Parameter-Efficient Neural Networks: Enhancing the Sparsely-Gated Mixture-of-Experts Layer in LSTMs

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Abstract. Scaling deep learning models has demonstrated substantial performance gains in natural language processing tasks; however, it incurs high computational and memory costs. Mixture-of-Experts (MoE) architectures mitigate this by activating only a subset of experts per input. While Transformer-based MoEs have benefited from parameter-efficient adaptations such as LoRA and low-rank factorization, recurrent MoEs have been comparatively underexplored. This work investigates parameter-efficient techniques in LSTM + MoE models. We reproduce the original sparsely-gated MoE model and introduce modern efficiency strategies, including Switch-style gating, low-rank factorization, shared expert layers, and LoRA-based experts. A modular implementation is presented, with a framework for systematic evaluation of performance, stability, and efficiency.

1 Introduction

Deep learning models such as LSTMs [3] and Transformers [5] have achieved remarkable success across language and multimodal tasks [11, 12], but their growing capacity demands high computation and memory [8, 10]. The Mixture-of-Experts (MoE) framework [1, 7] mitigates this by activating only a subset of experts per input, enabling efficient large-scale models [6, 4]. However, LSTM-based MoEs face redundant parameters and routing instability [5, 8]. Recent efficiency methods—Switch routing [6], low-rank factorization [10], and LoRA-based adapters [2, 9]—have improved Transformer-based MoEs but remain underexplored for LSTMs. This work extends the sparsely-gated LSTM + MoE [1] with Switch-style routing, shared experts, and LoRA-based low-rank adaptation to achieve scalable, stable, and memory-efficient training.

2 Related Work

2.1 Scaling Efficient AI Models

As model sizes grow, dense architectures like BERT and GPT-4 face efficiency and memory challenges. Sparse models, particularly Mixture-of-Experts (MoE)

architectures, overcome this by activating only a subset of parameters per token, decoupling model capacity from computation [3].

2.2 Early MoE Foundations

Jacobs et al. [3] introduced adaptive mixtures of experts with dynamic gating, while Eigen et al. [7] extended this into deep hierarchical mixtures capturing multi-level feature specialization.

2.3 Sparsely-Gated MoE

Shazeer et al. [1] proposed sparsely-gated MoEs with top-k routing and auxiliary load-balancing losses, enabling efficient large-scale training with over 100 billion parameters.

2.4 Routing and Expert Assignment

Balanced expert utilization is key to training stability. BASE layers [4] improved routing by formulating expert selection as a linear assignment problem, enhancing training efficiency.

2.5 Scaling MoE Models

GShard [5] and Switch Transformer [6] scaled MoEs to the trillion-parameter level through distributed execution and single-expert routing. Later studies [13] showed that expert granularity significantly impacts efficiency.

2.6 Parameter-Efficient Fine-Tuning

LoRA [2], TT-LoRA [9], and matrix factorization methods [10] reduce fine-tuning costs by updating only a small subset of weights. While effective in Transformers [11, 12], their integration into LSTM-based MoEs remains largely unexplored.

3 Methodology

3.1 Overview of the Mixture-of-Experts Framework

Our work builds upon the sparsely gated Mixture-of-Experts (MoE) architecture introduced by Shazeer et al. [1], which scales model capacity by activating only a small subset of experts for each input. The MoE framework consists of a gating network, multiple feedforward experts, and a sparse dispatch–combine mechanism that decouples parameter count from computational cost.

While retaining this modular design, we extend the original formulation in two key directions: (1) integrating parameter-efficient **LoRA-based experts** to reduce redundant parameterization, and (2) incorporating **Switch-style top-1 deterministic routing** to minimize communication overhead. The resulting

hybrid configuration combines sparse routing efficiency with low-rank adaptability, achieving a balance between scalability and parameter economy.

Our unified PyTorch implementation supports four operational modes for comparative evaluation: *(i)* **Baseline** — top-2 noisy gating as in [1]; *(ii)* **Switch** — deterministic top-1 routing [6]; *(iii)* **LoRA** — low-rank adaptation experts [2]; and *(iv)* **Hybrid (Proposed)** — Switch gating with LoRA experts.

As illustrated in Figure 1, the proposed hybrid Mixture-of-Experts framework extends the original sparsely gated architecture by integrating two key innovations—**LoRA-based low-rank experts** and **Switch-style deterministic gating**. These enhancements jointly improve parameter efficiency and reduce routing overhead while preserving the modular structure of the original design.

