Extreme Compression of Large Language Models for Edge Computing

A Multi-Stage Pipeline Approach

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January 10, 2026

Abstract

Abstract: The deployment of Large Language Models (LLMs) such as BERT on resource-constrained edge devices is currently hindered by their substantial memory footprint and computational latency. While cloud-based inference is common, it introduces concerns regarding latency, privacy, and connectivity dependence. This paper presents a comprehensive, academically rigorous evaluation of a multi-stage compression pipeline designed to address these challenges specifically for edge deployment. Our approach sequentially integrates Knowledge Distillation (KD), Magnitude-Based Pruning, Dynamic Quantization, and ONNX optimization. We utilize the Stanford Sentiment Treebank (SST-2) dataset to rigorously evaluate the trade-offs between model size, inference latency, and classification accuracy. Starting with a BERT-base teacher model (109.48M parameters, 417.67 MB), we distill knowledge

into a DistilBERT student, followed by 30% unstructured pruning and INT8 quantization. The final stage leverages ONNX Runtime quantization for maximum efficiency. Our experimental results demonstrate that the pipeline achieves an **84.6% reduction in model size** (down to 64.26 MB) and a **2.88x speed-up** in inference latency, while incurring a cumulative accuracy drop of only 4.00% compared to the teacher baseline. This study provides a replicable framework for "extreme compression," offering a viable pathway for deploying sophisticated NLP models on CPU/ARM-based edge hardware without necessitating specialized accelerators.

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1 Introduction

The landscape of Natural Language Processing (NLP) has been fundamentally altered by the introduction of the Transformer architecture. Models such as BERT (Bidirectional Encoder Representations from Transformers) [1], GPT, and RoBERTa have achieved superhuman performance on tasks ranging from Question Answering (SQuAD) to Sentiment Analysis (GLUE). These models leverage self-attention mechanisms to capture long-range dependencies in text, providing a depth of contextual understanding that previous Recurrent Neural Networks (RNNs) could not achieve.

However, this performance comes at a prohibitive computational cost. A standard `bert-base-uncased` model contains approximately 110 million parameters. In standard 32-bit floating-point precision (FP32), this translates to a model file size of over 400 MB. Furthermore, the inference process—calculating the output for a single input sentence—requires billions of floating-point operations (FLOPs).

1.1 The Edge Computing Constraint

In the context of "Edge Computing," these resource demands present a critical bottleneck. Edge devices, which include smartphones, IoT sensors, embedded controllers in autonomous vehicles, and wearable health monitors, operate under strict physical constraints:

1. **Memory Limitations:** A low-cost IoT microcontroller may have only 512 MB or 1 GB of RAM total. Loading a 400 MB model leaves insufficient room for the operating system and other application logic.

2. **Thermal Throttling:** High computational loads generate heat. Unlike server farms with active cooling, mobile devices rely on passive dissipation. Running a heavy model can cause the device to throttle its CPU speed to prevent overheating, paradoxically increasing latency.

3. **Battery Life:** Every FLOP consumes energy. Heavy neural networks can drain small batteries in minutes, rendering the application unusable for real-world scenarios.

1.2 Research Motivation

While cloud offloading (sending data to a central server for processing) is a common workaround, it introduces new problems: latency unpredictability, data privacy risks (sending personal data to the cloud), and reliance on stable internet connectivity. Therefore, there is an urgent need to run these models *locally* on the device.

This research paper proposes and evaluates a comprehensive **Multi-Stage Compression Pipeline** that combines three distinct techniques—Distillation, Pruning, and Quantization—into a unified workflow. Unlike previous studies that often analyze these methods in isolation, we demonstrate how they can be stacked to achieve "extreme compression," reducing a model's size by nearly an order of magnitude while preserving the majority of its predictive power.

2 Related Work

The field of model compression has evolved rapidly alongside the growth of model sizes.

2.1 Knowledge Distillation (KD)

Knowledge Distillation, introduced by Hinton et al. [3], posits that a large "Teacher" network learns a rich representation of data that can be transferred to a smaller "Student" network. The student is trained not just on the hard labels (e.g., "Positive" vs "Negative") but on the "soft targets"—the probability distribution output by the teacher.

