18): Resource prediction and dynamic scaling for ML workloads (Peng et al., 2018).
* Pollux (OSDI’21): Co-adaptive scheduling optimizing goodput with cost reductions (Qiao et al., 2021).

Research Gap: Existing systems address individual aspects (fairness, prediction, or elasticity) but lack systematic exploration of behavioral pattern recognition for predictive optimization. While event-sequence analysis has been applied to reliability engineering and anomaly detection, its systematic application to ML infrastructure optimization remains unexplored.

Related Methodologies:

* Netflix Atlas demonstrates scalable time-series data collection for pattern analysis (Netflix Tech Blog, 2017).
* Event-sequence analysis has shown promise in reliability engineering contexts (Prequel, 2024).
* Recent work identifies substantial optimization opportunities through pattern recognition in GPU scheduling (Weng et al., 2023).

# 5. Expected Contributions

Technical Contributions:

* Feasibility study of behavioral pattern recognition applied to ML infrastructure optimization
* Comparative analysis of event-sequence detection methods for resource waste identification
* Proof-of-concept framework demonstrating autonomous optimization recommendations
* Open-source prototype enabling community validation and extension

Academic Impact:

* Workshop paper documenting methodology and feasibility findings
* Reproducible research framework for future development
* Novel research direction at intersection of pattern recognition and infrastructure optimization

Sustainability and Social Impact:

* Quantified resource efficiency improvements through behavioral optimization
* Cost reduction analysis demonstrating improved accessibility for underserved institutions
* Framework enabling broader adoption of optimization techniques

# 6. Evaluation Plan

Datasets:

* Public traces (Alibaba PAI, Google Cluster traces, MLCommons benchmarks)
* Systematic data collection from university GPU clusters
* Controlled experimental environments for validation

Metrics:

* Cluster utilization efficiency, job completion time, queue wait time
* Resource waste reduction, cost per training job
* Accessibility improvements for diverse institution types

Baselines:

* Comparison against Gandiva, Tiresias, Optimus scheduling policies
* Evaluation against static allocation and reactive scheduling approaches

Methodology:

* Trace-driven simulations followed by controlled testbed validation
* Statistical significance testing for performance improvements

# 7. Implementation Timeline (11 weeks, 165 hours)

Weeks 1–3 (45 hours): Foundation and Pattern Analysis

* Literature synthesis on event-sequence analysis methods
* Dataset preparation from existing cluster traces
* Initial feasibility study of pattern detection approaches

Weeks 4–6 (45 hours): Behavioral Pattern Detection Development

* Implementation of multiple event-sequence analysis methods
* Comparative evaluation of pattern recognition approaches
* Development of basic pattern classification algorithms

Weeks 7–9 (45 hours): Proof-of-Concept Optimization

* Simple pattern-to-recommendation mapping prototype
* Validation experiments on controlled workloads
* Performance impact assessment of recommendations

Weeks 10–11 (30 hours): Documentation and Analysis

* Academic presentation preparation
* Feasibility findings documentation
* Future research direction identification

# 8. Success Criteria and Validation Framework

Minimum Viable Success (11-week scope)

Technical Feasibility Demonstration:

* Successfully implement detection on at least 3 ML workload types
* Achieve >70% accuracy in identifying resource hoarding patterns from historical traces
* Demonstrate proof-of-concept recommendations with measurable impact (>15% utilization improvement)

Academic Contribution:

* Workshop paper acceptance or submission-ready manuscript for systems conference
* Open-source prototype with documented methodology enabling community replication
* Validated experimental framework for pattern-based optimization research

Impact Assessment:

* Quantified resource efficiency improvements with statistical significance (p < 0.05)
* Cost reduction analysis showing potential democratization benefits for resource-constrained institutions
* Sustainability impact methodology with concrete efficiency metrics

Extended Success (Foundation for broader work)

Research Foundation for Future Development:

* Scalable architecture supporting multiple optimization algorithms
* Community adoption metrics (GitHub stars, forks, citations)
* Industry validation through pilot deployments or collaborations
* Grant funding secured for extended research

Failure Mitigation and Alternative Outcomes

If Pattern Detection Accuracy is Low (<70%):

* Document negative results as valuable contribution (what doesn’t work and why)
* Focus on methodology development and experimental framework validation
* Pivot to comparative analysis of different pattern detection approaches

If Autonomous Optimization Shows Limited Impact (<15% improvement):

* Emphasize feasibility study contribution and framework development
* Document limitations and requirements for production deployment
* Focus on sustainability and social impact analysis rather than performance claims

# 9. Resource Requirements

Computing Infrastructure:

* Google Cloud ($300 free credits), AWS SageMaker Studio Lab (free tier)
* NVIDIA Academic Grant Program application for extended resources
* MLCommons benchmark datasets for reproducible validation

Software Development:

* eBPF development framework (BCC, libbpf) for kernel instrumentation
* Python ML ecosystem (scikit-learn, PyTorch) for behavioral analysis
* OpenTelemetry integration for monitoring extension
* Kubernetes cluster for controlled experimental environments

Expected Budget:

* Cloud computing: $200–$500 for extended experiments beyond free tiers
* Development tools: $0 (open source ecosystem)
* Total investment: <$500 for comprehensive 11-week research validation

# 10. Conclusion

This proposal outlines a systematic approach to ML cluster optimization through behavioral pattern recognition and autonomous resource management. By applying event-sequence analysis methodologies to infrastructure optimization, the framework addresses resource hoarding and queue spiraling while advancing sustainability and social responsibility objectives. The expected outcome is improved cluster efficiency, reduced costs, and enhanced accessibility for diverse research communities.

The 11-week research period will establish a solid foundation for this emerging research area, with clear success criteria and fallback strategies ensuring valuable academic contribution regardless of specific technical outcomes. This work represents the systematic exploration of autonomous infrastructure learning for ML environments, opening new possibilities for sustainable and equitable computing.

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