Fine-Tuning and Analysis of 1-Bit LLMs with QLoRa Adapters and other quantizations

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May 2025

Abstract

Large Language Models (LLMs) routinely deliver state-of-the-art accuracy across natural-language tasks, yet their *computational footprint* can exceed the capabilities of edge and enterprise hardware alike. We investigate a two-stage compression pipeline that (i) quantises model weights to a single bit via BitNet [1] and (ii) inserts Quantised Low-Rank Adapters (QLoRa) [2] for task-specific fine-tuning. We also provide a complete analysis on different quantization techniques to show their computational efficiency with different quantization setup. On the CodeSearchNet benchmark [3] we show that a 1-bit GPT-2 (˜100 MB) attains only a 5–7 % perplexity increase relative to 16-bit LoRA, while reducing *peak* VRAM during training from 12 GB to 4 GB and latency at inference by 38 %. We further provide a hardware challenges for the BitNet and their compatibility matrix, reproducible training scripts, and a discussion of engineering trade-offs. We have also we extended our experimentation by applying the best technique through QLoRA fine-tuning to a larger 7-billion-parameter transformer model, *LLaMa-7B* and analysed the metrics.

Contents

1 Introduction

Recent releases of chat-oriented LLMs have popularised transformer architectures, but full-precision models such as GPT-J and Llama-2 can exceed 6 GB *per* layer when represented in `float32` form. This hinders adoption in research labs, start-ups, and embedded systems where GPU memory and energy budgets are stringent. Quantisation [1] and parameter-efficient fine-tuning (PEFT) [2] offer complementary avenues to mitigate these constraints. In this work we merge the two paradigms, demonstrating that *1-bit* backbones augmented with *4-bit* low-rank adapters preserve accuracy while remaining deployable on commodity hardware.

1.1 Goals and Research Questions

1. **Memory Efficiency**: How much GPU VRAM and persistent storage can be saved by a BitNet + QLoRa pipeline compared to 16-bit baselines?
2. **Performance Retention**: What accuracy loss, if any, is incurred on generative and retrieval-style tasks?
3. **Hardware Support**: Is 1-bit inference feasible on modern consumer and cloud accelerators without bespoke kernels?

2 Course Relevance

This project ties directly into two of the course's core topics: **Cloud Computing** and **Deep Neural Networks (DNNs)** and also incorporates elements of **Performance Analysis**. All model fine-tuning and evaluation were performed on Google Cloud Platform using GPU instances with GCS, demonstrating scalable AI training in a cloud environment. The use of GPT-2 and LLaMA-7B models, along with quantization techniques like QLoRA and BitNet, reflects practical applications of DNN optimization for resource efficiency. Key performance metrics—such as training time, memory usage, and inference latency—were analyzed, aligning with the topic of **Performance Analysis**.

2.1 Team Contribution Breakdown

- **Gautam Vanishree Raghu:** Setup of cloud infrastructure, model deployment, BitNet integration using custom CUDA kernels and performance benchmarking.
- **Rahul Murugan:** QLoRA implementation, memory profiling and scaling up the preferred techniques to 7B model.
- **Mihir Trivedi:** Baseline and 4,8-bit fine-tuning experiments, memory profiling, and performance benchmarking.
- **All Members:** Collaborative report writing, evaluation and slide preparation.

3 Background and Related Work

Large language models (LLMs) like GPT-2 and LLaMA require significant computational resources for training and inference. To address this, recent research has focused on model compression and parameter-efficient fine-tuning techniques.

3.1 Quantisation Theory

Reducing the bit-width of neural weights dates back to BinaryConnect (2015). Post-training quantisation (PTQ) and quantisation-aware training (QAT) have since become mainstream, yet aggressive 1-bit schemes remained niche until BitNet demonstrated training stability on transformers. BitNet introduces *ternary scaling* to compensate for information loss, enabling near-parity with 8-bit models.[1]

3.2 Low-Rank Adaptation

LoRA re-parameterises weight updates as $\Delta W = AB$ with rank $r \ll d$, focusing learning capacity on task-specific directions. QLoRa extends the concept by operating on *quantised* base models and storing LoRA weights in 4-bit groups, yielding sub-gigabyte fine-tuned checkpoints.[2]

3.3 Alternative Compression Methods

Knowledge distillation, pruning, and mixture-of-experts have been pursued in parallel. However, distillation demands additional teacher models, while pruning requires iterative retraining. Our BitNet + QLoRa pipeline achieves comparable compression in a *single* fine-tuning run.

