Dynamic Quantization of LLMs via Reinforcement Learning (DynaQuant)

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Introduction

Large Language Models (LLMs) are powerful but resource-intensive. Quantization reduces model size and speeds up inference, but uniform quantization can be suboptimal. We propose a **dynamic**, per-layer quantization approach using Reinforcement Learning (RL) to find an optimal mixed-precision scheme during fine-tuning. This balances accuracy and memory footprint.

Key points:

- **Motivation:** Exploit the fact that not all layers are equally sensitive to precision loss.
- **Approach:** Use **PPO** to pick layer-specific quantization types (e.g. nf4, fp4, int8, fp16), then do short fine-tuning to recover from possible performance drops.
- **Key Idea:** Adaptive fine-tuning after **each** layer's quantization captures the dynamic interaction between layers.
- **Goal:** Learn a per-layer quantization policy for LLMs that optimizes accuracy and memory usage.

Related Work

Our work builds upon several key areas:

- **LLM Quantization:** Techniques like GPTQ [5], QLoRA [2], bitsandbytes [1] and extreme LLM compression efforts [4, 6] have demonstrated the effectiveness of quantization for LLMs.
- **RL for Architecture Search:** Methods like NASNet [8] and APQ [7] use RL to optimize neural network architectures and quantization.
- **Mixed-Precision Quantization:** HAWQ [3] and other methods explore layer-wise bit-width selection.

Our approach differs by using RL to *dynamically* determine the mixed quantization scheme *during* fine-tuning, allowing the model to adapt to the specific quantization choices.

Reinforcement Learning Environment

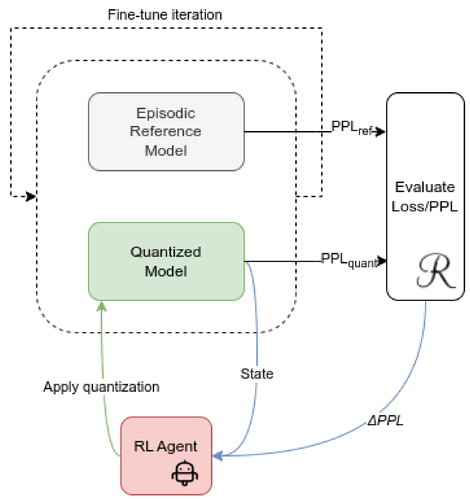


Figure 1. RL-based dynamic quantization loop. Agent picks a quant type for the current layer, then fine-tunes and compares performance (losses/perplexities).

- **State:** Layer statistics (weight mean/std, gradient norm, attention entropy), current layer index, previous layer's quantization, and EMA of rewards.
- **Action:** Choice of quantization type: {'nf4', 'fp4', 'int8', 'fp16', 'bf16', 'fp32'}.
- **Reward:** Combination of perplexity difference (sigmoid-shaped), KL divergence, attention entropy difference, and memory savings.
- **Episode:** Quantizing all layers of the model sequentially.
- **Adaptive Fine-tuning:** Crucially, we fine-tune *both* the quantized model *and* an episodic reference model after *each* layer's quantization, using *identical* training data, for a fixed number of steps. This captures the dynamic impact of quantization.

Reward Function (Multi-Objective)

We define the per-layer reward as a weighted sum of performance, distribution alignment, attention preservation, and memory savings:

$$\begin{aligned} R \;=\; & w_{\text{perf}}\,\sigma\big(\alpha\,(\mathrm{PPL}_{\text{ref}} - \mathrm{PPL}_{\text{quant}})\big) \\ & -\; w_{\text{KL}}\,\mathrm{KL}\big(p_{\text{quant}} \,\|\, p_{\text{ref}}\big) \\ & +\; w_{\text{entropy}}\,\big(\mathrm{Ent}_{\text{quant}} - \mathrm{Ent}_{\text{ref}}\big) \\ & +\; w_{\text{memory}}\,\mathrm{MemSave}. \end{aligned}$$

Interpretation:

- $\mathrm{PPL}_{\text{ref}} - \mathrm{PPL}_{\text{quant}}$: difference in perplexities, run through a sigmoid (σ) to keep reward in (0,1).
- $\mathrm{KL}(p_{\text{quant}} \| p_{\text{ref}})$: penalize large distribution shift.
- $\mathrm{Ent}_{\text{quant}} - \mathrm{Ent}_{\text{ref}}$: preserve attention diversity.
- $\mathrm{MemSave}$: bit savings relative to a 16-bit baseline, scaled by fraction of total params in that layer.

We also employ an exponential moving average (EMA) of the total reward to stabilize training updates in PPO.