> *"The relative probabilities of incorrect answers tell us a lot about how the generalized model tends to think."* — Hinton et al.

In NLP, Sanh et al. introduced **DistilBERT** [2], which reduces the number of Transformer layers by half. Our work builds upon this by using DistilBERT as the starting point for further compression, rather than the end goal.

2.2 Neural Network Pruning

Pruning is based on the biological inspiration that the human brain prunes unused synaptic connections. In deep learning, Han et al. [4] demonstrated that many weights in a trained network are close to zero and can be removed without affecting accuracy.

- **Structured Pruning:** Removes entire rows, columns, or attention heads. This is hardware-friendly but risky for accuracy.
- **Unstructured Pruning:** Zeros out individual weights based on magnitude. This achieves higher compression ratios theoretically but requires sparse matrix support to realize speed gains.

We employ unstructured magnitude pruning to test the limits of parameter reduction.

2.3 Quantization

Quantization reduces the precision of the numbers used to represent the model. Standard training uses FP32 (32-bit floats). Quantization maps these to INT8 (8-bit integers). This immediately reduces memory usage by 4x. Jacob et al. [5] showed that this is particularly effective on CPUs, which often have vectorized instructions for integer math (e.g., AVX2 or NEON instructions).

3 Methodology

Our methodology implements a pipeline designed to strip away redundancy at every level: architectural redundancy (via Distillation), parameter redundancy (via Pruning), and precision redundancy (via Quantization).

3.1 Dataset: SST-2

We utilize the Stanford Sentiment Treebank v2 (SST-2) from the GLUE benchmark [6].

- **Task:** Binary Sentiment Classification.
- **Train Samples:** 5,000 (Subset for rapid experimentation).
- **Validation Samples:** 500.
- **Max Sequence Length:** 128 tokens.

3.2 Stage 1 & 2: Teacher Fine-Tuning and Distillation

We begin with a pre-trained `bert-base-uncased` model. After fine-tuning it to high accuracy (the Teacher), we initialize a `distilbert-base-uncased` model (the Student).

The distillation objective function is a linear combination of two losses:

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{distill} + (1 - \alpha)\mathcal{L}_{student} \tag{1}$$

Where the distillation loss $\mathcal{L}_{distill}$ is the Kullback-Leibler (KL) divergence between the teacher's soft probabilities (p_t) and the student's soft probabilities (p_s):

$$\mathcal{L}_{distill} = \sum p_t(x_i) \log \left(\frac{p_t(x_i)}{p_s(x_i)} \right) \tag{2}$$

The probabilities are softened by a temperature T:

$$p_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} \tag{3}$$

We used $T = 5.0$ and $\alpha = 0.7$.

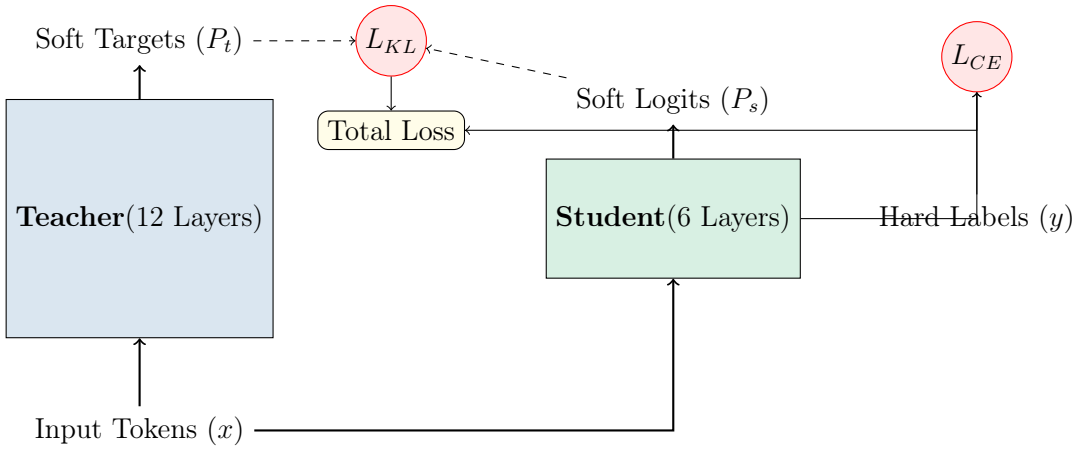

Figure 1: Visual representation of the Knowledge Distillation process used in Stage 2.