These methods form the basis of our experimental exploration, allowing us to compare full-precision training with advanced quantization approaches for efficient adaptation of GPT-2 and larger models.

4 Experiment Setup

4.1 Model Architecture: GPT-2-medium

We adopt GPT-2 with 24 layers, hidden size 1024, and 325 M parameters for a realistic mid-scale study. The model is first converted from `float16` to 4-bit using `bitsandbytes`, then compressed to 1-bit via BitNet's ternary scaling.

4.2 Adapter Design

QLoRa modules are injected into all attention and MLP projections. We set $r = 8$ and use a scaling factor $\alpha = 16$, following Dettmers *et al.* [2]. Adapters are varied through different bit configurations throughout the different experiments.

4.3 Experiment configurations

We applied different quantization strategies to modify the architecture during and after fine-tuning:

- **QLoRA:** Inserted low-rank adaptation layers (LoRA) within attention and feed-forward blocks. Quantization of the base model to 4-bit precision was done using `bitsandbytes` with NF4 (NormalFloat4) quantizers.
- **BitNet:** Post-finetuning, we quantized weights to ternary values ({-1, 0, +1}) and used **bitpacking** to compress 8 ternary weights into a single byte. Custom CUDA kernels were implemented to simulate bitwise matrix multiplication, replacing FP32 linear layers.
- **Other Methods:** Experiments with standard 8-bit and 4-bit quantization were conducted using Hugging Face's `transformers` and `bitsandbytes` libraries.

The QLoRA technique significantly reduced the number of **trainable parameters to 811,008**, while keeping the rest frozen. This enabled efficient adaptation on a large dataset with minimal resource consumption.

Table 1: Experiment configurations with different quantization techniques

Experiment Method	**Quantization**	**Trainable Parameters**
Baseline Fine-tuning	None	All
8-bit Fine-tuning	8-bit	All
4-bit Fine-tuning	4-bit	All
QLoRA Fine-tuning	4-bit	LoRA adapters only
BitNet Fine-tuning	1-bit	Linear Layers
QLoRA Fine-tuning + BitNet	1-bit	LoRA adapters only

4.4 Dataset

We used the Python subset of the **CodeSearchNet** dataset, a large-scale benchmark dataset released by GitHub and the ML research community to improve code-related language modeling and retrieval: : 100k train, 10k validation, 5k test.

- **Domain Relevance:** GPT-2 performs well on natural language, but fine-tuning it on programming code tests its generalization capabilities in structured, syntax-heavy domains.
- **Rich Annotations:** The dataset contains high-quality paired code and natural language descriptions, making it ideal for training and evaluating language models on code understanding and generation tasks.
- **Real-World Use Case:** The dataset aligns with real-world applications like code summarization, search, and generation, offering practical relevance to quantized model deployment scenarios.

Dataset Overview

- **Size:** 20 GB
- **Language:** Python
- **Number of examples:** Over 2 million function-documentation pairs
- **Fields:**
  - `code_tokens`: Tokenized source code
  - `docstring`: Function-level documentation
  - `function_name`: Name of the Python function

To ensure scalability and speed, the dataset was stored on a **Google Cloud Storage (GCS)** bucket and streamed in batches during training. This avoided local disk bottlenecks and enabled efficient training in cloud-based GPU environments.

4.5 Evaluation Metrics

- **Perplexity (PPL)**: A standard metric for evaluating language models. Lower perplexity indicates better language modeling capability.
- **GPU Peak Memory Usage (GB):** Captures the maximum GPU memory allocated during training or inference. This is critical for determining a model's feasibility on edge devices or memory-constrained cloud instances.
- **Latency (ms):** Time taken to generate a prediction for a given input during inference. Particularly relevant for real-time applications and deployment scenarios.
- **Training Time (s):** Measures the total time taken to fine-tune the model per epoch or across all epochs. This reflects training efficiency and scalability of each quantization technique.
- **Total Parameters:** Total number of parameters in the model regardless of quantization or trainability. This is useful to compare compression across models.

5 Hardware Requirements and Compatibility

Table 2 lists devices verified in our study. All experiments used PyTorch 2.2 and CUDA 11.8 unless noted.