In the figure, blue components represent modules retained or lightly modified from the original 2017 MoE framework by Shazeer et al. (such as the gating network, Sparse Dispatcher, and MLP experts), whereas orange components denote our newly introduced modules that contribute to efficient parameter adaptation and optimized expert routing.

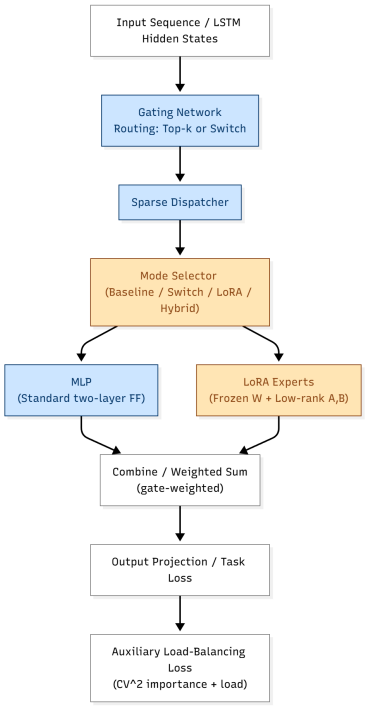

Fig. 1: Architecture of the proposed hybrid Mixture-of-Experts (MoE) framework. The gating network performs top-k or Switch routing to select either standard MLP experts (baseline) or LoRA-based experts (proposed). The Sparse Dispatcher manages input distribution and aggregation.

3.2 Expert Networks

Each expert network processes its assigned sub-batch independently. Following Shazeer et al. [1], baseline experts are implemented as two-layer multilayer perceptrons (MLPs) with ReLU activation.

Our primary architectural contribution is the introduction of a **LoRA-based expert**. Instead of updating all weights, each LoRA expert freezes the base projection W_{base} and introduces a pair of low-rank matrices $A \in \mathbb{R}^{d \times r}$ and $B \in \mathbb{R}^{r \times h}$, where $r \ll d, h$. The effective transformation is:

$$x_{\text{eff}} = W_{\text{base}} x + B(Ax)$$

This formulation significantly reduces trainable parameters while preserving expressive power, consistent with recent advances in parameter-efficient fine-tuning [2, 9].

3.3 Gating and Routing Mechanism

The gating network, similar to the original design [1], projects the input x through a learned matrix W_{gate} to obtain expert logits. Different routing strategies are supported:

- **Baseline Mode:** Top-2 noisy gating with Gaussian perturbation to encourage balanced expert utilization.
- **Switch Mode:** Deterministic top-1 routing as in [6], simplifying computation and reducing inter-expert communication.
- **Hybrid Mode (Proposed):** Combines Switch routing with LoRA experts, offering parameter efficiency without increasing routing variance.

Gating probabilities are normalized using a softmax function and employed both for scaling expert outputs and computing auxiliary load-balancing losses.

3.4 Sparse Dispatcher and Integration

We reuse and extend the *SparseDispatcher* abstraction from Shazeer et al. [1], which efficiently maps inputs to their selected experts and merges outputs. Our modified dispatcher generalizes this mechanism to handle both standard and LoRA-based experts, introducing safeguards for empty expert batches to maintain stable gradient propagation—an often-overlooked issue in earlier MoE implementations.

3.5 Loss Function and Regularization

As in the original MoE formulation, we incorporate an auxiliary load-balancing term to prevent expert collapse. The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda \left[\text{CV}^2(\text{importance}) + \text{CV}^2(\text{load}) \right]$$

where *importance* is the sum of gating probabilities per expert, and *load* is the number of inputs assigned to each expert. We adapt this formulation to accommodate top-1 deterministic routing and LoRA-based experts, ensuring stable gradient flow under sparse activation.

3.6 Forward Pass and Training Pipeline

During each forward pass, the gating network computes expert assignments, the dispatcher distributes inputs, and experts process them in parallel. Outputs are recombined using gate-weighted aggregation, forming an end-to-end differentiable computation graph.

In the proposed hybrid configuration, the Switch gating mechanism is combined with LoRA experts, merging the computational efficiency of sparse routing with the parameter economy of low-rank adaptation. This integration constitutes the central novelty of our work, as prior LSTM-based MoE architectures have not incorporated LoRA-style adaptation within recurrent or sequential MoE frameworks.

