Investigating Training-Time Optimizations for Deep Learning on Low-Cost Consumer Hardware

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Abstract

Efficient model training remains a critical challenge for deep learning practitioners with limited access to high-performance hardware. This proposal investigates how early stopping and learning rate scheduling can improve training efficiency on low-resource platforms such as CPU-only systems, entry-level GPUs like the NVIDIA GeForce RTX 3050 Ti, and free cloud computing environments. The study aims to analyze the individual and combined impact of these optimization techniques on model performance and training duration. Through a series of controlled experiments across multiple hardware configurations, this proposal seeks to provide practical insights for optimizing deep learning workflows in resource-constrained settings.

CCS Concepts

• **Computing methodologies** → *Supervised learning*; **Optimization algorithms**; **Neural networks**.

Keywords

Early Stopping, Learning Rate Scheduling, Deep Learning, Model Efficiency, Low-resource Training

1 Background

Training deep learning models often requires high-end hardware, which poses a significant barrier for students, researchers, developers, and enthusiasts. Although free platforms like Google Colab offer access to capable hardware, they often come with strict resource constraints - including session-time limits, limited RAM and VRAM, and shared GPU environments.

In response to this challenge, this research investigates optimizations, specifically early stopping and learning rate scheduling, as methods to reduce training time, improve model performance, and make deep learning more feasible for those with limited resources. By focusing on practical solutions, this study aims to provide valuable insight to current practitioners and aspiring deep learning researchers by providing quantifiable results across different hardware configurations, including CPU-only systems, entry-level GPUs, and free cloud computing platforms.

2 Objectives

This study aims to systematically evaluate and compare training-time optimizations for deep learning on low-cost consumer hardware. In particular, we will:

1 **Measure Training Time Reduction** - Quantify how early stopping alone shortens total training time compared to a fixed-epoch baseline on:
   a CPU-only
   b Entry-level GPU
   c Free Cloud GPU Tiers

2 **Assess Impact on Model Performance** - Evaluate how early stopping affects validation accuracy and generalization, ensuring that quality is not unduly sacrificed for speed.

3 **Evaluate Learning Rate Scheduling Strategies** - Compare different schedules (e.g. ReduceLROnPlateau, Exponential Decay) in terms of convergence speed and final accuracy across the same hardware setups.

4 **Compare Combined vs. Individual Techniques** - Analyze whether applying early stopping and learning rate scheduling together yields additive (or synergistic) benefits over using each method in isolation.

5 **Profile Resource Utilization** - Track and report key resource metrics - GPU/CPU utilization, RAM/VRAM usage, and per-epoch time - to understand the trade-offs on each hardware platform.

6 **Derive Practical Guidelines** - Based on the above experiments, formulate actionable recommendations that map specific optimization settings to given hardware constraints, helping researchers with similar resource profiles.