Implementation

- **Model:** GPT-2 (small, medium, large).
- **Quantization:** 'bitsandbytes' library and custom.
- **RL Algorithm:** Proximal Policy Optimization (PPO).
- **Fine-tuning Data:** CommonsenseQA.
- **Evaluation:** Perplexity, memory usage and inference speed. Datasets: BoolQ, PIQA
- **Infrastructure:** Training performed on H100 GPUs using the Modal platform. We gratefully acknowledge Modal for providing a free compute budget.

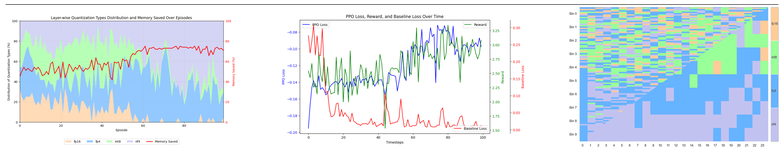
Results

Table 1. Results on GPT-2 Small (PIQA). We compare perplexity (PPL), accuracy (Acc), and peak GPU memory (Mem). All deltas (%) are computed relative to FP32 as the baseline.

Method	PPL	ΔPPL(%)	Acc(%)	ΔAcc(pp)	Mem (MB)	ΔMem(%)
Baseline (FP32)	25.31	—	60.72	—	574.22	—
Baseline (FP16)	25.31	+0.01%	60.72	+0.00	422.69	-26.38%
Uniform NF4	22.66	-10.47%	60.77	+0.05	300.95	-47.60%
DynaQuant (mixed)	21.44	-15.29%	61.53	+0.82	464.29	-19.14%

Notes: The reported DynaQuant configuration uses a mixed schema `{fp16, int8, fp16, nf4, fp16, int8, fp16, int8, fp4, nf4, int8, fp4}`. Perplexities are scaled by dividing raw values by 100. For instance, a raw PPL of 2531.21 is shown as 25.31. FP32 is the reference baseline. FP16 yields a memory reduction of about 26% with negligible changes in perplexity and accuracy. Uniform NF4 offers a larger perplexity drop (-10.47%) while cutting memory nearly in half. **DynaQuant** achieves the best overall trade-off: a -15.29% drop in perplexity, a +0.82 percentage point gain in accuracy, and a -19.14% memory reduction relative to FP32.

Training Dynamics



(a) Quantization types distribution and memory savings over episodes.

(b) Training metrics over episodes: reward, PPO loss, and baseline loss.

(c) Binned quantization of layers across 100 episodes

Figure 2. The evolution of quantization types over episodes in the training phase, the plots show the trade-off between memory savings and PPO loss - as memory savings increase, the PPO loss tends to increase as well, but the reward overall increases.

Observations

- **Reward Dynamics:** Although the reward trends upward as the agent refines its per-layer decisions, it can be noisy. Sudden drops or oscillations may occur, especially when reward weights, batch sizes, or the number of fine-tuning steps change.
- **Policy Sensitivity:** By adjusting reward weights, one can steer the agent toward more aggressive compression (prioritizing memory savings) or more performance-preserving (accuracy-focused) quantization strategies.
- **Validation Loss Stability:** Even with layer-by-layer quantization, the quantized model's validation loss stays reasonably close to that of the reference, thanks to short post-quantization fine-tuning.
- **Layer-Specific Choices:** Some layers often tolerate lower-precision (e.g. 4-bit), while more sensitive layers might require int8 or float16.
- **Compute Cost vs. Benefits:** This approach is compute-intensive. However, it can be justified by the overall memory/accuracy trade-off gains in scenarios where quality on user specific data sets is paramount.

Conclusion and Future/In-progress Work

We presented an RL-based approach for dynamic, per-layer quantization of LLMs. Our method learns a policy that balances accuracy (perplexity) and memory usage, achieving a better trade-off than uniform quantization. Key features include:

- **Dynamic:** The policy adapts to each layer's characteristics.
- **Adaptive Fine-tuning:** Captures the interplay between quantized layers.
- **Multi-Objective Reward:** Balances perplexity, KL divergence, entropy, and memory.

Future work includes:

- Scaling to larger models (e.g., `DeepSeek-R1-Distill-Qwen-1.5B` or `phi-2`).
- Hyperparameter tuning and exploration of different reward weightings.
- Adding a "skip" action to the policy, allowing it to choose not to quantize a layer.
- Exploring a policy network with a transformer architecture to leverage past decisions for better future choices. With enough training on diverse models/datasets, such a policy could infer a robust mixed-precision scheme from only a few fine-tuning steps for new scenarios.

References

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