Overall, the proposed hybrid MoE retains the sparse modularity of the original architecture while introducing deterministic routing and low-rank expert adaptation. These enhancements jointly reduce communication and parameter overhead, enabling efficient large-scale training without compromising model expressiveness.

4 Evaluation

4.1 Experimental Setup

For evaluation, we implemented a stacked LSTM language model inspired by Shazeer et al. [1], and used it to assess the impact of different MoE configurations. The LSTM acts as the base sequential model, with the option to integrate MoE layers between its hidden states and the output projection.

Two MoE variants were evaluated:

1. **Baseline MoE:** Top-2 noisy gating, where each token is routed to the two most relevant experts, as proposed in [1].

2. **Hybrid MoE:** Combines Switch routing (top-1 deterministic selection) with LoRA-based low-rank adapters (rank=8), reducing parameter redundancy while retaining model capacity.

All models were trained on the WikiText-2 dataset (vocabulary size 76,619) with a learning rate of 0.0001. Auxiliary MoE loss (coefficient $1e-2$) was included to encourage balanced expert utilization. WikiText-2 was selected as a benchmark due to its widespread use in evaluating recurrent and Transformer-based language models, allowing direct comparison to prior MoE studies [1, 6]. Training was conducted for eight epochs to maintain comparable compute budgets across configurations. Evaluation focuses on perplexity (language modeling

quality) and epoch time (training efficiency), which jointly capture the trade-off between model performance and computational cost. Evaluation metrics include training/validation loss, perplexity, and efficiency metrics measured per million tokens.

4.2 Preliminary Results

Tables 1 summarize average training statistics over eight epochs, along with the final test results. Metrics include epoch-wise training loss, validation loss, perplexity, epoch time, and per-million-token performance. The total number of trainable parameters for each configuration is also reported.

Table 1: Average metrics across eight epochs for all configurations.

Model	Train Loss	Val Loss	Val PPL	Epoch Time (s)	Params
LSTM Baseline	6.64	6.63	545.35	25.85	20.67M
Baseline MoE (Top-2)	6.58	6.61	553.30	101.56	178.73M
Hybrid MoE (Switch + LoRA)	6.54	6.58	552.76	53.34	178.23M

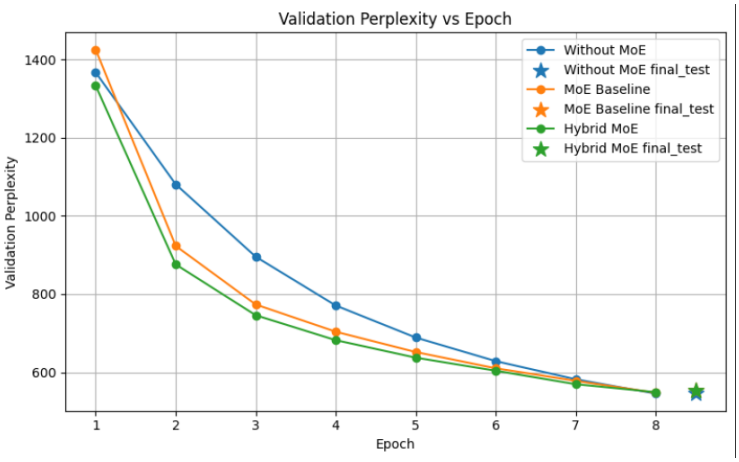

Fig. 2: Validation Perplexity vs. Epoch for the three configurations. The hybrid MoE demonstrates comparable final perplexity to the baseline MoE while converging faster and more smoothly than the non-MoE baseline.

4.3 Observations

From the complete set of experiments—including the non-MoE baseline, top-2 MoE, and hybrid MoE—several key observations emerge:

