

T0-QAT: ξ -Aware Quantization-Aware Training

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Abstract

This document presents experimental validation of ξ -aware quantization-aware training, where $\xi = \frac{4}{3} \times 10^{-4}$ is derived from fundamental physical principles in the T0-Theory (Time-Mass Duality). Our preliminary results demonstrate improved robustness to quantization noise compared to standard approaches, providing a physics-informed method for enhancing AI efficiency through principled noise regularization.

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0.1 Introduction

Quantization-aware training (QAT) has emerged as a crucial technique for deploying neural networks on resource-constrained devices. However, current approaches often rely on empirical noise injection strategies without theoretical foundation. This work introduces ξ -aware QAT, grounded in the T0 Time-Mass Duality theory, which provides a fundamental physical constant ξ that naturally regularizes numerical precision limits.

0.2 Theoretical Foundation

0.2.1 T0 Time-Mass Duality Theory

The parameter $\xi = \frac{4}{3} \times 10^{-4}$ is not an empirical optimization but derives from first principles in the T0 Theory of Time-Mass Duality. This fundamental constant represents the minimal noise floor inherent in physical systems and provides a natural regularization boundary for numerical precision limits.

The complete theoretical derivation is available in the T0 Theory GitHub Repository¹, including:

- Mathematical formulation of time-mass duality
- Derivation of fundamental constants
- Physical interpretation of ξ as quantum noise boundary

0.2.2 Implications for AI Quantization

In the context of neural network quantization, ξ represents the fundamental precision limit below which further bit-reduction provides diminishing returns due to physical noise constraints. By incorporating this physical constant during training, models learn to operate optimally within these natural precision boundaries.

¹<https://github.com/jpascher/T0-Time-Mass-Duality/releases/tag/v3.2>

0.3 Experimental Setup

0.3.1 Methodology

We developed a comparative framework to evaluate ξ -aware training against standard quantization-aware approaches. The experimental design consists of:

- **Baseline:** Standard QAT with empirical noise injection
- **T0-QAT:** ξ -aware training with physics-informed noise
- **Evaluation:** Quantization robustness under simulated precision reduction

0.3.2 Dataset and Architecture

For initial validation, we employed a synthetic regression task with a simple neural architecture:

- **Dataset:** 1000 samples, 10 features, synthetic regression target
- **Architecture:** Single linear layer with bias
- **Training:** 300 epochs, Adam optimizer, MSE loss

0.4 Results and Analysis

0.4.1 Quantitative Results