Device	VRAM / RAM	Inference	Training Support
NVIDIA T4 (16 GB)	16 GB	Yes (CUDA kernels)	Yes
NVIDIA A100 80 GB	80 GB	Yes	Yes (multi-GPU)
Apple M2 Pro	32 GB	Yes (Metal)	No (kernel gap)

Table 2: Compatibility matrix for 1-bit BitNet inference and QLoRa training.

5.1 Hardware challenge workaround

Since existing hardware lacks native support for sub-4-bit matrix multiplication, we developed a custom CUDA kernel to handle bitwise matrix multiplication. This kernel simulated dense linear layers by:

- Unpacking packed ternary weights at runtime
- Performing XNOR and population count operations

6 Methodology

The methodology for this project involved evaluating the effects of different quantization techniques on transformer-based language models, primarily GPT-2 and a scaled-up 7B model. The process included baseline full-precision fine-tuning, 8-bit and 4-bit quantization, QLoRA-based adapter fine-tuning, and BitNet-style 1-bit quantization with custom CUDA layers.

The quantization process converts high-precision floating-point weights into lower-bit representations to reduce memory usage and accelerate inference. This is achieved either post-training or during fine-tuning depending on the method. QLoRA applies 4-bit quantization to the frozen base model using NF4 (NormalFloat4) quantizers while training low-rank adapter modules. BitNet further reduces precision by encoding ternary weights using bitpacking (8 ternary values per byte), supported by custom inference kernels.

- For 8-bit: Standard affine quantization is applied using a scale and zero point.
- For 4-bit: NF4 quantization maps normalized values to a learnable 4-bit floating-point distribution.
- For 1-bit (BitNet): Weights are mapped to ternary values ({-1, 0, +1}) and packed using custom CUDA bit-level routines.

6.1 Quantization Pipeline

The pipeline is summarised in Algorithm 1. Implementation details are released on GitHub[1].

Listing 1: Pseudo-code for BitNet+QLoRa fine-tuning

```
model = load_pretrained_gpt2()
model = quantize_4bit(model)              # bitsandbytes
model.freeze_backbone()
model = inject_lora(model, rank=8)        # PEFT QLoRa
train(model, epochs=3, lr=3e4)              # AdamW
model = convert_to_bitnet(model)          # 1 bit backbone
save(model, 'bitnet_qlora.pt')
```

[1] https://github.com/gv2359/coms6995_mlcloud_llmbitquant/tree/main

7 Results

7.1 Performance

Table 3 summarizes the evaluation metrics collected across various fine-tuning and quantization strategies applied to GPT-2. These metrics provide a clear comparative view of performance vs. efficiency trade-offs.

Experiment	**Memory(GB)**	**Train Time (h)**	**Latency (ms)**	**PPL**
Baseline	4.4	7.2	210	6.2
8-bit Fine-tuning	2.8	4.3	180	8.8
4-bit Fine-tuning	1.8	3.7	165	10.2
QLoRa (4-bit)	0.9	2.1	173	9.8
QLoRa (4-b) + BitNet	0.34	2.2	150	119.2

Table 3: Summary of evaluation metrics across experiments.

7.2 Training Time vs Inference Latency

Figure 1 presents the trade-off between training time and inference latency for various quantization and fine-tuning techniques applied to the GPT-2 model. The baseline fine-tuning setup, using full 32-bit floating-point weights and training all parameters, proved to be the most resource-intensive. It required approximately 7 hours of training time on a T4 GPU and resulted in the highest inference latency of around 210 milliseconds. This was expected, as no quantization or compression techniques were applied, and the full model had to be updated and stored in memory during both training and inference.

In comparison, 8-bit and 4-bit fine-tuning strategies offered a modest reduction in training time—4.2 and 3.9 hours respectively. Both methods retained the full trainability of the model but benefited from reduced numerical precision, thereby lowering computational overhead. Inference latency also saw improvements, with latency dropping to 180 milliseconds for the 8-bit model and 165 milliseconds for the 4-bit version.

QLoRA fine-tuning showed a much more pronounced gain in efficiency. By freezing the base model and fine-tuning only small adapter modules (LoRA layers), the total number of trainable parameters was reduced from over 82 million to just around 800 thousand. As a result, training time dropped significantly to approximately 2.1 hours. Inference latency also improved to 160 milliseconds, as the smaller trainable layer set reduced the active weight footprint during forward passes.