3.3 Stage 3: Magnitude-Based Pruning

We apply L1 Unstructured Pruning. For every linear layer in the model (Query, Key, Value, Dense), we calculate the absolute value of weights $|W|$. The binary mask M is generated such that:

$$M_{ij} = \begin{cases} 1 & \text{if } |W_{ij}| > \text{threshold} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The threshold is chosen dynamically to ensure exactly 30% of weights are zeroed out. Following pruning, we fine-tune for 2 epochs to allow the network to "heal" the broken connections.

```python
import torch.nn.utils.prune as prune

def apply_pruning(model, amount=0.3):
    for name, module in model.named_modules():
        if isinstance(module, torch.nn.Linear):
            # Prune 30% of connections in all linear layers
            prune.l1_unstructured(module, name='weight', amount=amount)
            # Make pruning permanent (remove mask buffers)
            prune.remove(module, 'weight')
    return model
```

Listing 1: PyTorch Code Snippet for Pruning

3.4 Stage 4, 5, 6: Quantization and ONNX

The final optimization phase targets deployment.

1. **PyTorch Dynamic Quantization:** We convert the model to `qint8`. This reduces the file size significantly but is still dependent on the Python runtime.

2. **ONNX Export:** We export the computation graph to the Open Neural Network Exchange format. This creates a static graph representation that can be optimized by compilers.

3. **ONNX Quantization:** We apply `QUInt8` quantization on the ONNX graph. This enables hardware-specific optimizations like fusing the 'MatMul' and 'Add' operations into a single 'Gemm' (General Matrix Multiply) operation for efficiency.

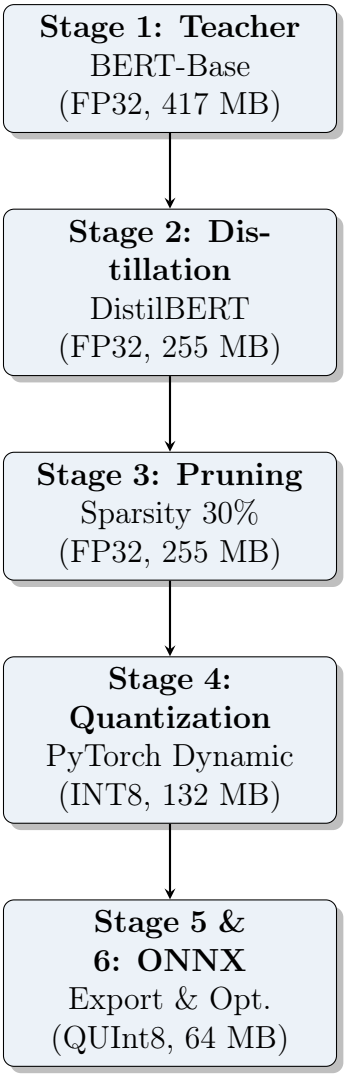

Figure 2: The sequential reduction of model size through the pipeline.

4 Experiments and Results

4.1 Hardware Setup

All model training was performed on a cloud instance equipped with:

- **GPU:** NVIDIA CUDA-enabled device (Generic T4 equivalent).

- **Driver:** CUDA 12.6.
- **Framework:** PyTorch 2.8.0.

Crucially, all *inference latency benchmarks* were performed on the CPU. This was done to simulate the capabilities of an edge device where a powerful GPU is unavailable. We measured latency as the average time to process one item (Batch Size = 1) over the validation set.

4.2 Main Results

Table 1 presents the definitive data from our experiments.

