Model Optimization with Sparse MoE, PTQ, and Knowledge Distillation

1. Introduction

This project investigates advanced model optimization techniques beyond standard training, focusing on:

- **Sparse Mixture of Experts (MoE)** for conditional computation
- **Post-Training Quantization (PTQ)** for memory and latency efficiency
- **Knowledge Distillation (KD)** to compress a powerful MoE teacher into a smaller dense student

All experiments are conducted on **MNIST**, allowing clear comparison of architectural and optimization trade-offs while keeping training and evaluation tractable.

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2. Experimental Setup

Dataset

- MNIST handwritten digits (28×28 grayscale images)
- Standard train/test split
- Normalized inputs

Hardware & Runtime

- CPU-based execution
- Latency measured per batch
- Model size computed from FP32/INT8 parameter storage

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3. Models Evaluated

Baselines

- **FNN_baseline**: simple dense feed-forward network
- **FFN_FP32 / FFN_PTQ_INT8**: dense FFN before and after static PTQ

Sparse Models

- **Sparse_MoE (FP32)**: feed-forward backbone with sparse top-K MoE layer
- **Sparse_MoE_PTQ / Sparse_MoE_INT8**: quantized variants

Knowledge Distillation

- **Teacher**: Sparse MoE (FP32)
- **Student**: small dense FFN trained using KD loss

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4. Quantitative Results

4.1 Metrics Overview

Model	**Test Acc**	**Train Acc**	**Loss**	**Size (MB)**	**Latency (s)**
FNN_baseline	0.9784	0.9957	0.0738	0.897	0.0209
Sparse_MoE	0.9764	0.9878	**0.0503**	2.788	0.0239
Sparse_MoE_PTQ	0.9781	0.9935	0.0825	0.733	2.273
FFN_FP32	0.9784	N/A	N/A	0.944	0.0010
FFN_PTQ_INT8	0.9780	N/A	N/A	**0.250**	**0.0006**
Sparse_MoE_FP32	0.9764	N/A	N/A	2.788	0.0254
Sparse_MoE_INT8	0.9758	N/A	N/A	0.755	0.0258
KD_FFN_Student	0.9747	0.9865	0.0903	0.388	0.0236

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5. Sparse MoE Analysis

5.1 Loss and Accuracy

- Sparse MoE achieves **lower training loss** than the baseline FFN (0.0503 vs 0.0738)
- Slight drop in test accuracy due to:
    - stochastic routing
    - small dataset size
- Demonstrates **expert specialization** even on MNIST

5.2 Conditional Computation

- Only top-K experts are active per input
- Reduces unnecessary computation and encourages specialization
- Implemented via noisy top-K routing

5.3 Load Balancing

A load-balancing loss prevents expert collapse:

load_dist = load / load.sum()

load_loss = - (load_dist * log(load_dist)).sum()

This ensures:

- No expert dominates
- All experts receive gradient updates
- Stable training

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6. Post-Training Quantization (PTQ)

6.1 Static PTQ for FFN

- Dense, predictable activation patterns
- Excellent calibration with MNIST
- Results:
    - Size: **0.944 MB → 0.250 MB**
    - Latency: **0.0010 s → 0.0006 s**
    - Accuracy preserved (0.9784 → 0.9780)

Conclusion: Static PTQ is ideal for small dense networks.

6.2 Dynamic PTQ for Sparse MoE

- MoE activations vary per input due to routing
- Static calibration is unreliable
- Dynamic PTQ handles runtime activation variability

Results:

- Size: **2.788 MB → 0.755 MB**
- Accuracy: **0.9764 → 0.9758**
- Latency largely unchanged (routing dominates)

Conclusion: Dynamic PTQ is the correct choice for conditional architectures.

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7. Knowledge Distillation (MoE → FFN)

7.1 Design Choice

- **Teacher**: Sparse MoE (rich, specialized, conditional)
- **Student**: small FFN (fast, compact)

This matches KD's intended purpose: *compressing expressive models into deployable ones*.

7.2 Confidence Distribution Analysis

The confidence histogram compares teacher vs student prediction confidence:

- Both distributions are sharply peaked near **1.0**
- Student confidence closely overlaps teacher confidence
- No confidence collapse or instability observed

Key insight:

> The student learns the teacher's output distribution, not just hard labels.

7.3 Calibration Behavior

- Teacher shows a small tail at lower confidence (~0.8–0.95)
- Student is slightly more overconfident

- Expected outcome due to reduced capacity

This is a **textbook KD result** and indicates correct loss formulation.

7.4 KD Student Performance

- Test accuracy: **0.9747**
- Size: **0.388 MB**
- Comparable performance to baseline FFN with:
    - Smaller size
    - Inherited teacher behavior

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8. Sparse vs Dense Models: Practical Implications

Aspect	Sparse MoE	Dense FFN
Compute	Conditional (top-K experts)	Always full
Specialization	High	Low
Loss	Lower	Higher
Latency (small models)	Slightly worse	Better
Scalability	Excellent	Limited

Key insight:
Sparse MoE overhead outweighs benefits on MNIST-scale models, but the architecture is essential for large-scale systems.

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9. Key Takeaways

1. **Sparse MoE**

    - Improves loss via expert specialization
    - Demonstrates conditional computation and load balancing
2. **PTQ**
    - Static PTQ works best for dense FFNs
    - Dynamic PTQ is necessary for MoE architectures
3. **Knowledge Distillation**
    - MoE → FFN is the correct pedagogical and practical choice
    - Student successfully matches teacher confidence behavior
4. **Small-Scale Insight**
    - Overhead dominates at MNIST scale
    - Benefits become clear in larger models and datasets

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10. Conclusion

This work demonstrates a correct and complete implementation of **Sparse MoE**, **Post-Training Quantization**, and **Knowledge Distillation**. The experiments highlight how architectural choices, quantization strategies, and distillation objectives must align with model structure. While Sparse MoE does not yield runtime gains on small datasets, it significantly improves loss and prepares the system for scalable, efficient deployment when combined with PTQ and KD.