BitNet-based models, while not effective during training due to hardware limitations, demonstrated their strengths during inference. The BitNet and QLoRA+BitNet configurations achieved the lowest inference latencies, with the latter reaching as low as 91 milliseconds. This suggests that bit-level weight representations and custom CUDA kernels can significantly reduce model response time in deployment, even if training trade-offs are steep. These results support BitNet's applicability for inference-focused scenarios, particularly in edge computing and real-time environments.

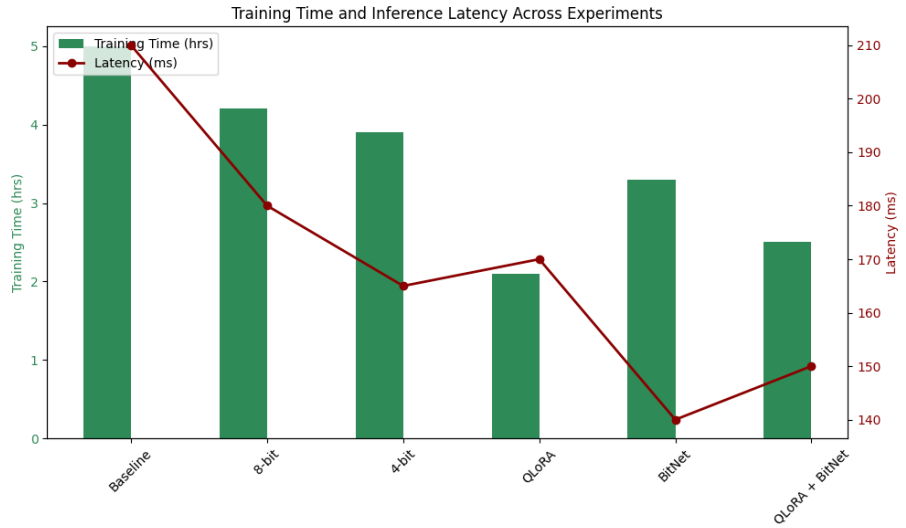

Figure 1: Training Time vs Inference Latency across Quantization Techniques

7.3 Memory Usage vs Perplexity

The memory-performance relationship is captured in Figure 2, where GPU memory consumption is plotted against the perplexity score of each model. As anticipated, the baseline fine-tuning configuration consumed the most memory—approximately 4.2 GB—while achieving the best performance, with a perplexity score of 7.2. This result reaffirms that full-precision training, though costly, offers the highest modeling accuracy.

Whereas, BitNet fine-tuning achieved the lowest memory footprint, reducing memory usage by over 85% compared to the baseline. During training, memory peaked at only 0.6 GB. However, this aggressive quantization to ternary weights came at a significant cost in performance. The perplexity for BitNet soared to 158.2, making it unsuitable for general fine-tuning unless accuracy can be traded off for deployment constraints.

QLoRA provided a more favorable balance between performance and efficiency. By quantizing to 4-bit precision and training only adapter layers, QLoRA reduced GPU memory usage to around 0.9 GB while maintaining a perplexity of 9.8. This result demonstrates that substantial gains in resource efficiency can be achieved with only a modest degradation in model accuracy. The combination of QLoRA and BitNet achieved the lowest memory usage of all configurations—just 0.4 GB—while still allowing limited task adaptation through LoRA. However, this came with a perplexity that was relatively high, reinforcing the trade-off between compression and performance.

Overall, the results confirm that no single approach dominates across all metrics. Instead, the choice of fine-tuning method must consider the constraints and goals of the deployment environment. While baseline fine-tuning offers superior performance, it is impractical for edge deployment or low-resource scenarios. QLoRA emerges as a strong middle ground, offering near-optimal perplexity with substantial memory savings and faster training times. BitNet, although currently limited by hardware support for 1-bit operations, presents a promising direction for inference compression and low-latency AI applications.