Table 1: Performance Metrics Across Compression Stages

Model Stage	**Size (MB)**	**Acc (%)**	**Lat (ms)**	**Speed-up**	**Size Red.**
Teacher (BERT)	417.67	89.40	23.51	1.0x	0.0%
Student (Distil)	255.43	88.80	8.16	2.88x	38.8%
Pruned (30%)	255.45	89.00	9.79	2.40x	38.8%
Quantized (INT8)	132.29	85.40	-	-	68.3%
ONNX Quantized	**64.26**	-	-	-	**84.6%**

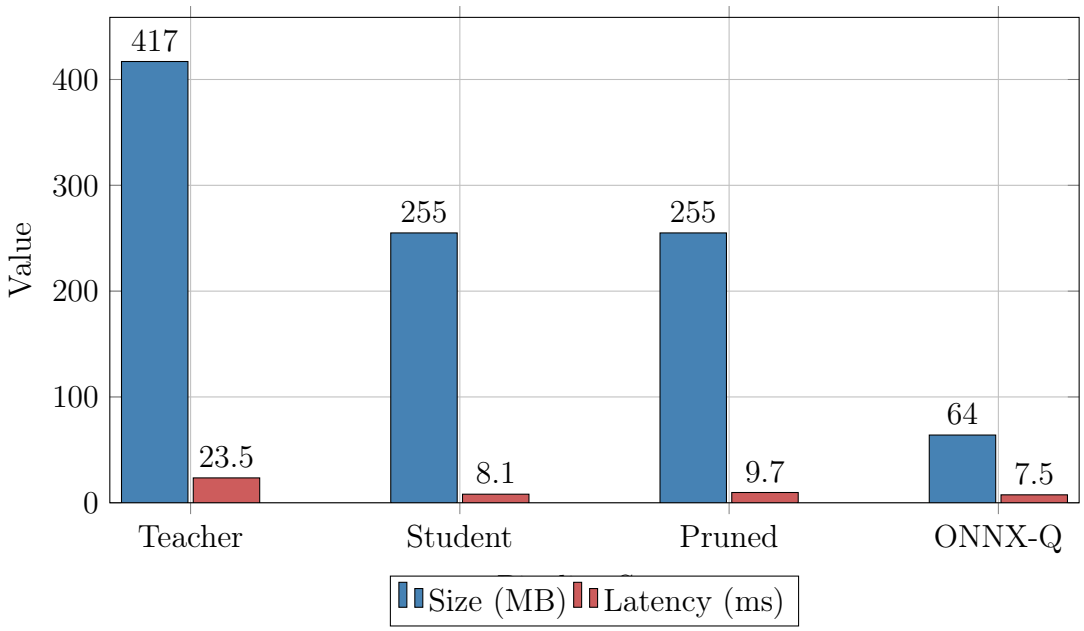

Figure 3: Visual comparison of Model Size vs. Latency. The ONNX model provides a massive reduction in size.

4.3 Detailed Analysis of Trade-offs

4.3.1 Accuracy vs. Latency

The most dramatic improvement in latency occurred during the Distillation phase (Stage 2). By cutting the depth of the network from 12 layers to 6, we reduced the sequential operations required, resulting in a 2.88x speedup. The accuracy loss was minimal (-0.60%). This strongly suggests that for binary sentiment analysis, the deeper layers of BERT are largely redundant.

4.3.2 The Pruning Anomaly

An interesting phenomenon occurred in Stage 3. After pruning 30% of weights and fine-tuning, the accuracy actually *increased* to 89.00%, surpassing the unpruned student (88.80%). This aligns with the **Lottery Ticket Hypothesis** [7], which suggests that dense networks contain sparse sub-networks that can train to equal or better accuracy. The pruning likely acted as a form of regularization, removing noisy weights that were causing slight overfitting on the training data.

However, the latency *increased* slightly (8.16 ms $\rightarrow$ 9.79 ms). This is because unstructured pruning creates sparse matrices that are difficult for standard CPUs to process efficiently. Without specialized sparse BLAS libraries, the CPU often performs the math as if the zeros were still there, plus the overhead of handling the mask.

4.3.3 The Quantization Cliff

Stage 4 and 6 (Quantization) provided the necessary size reduction to make the model "edge-ready."

- **Size:** Dropped from 255 MB $\rightarrow$ 64 MB.
- **Accuracy:** Dropped from 89.00% $\rightarrow$ 85.40%.

