**Technical Report**

# **Fine-Tuning TinyLlama for Instruction-Following using QLoRA**

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**Repository:** <https://github.com/navishashetty/llm-finetuning-on-kubernetes>  
**Model:** <https://huggingface.co/shettynavisha25/tinyllama-alpaca-finetuned>

## Abstract

This project implements production-grade fine-tuning of TinyLlama-1.1B on the Stanford Alpaca dataset using QLoRA (Quantized Low-Rank Adaptation) for memory-efficient training. The implementation demonstrates MLOps best practices including Kubernetes orchestration on AWS GPU infrastructure, containerized training pipelines, and comprehensive multi-dataset evaluation. Results show 27.5% METEOR improvement on in-distribution data and 26.4% improvement on out-of-distribution generalization (Dolly-15k), validating the effectiveness of parameter-efficient fine-tuning. However, catastrophic performance degradation on complex reasoning tasks (OpenOrca: -33.4% METEOR) reveals critical limitations and highlights the importance of training data diversity for robust generalization.

## 1. Introduction

### 1.1 Motivation

Large language models demonstrate remarkable capabilities but face two critical challenges: (1) computational costs prohibiting widespread adoption, and (2) generic pre-training limiting task-specific performance. This project addresses the accessibility gap in LLM fine-tuning by implementing QLoRA, which combines 4-bit quantization with Low-Rank Adaptation to reduce memory requirements by 75% without sacrificing model quality. By deploying on a single NVIDIA Tesla T4 GPU (16GB VRAM), the project demonstrates that high-quality instruction tuning is achievable on modest hardware.

### 1.2 Objectives

1. Implement memory-efficient fine-tuning of TinyLlama-1.1B on 52,000 Alpaca instruction-response pairs using QLoRA
2. Deploy production-ready inference pipeline on Kubernetes with GPU resource management
3. Conduct comprehensive evaluation on held-out test sets measuring instruction-following improvement
4. Evaluate out-of-distribution generalization on unseen datasets (Dolly-15k, OpenOrca)
5. Perform error analysis to identify failure modes and deployment limitations

## 2. Methodology

### 2.1 Dataset Selection and Preparation

**Training Dataset: Stanford Alpaca (52,002 samples)**

Selected for its proven effectiveness in instruction tuning, diverse task coverage, and computational feasibility. The dataset contains GPT-3.5-generated instruction-response pairs with the following distribution: Creative writing (23%), Question answering (31%), Reasoning (18%), Summarization (14%), Other (14%)

**Evaluation Datasets:**

1. **Dolly-15k (156 samples evaluated):** Human-generated by Databricks, similar conversational style to Alpaca. Tests generalization to similar-but-unseen instruction formats.
2. **OpenOrca (111 samples evaluated):** GPT-4 augmented FLAN reasoning traces with complex multi-step logic. Stress tests distribution shift and model capacity limits.

**Data Split Strategy:** Due to computational constraints, training was performed on the full 52,002 samples. Post-training evaluation was conducted on randomly sampled held-out test sets. While this represents optimistic performance estimation for Alpaca, out-of-distribution datasets (Dolly, OpenOrca) provide unbiased generalization estimates.

### 2.2 Model Architecture

**Base Model: TinyLlama-1.1B-Chat-v1.0**

The Chat variant was chosen for its instruction-following pre-training, enabling faster convergence.

**QLoRA Configuration:**

| **Parameter** | **Value** | **Justification** |
| --- | --- | --- |
| Rank (r) | 16 | Sufficient capacity for 1.1B model without overfitting |
| Alpha (α) | 32 | Standard 2r scaling for stable learning |
| Dropout | 0.05 | Conservative regularization |
| Target Modules | q\_proj, k\_proj, v\_proj, o\_proj | Attention projection layers |
| Trainable Parameters | 16.7M (1.5% of total) | Parameter-efficient adaptation |

QLoRA reduces model weights from FP16 to 4-bit NormalFloat quantization, achieving 75% memory reduction while maintaining quality through low-rank adapter matrices: W' = W + (α/r) × BA^T

### 2.3 Training Configuration

**Infrastructure:**

* **Compute:** AWS G4DN instances (NVIDIA Tesla T4, 16GB VRAM)
* **Storage:** Amazon EBS for persistent checkpoint storage
* **Orchestration:** Kubernetes 1.27 with NVIDIA Device Plugin

**Hyperparameters:**

| **Parameter** | **Value** | **Justification** |
| --- | --- | --- |
| Learning Rate | 2e-4 | QLoRA standard for 1B models |
| Batch Size | 4 | Maximum fitting in available VRAM |
| Gradient Accumulation | 4 steps | Effective batch size = 16 |
| Optimizer | paged\_adamw\_8bit | Memory-efficient Adam variant |
| Epochs | 3 | Alpaca paper standard |
| Warmup Steps | 100 | 3% of total steps for stability |
| Max Sequence Length | 512 | Covers 95th percentile of samples |

### 2.4 Evaluation Protocol

**Metrics:**

1. **METEOR:** Harmonic mean of precision/recall with synonym matching. Primary metric for semantic quality.
2. **ROUGE-L:** F1 score based on longest common subsequence. Measures structural similarity.
3. **BLEU:** Geometric mean of n-gram precisions. Secondary metric (length-sensitive).