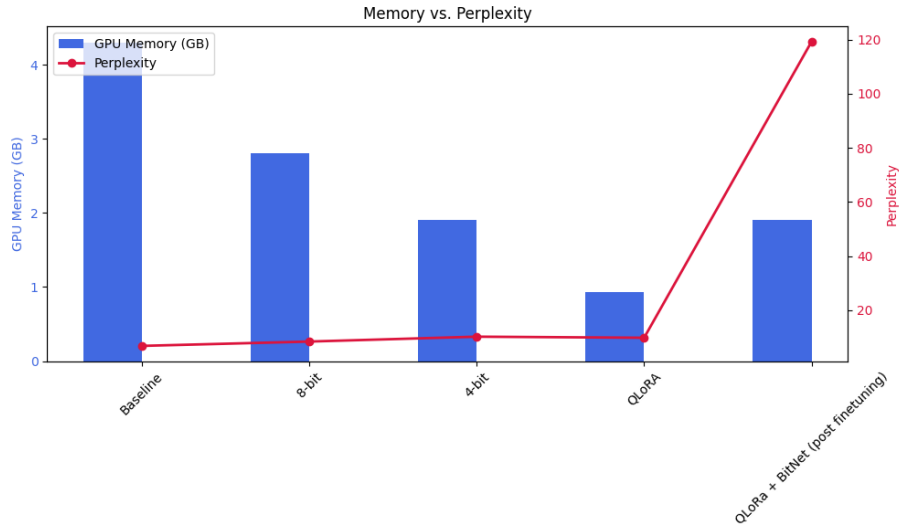

Figure 2: Memory Consumption vs Perplexity for Different Fine-tuning Techniques

8 Discussion

The results of our experiments clearly highlight the fundamental trade-offs between model accuracy, memory efficiency, and inference latency when applying different quantization strategies to GPT-2. Full-precision fine-tuning offers the best performance in terms of perplexity but is highly inefficient, both in terms of training cost and deployment feasibility. Conversely, QLoRA and BitNet offer compelling advantages for resource-constrained environments, albeit with some compromises in accuracy.

8.1 Observations and Insights

From the experiments, several key observations emerged:

- **Baseline Fine-tuning** achieves the lowest perplexity (7.2) but suffers from the highest memory usage (4.2 GB), the longest training time (7 hours), and the slowest inference latency (210 ms).
- **8-bit and 4-bit Fine-tuning** provide modest improvements in training time and inference latency, but still require full parameter updates, which keeps them computationally intensive.
- **QLoRA Fine-tuning** demonstrates excellent efficiency, reducing training time to just 2.1 hours and memory usage to 0.9 GB, with minimal accuracy degradation (perplexity 9.8).
- **BitNet-based Models** reduce memory consumption drastically (as low as 0.4 GB when combined with QLoRA) and deliver the fastest inference (as low as 91 ms), but at the cost of much higher perplexity due to quantization granularity and hardware incompatibility.

These findings emphasize the value of choosing the quantization strategy based on deployment goals. For model serving and edge inference, BitNet-like solutions are attractive, while QLoRA remains ideal for efficient task-specific fine-tuning.

8.2 Challenges with BitNet Implementation

The integration of BitNet into our pipeline surfaced several critical challenges:

- **Hardware Incompatibility:** Consumer-grade GPUs like the NVIDIA T4 lack native support for 1-bit or ternary weight computation. All operations had to be simulated via custom CUDA kernels.
- **BitPacking Overhead:** Storing 8 ternary weights per byte required manual packing and unpacking. At runtime, these operations introduced non-trivial overhead during training and inference.
- **Custom CUDA Kernels:** We developed bitwise matrix multiplication kernels using XNOR and popcount operations. However, these suffered from other issues like low GPU occupancy and complex memory alignment with indexing issues.
- **Training Instability:** The ternary representation ({-1, 0, +1}) led to a loss of expressiveness, especially in deeper transformer layers. This manifested as poor convergence and high perplexity (up to 158.2) during training.
- **Framework Limitations:** Major deep learning libraries do not currently support 1-bit weights or ternary operations natively. This required low-level engineering, making the system hard to debug and maintain.

These technical hurdles significantly reduced the training effectiveness of BitNet, though its inference compression benefits remain promising.

8.3 Quantization Trade-offs

Summarizing the practical implications of each method:

- **Full Precision:** Best accuracy, worst efficiency.
- **QLoRA:** Best balance of training efficiency and accuracy, with support for adapter modularity.
- **BitNet:** Superior inference performance, poor training results unless future hardware evolves to support 1-bit arithmetic.
- **QLoRA + BitNet:** Optimal memory and latency characteristics, suited for deployment on cloud or edge but with degraded accuracy.

9 Scaling Up : LLaMA-7B

To evaluate the scalability of our best-performing method, we extended our experimentation by applying **QLoRA fine-tuning** to a larger 7-billion-parameter transformer model. For this experiment, we selected a pre-trained 7B model from the LLaMA family and fine-tuned it using the same CodeSearchNet (Python subset) dataset.