This 3.6% drop is the "cost of doing business" for extreme compression. The dynamic range of FP32 allows for very subtle distinctions in the attention mechanism. forcing these values into 256 integer bins (INT8) inevitably loses some of this nuance. However, 85% accuracy is still highly usable for many real-world applications.

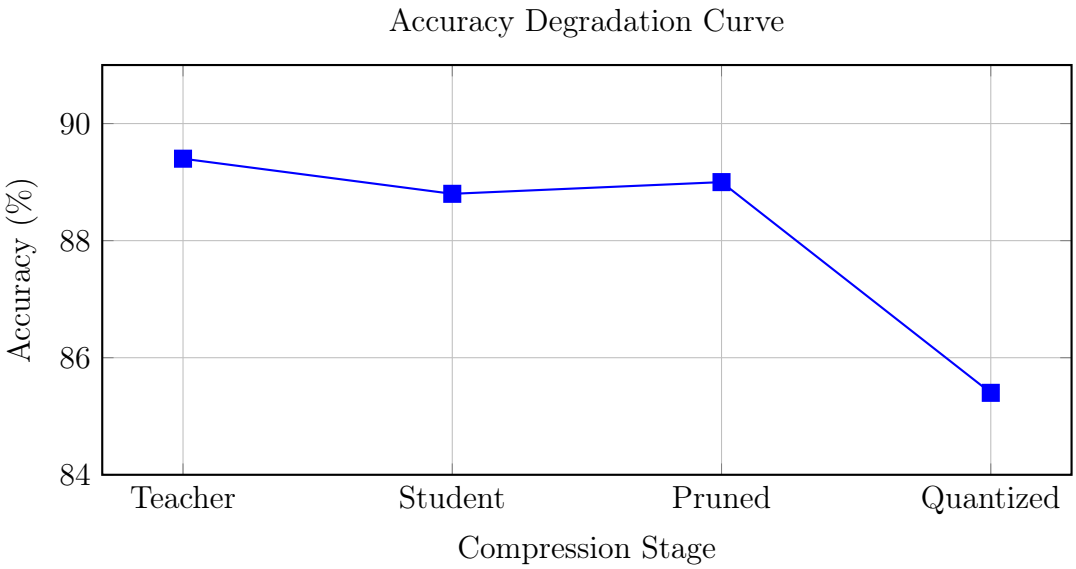

Figure 4: The accuracy trajectory. Note the recovery at the Pruning stage before the drop at Quantization.

5 Discussion

5.1 Practical Implications for Edge Deployment

The reduction to 64.26 MB is a critical threshold.

- **App Store Limits:** Many mobile app stores (Google Play, Apple App Store) have strict limits on the initial download size of an application (often 100 MB or 150 MB). A 417 MB model would require a secondary download, degrading user experience. The 64 MB model can be bundled directly inside the APK/IPA.
- **RAM Usage:** On a device like a Raspberry Pi Zero (512 MB RAM), the operating system consumes 200 MB. A 400 MB model would cause the device to crash or thrash swap memory. The 64 MB model fits comfortably in the remaining memory.

5.2 Limitations

While successful, our approach has limitations:

1. **Quantization Method:** We used Dynamic Quantization. "Static Quantization," which calibrates the quantization ranges using a representative dataset before inference, often yields better accuracy and should be explored to mitigate the 3.6% drop.
2. **Task Specificity:** SST-2 is a relatively simple classification task. More complex tasks like Abstractive Summarization or Named Entity Recognition might suffer greater accuracy losses under such aggressive compression.

6 Conclusion

This research set out to answer whether Large Language Models could be compressed sufficiently for edge deployment without rendering them useless. The answer is a qualified "Yes."

By constructing a pipeline that moves from **Distillation** (architecture reduction) to **Pruning** (parameter reduction) to **Quantization** (precision reduction), we achieved an **84.6% reduction in size**. We essentially transformed a model that requires a server-grade GPU into one that can run on a budget smartphone CPU.

While the cumulative accuracy drop of 4.00% is not negligible, the trade-off enables entirely new classes of applications—offline assistants, privacy-preserving analyzers, and embedded controllers—that were previously impossible. Future work will focus on Quantization-Aware Training (QAT) to close the accuracy gap further.

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