**Evaluation Procedure:** For each sample, generate responses from both base and fine-tuned models, compute metrics against reference answers, and calculate improvement: Δ = (fine-tuned - base) / base × 100%

## 3. Results

### 3.1 Quantitative Evaluation

**Table 1: Performance on Alpaca Test Set (n=198 samples)**

| **Metric** | **Base Model** | **Fine-tuned Model** | **Absolute Δ** | **Relative Δ** |
| --- | --- | --- | --- | --- |
| METEOR | 0.2406 | 0.3068 | +0.0662 | **+27.5%** |
| ROUGE-L | 0.1891 | 0.1988 | +0.0097 | **+5.1%** |
| BLEU | 0.0743 | 0.0727 | -0.0016 | -2.1% |

**Key Findings:**

* Strong semantic improvement (+27.5% METEOR) demonstrates substantial alignment with reference answers
* Moderate structural improvement (+5.1% ROUGE-L) shows better response organization
* BLEU decline (-2.1%) caused by increased response length (41.8 → 76.5 words), not quality degradation

**Table 2: Performance on Dolly-15k (n=156 samples)**

| **Metric** | **Base Model** | **Fine-tuned Model** | **Relative Δ** |
| --- | --- | --- | --- |
| METEOR | 0.1926 | 0.2434 | **+26.4%** |
| ROUGE-L | 0.1651 | 0.1661 | +0.6% |
| BLEU | 0.0587 | 0.0473 | -19.4% |

**Analysis:** Improvement nearly matches Alpaca performance (+26.4% vs +27.5% METEOR), indicating robust transfer to similar instruction formats. Model successfully generalized instruction-following patterns to unseen conversational tasks.

**Table 3: Performance on OpenOrca (n=111 samples)**

| **Metric** | **Base Model** | **Fine-tuned Model** | **Relative Δ** |
| --- | --- | --- | --- |
| METEOR | 0.2315 | 0.1543 | **-33.4%** |
| ROUGE-L | 0.1940 | 0.1605 | -17.3% |
| BLEU | 0.0615 | 0.0044 | **-92.8%** |

**Critical Failure:** Fine-tuning hurt performance across all metrics, representing catastrophic distribution shift failure.

**Cross-Dataset Summary:**

| **Metric** | **All Datasets Avg** | **In-Distribution (Alpaca)** | **OOD Average** |
| --- | --- | --- | --- |
| METEOR Δ | +6.9% | +27.5% | -3.5% |
| ROUGE-L Δ | -3.9% | +5.1% | -8.4% |
| BLEU Δ | -38.1% | -2.1% | -56.1% |

### 3.2 Qualitative Analysis

**Success Case (Alpaca):**

* Instruction: "Explain machine learning in simple terms"
* Base Output (41 words): Generic definition without examples
* Fine-tuned Output (76 words): Clear definition + concrete examples (image recognition, speech recognition) + practical applications (business efficiency, cost reduction)
* **Analysis:** Demonstrates improved elaboration and structure

**Failure Case (OpenOrca):**

* Instruction: "What is the missing first step: 'Air goes down esophagus, air moves into lungs...'"
* Reference: "Inhale air through the nose or mouth"
* Fine-tuned Output: "The missing first step is for the oxygen to be removed from the air before it reaches the lungs..." [factually incorrect + incomplete]
* **Analysis:** Hallucinated incorrect biological process, ignored obvious answer

## 4. Error Analysis: OpenOrca Failure Root Causes

**Error Type Distribution:**

| **Error Category** | **Frequency** | **Severity** | **Primary Cause** |
| --- | --- | --- | --- |
| Premature Truncation | 60% | Critical | MAX\_LENGTH=150 too restrictive |
| Factual Hallucination | 25% | Critical | Model scale limitation + forgetting |
| Format Non-Compliance | 10% | High | No system prompt training |
| Off-Topic Response | 5% | Medium | Instruction misunderstanding |

**Root Cause 1: Generation Length Constraint (60% of failures)**

* OpenOrca reference answers average 280 words vs. 150 token limit (≈120 words)
* Truncation rate: 60% of responses incomplete
* Impact: BLEU -92.8% directly reflects length mismatch

**Root Cause 2: Task Complexity Mismatch (25% of failures)**

* OpenOrca includes GPT-4 level multi-step reasoning
* Alpaca training: primarily single-step instructions
* Model never exposed to system prompts or structured output formats

**Root Cause 3: Catastrophic Forgetting (25% of failures)**

* Fine-tuning optimized for Alpaca conversational style
* LoRA rank (r=16) insufficient to preserve both base knowledge AND new patterns
* Evidence: Factual knowledge degraded (e.g., incorrect A Song of Ice and Fire character genealogy)

## 6. Future Work

1. **Dynamic Generation Length:** Implement prompt-based length prediction to reduce 60% truncation rate
2. **Mixed Dataset Training:** Blend Alpaca (60%), Dolly (25%), OpenOrca (15%) for 52K samples
3. **Increase LoRA Rank:** Test r ∈ {32, 64} to reduce catastrophic forgetting
4. **Model Scale Upgrade:** Fine-tune Mistral-7B or Llama-3-8B (expected +40-50% OpenOrca METEOR)
5. **Structured Output Training:** Add 5K samples for classification, extraction, multiple-choice formats

## 7. Conclusion

This project successfully demonstrated memory-efficient instruction tuning of TinyLlama-1.1B using QLoRA, achieving 27.5% METEOR improvement on in-distribution tasks and 26.4% on out-of-distribution generalization at $6 total compute cost. The production-ready Kubernetes pipeline showcases practical MLOps implementation for reproducible LLM fine-tuning.

## References

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