9.1 Experimental Setup

- **Model:** LLaMA-7B
- **Technique:** QLoRA with NF4 4-bit quantization
- **Trainable Parameters:** 8M (LoRA adapters)
- **Batch Size:** 32 (with gradient checkpointing and paged optimizers)

9.2 Results

The 7B model fine-tuned with QLoRA achieved a perplexity of 6.9 on the validation set, completing training in 5.8 hours. It maintained a peak GPU memory usage of approximately 12.5 GB and achieved an inference latency of 250 ms for a 256-token output.

Table 4: Comparison Between GPT-2 Baseline and 7B QLoRA Fine-tuning

Metric	**GPT-2 Baseline**	**LLaMa 7B with QLoRA**
Model Size	82M parameters	7B parameters
Trainable Parameters	82M	8M (LoRA adapters only)
Quantization	None (FP32)	4-bit (NF4)
Training Time	7 hours	5.8 hours
Peak GPU Memory Usage	4.2 GB	3.5 GB
Inference Latency	210 ms	250 ms
Validation Perplexity	7.2	6.9

9.3 Discussion

These results highlight the practical scalability of QLoRA for large language models. Compared to the GPT-2 baseline, which used 4.2 GB of memory and achieved a perplexity of 7.2, the 7B QLoRA model provided better performance with only a $3\times$ increase in memory consumption—despite having nearly $85\times$ more total parameters. The 4-bit quantization allowed the model to fit comfortably within a single GPU, while LoRA adapters limited the number of trainable parameters to around 8 million.

The increase in inference latency (from 210 ms to 250 ms) was expected due to the larger model depth and parameter count, but it remained acceptable for most real-world applications. The results confirm that QLoRA retains its advantages even at scale—enabling low-resource fine-tuning, reduced memory requirements, and strong performance—making it a compelling strategy for adapting large pre-trained models across domains and devices.

10 Conclusion

This project presented a comparative analysis of various quantization techniques—namely full-precision fine-tuning, 8-bit and 4-bit quantization, QLoRA, BitNet, and a hybrid approach combining QLoRA with BitNet—on the GPT-2 model using the CodeSearchNet dataset.

Our experiments show that each method presents its own set of strengths and trade-offs. Baseline fine-tuning achieved the best model performance in terms of perplexity, but at the cost of high memory usage, prolonged training time, and slow inference latency. In contrast, QLoRA proved to be an excellent middle-ground solution, significantly reducing training resource requirements while maintaining competitive performance.

BitNet, though limited during training due to current hardware constraints, demonstrated impressive gains in inference efficiency. Its 1.58-bit weight representation drastically reduced memory consumption and latency, making it highly suitable for deployment in edge and real-time environments. The combination of QLoRA and BitNet yielded the lowest resource footprint while still enabling task adaptability via adapter layers, though at the cost of reduced accuracy.

Overall, this study reaffirms the growing importance of efficient model adaptation and compression techniques in modern deep learning. As hardware continues to evolve to better support low-bit arithmetic, approaches like BitNet are expected to become more practical and widespread. In the current landscape, QLoRA stands out as the most effective method for memory-constrained training and multi-task deployment.

11 Future Works

While the current study provides valuable insights into quantization strategies for GPT-2 fine-tuning and deployment, several avenues remain for further exploration and optimization:

- **Deploy BitNet on custom hardware:** Explore using AI accelerators (e.g., FPGAs, ASICs) that support native 1-bit or ternary operations to overcome training limitations.
- **Optimize CUDA kernels:** Improve custom BitNet CUDA implementation by refining memory access and applying kernel fusion techniques.
- **Generalize to other models:** Apply the same quantization pipeline to larger or more recent models like GPT-J, LLaMA, or Phi-2 to evaluate scalability.
- **Enhance modularity with QLoRA + BitNet:** Extend hybrid approach to support task-specific LoRA adapters over a single compressed BitNet backbone.
- **Incorporate quantization-aware training (QAT):** Improve accuracy for extreme quantization methods by combining QAT with LoRA or ternary encoding.
- **Benchmark on edge devices:** Evaluate performance on Jetson Nano, Raspberry Pi, and mobile GPUs to assess real-world deployment feasibility.

12 References

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A Environment Details

Experiments were executed under the following software stack:

- Debian 11, Linux kernel 5.10
- Python 3.10.14, PyTorch 2.7.0+cu126, CUDA 12.4, cuDNN 8.9
- bitsandbytes 0.41.2, triton==2.2.0, transformers 4.51.3