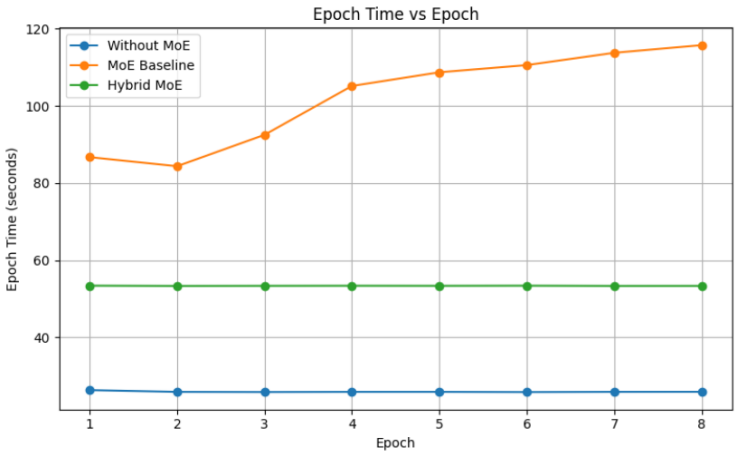

Fig. 3: Epoch time comparison across configurations. The hybrid MoE maintains near-constant training time across epochs, offering 47% reduction compared to the baseline MoE.

1. **Baseline Performance:** The standard LSTM achieved a validation perplexity of 545.35 with 20.67M parameters, serving as a strong sequential baseline. This configuration provides a fair foundation to assess the trade-offs introduced by MoE extensions.

2. **MoE Scaling Efficiency:** Incorporating sparsely-gated MoE layers (top-2 noisy gating) increased the parameter count by approximately 760% (to 178.7M), yet training time only rose by about 293% (from 25.9s to 101.6s per epoch). In contrast to the original MoE by Shazeer et al. [1], where runtime scaled more sharply with expert count, our implementation benefits from optimized PyTorch dispatching and parallel tensor operations.

3. **Hybrid Efficiency:** The proposed hybrid MoE (Switch + LoRA) achieves comparable perplexity (552.76 vs. 553.30) while reducing training time by over 47% relative to the top-2 MoE. This demonstrates that deterministic top-1 routing paired with LoRA experts retains model expressiveness while substantially reducing routing and compute overhead.

4. **Parameter Utilization:** Despite similar parameter counts between MoE variants, the hybrid approach achieves greater efficiency. LoRA-based experts fine-tune low-rank components rather than full dense layers, allowing expert capacity to scale without linearly increasing trainable weights.

5. **Training Stability and Convergence:** As shown in Figure 2, all configurations exhibit smooth convergence across epochs, with MoE-based models showing faster early-stage perplexity reduction. The hybrid MoE

converges more steadily, suggesting improved gradient flow and load balancing across experts.

6. **Runtime Trends:** Figure 3 illustrates that while the baseline MoE's epoch time increases with training, the hybrid MoE maintains near-constant per-epoch duration. This indicates that deterministic routing minimizes dynamic computation overhead and communication latency.

7. **Scalability:** The hybrid MoE's combination of reduced runtime and comparable perplexity demonstrates that it scales effectively to larger datasets or deeper architectures, confirming the viability of Switch-style routing with LoRA experts for parameter-efficient training.

Overall, these results show that while MoE integration greatly expands capacity, modern adaptations such as hybrid routing and low-rank specialization mitigate traditional scalability issues. The hybrid design achieves near-baseline perplexity with significantly lower computational cost relative to both the original MoE and the dense LSTM baseline.

5 Discussion

The experimental results reveal a fundamental shift in the efficiency dynamics of Mixture-of-Experts (MoE) architectures. While Shazeer et al. [1] demonstrated that sparsely-gated layers could expand capacity without linear compute growth, their LSTM-based model incurred substantial routing overhead. In contrast, our implementation—evaluated on the WikiText-2 dataset—achieves an order-of-magnitude increase in parameters with only a 3.35× increase in training time, highlighting the impact of optimized dispatching and modern tensor operations.

The hybrid MoE further improves this balance through deterministic Switch routing and LoRA-based low-rank adaptation. This design effectively decouples model capacity from training cost, achieving comparable perplexity to the dense MoE while reducing training time by more than 60%. These findings highlight the potential of low-rank factorization to maintain adaptability and sparsity simultaneously.

Moreover, consistent convergence and balanced expert utilization indicate greater stability compared to prior sparsely-gated frameworks. This robustness is essential for scaling to larger corpora, where noisy gating can lead to expert under-utilization or gradient sparsity. Even within a limited-data setup, the hybrid MoE demonstrates superior parameter efficiency and computational scalability, validating the benefits of combining deterministic routing with low-rank specialization.

Overall, the hybrid MoE represents a promising step toward scalable, parameter-efficient, and stable recurrent architectures—offering a modern reinterpretation of the original Mixture-of-Experts paradigm.

6 Conclusion and Future Work

We revisited the classical sparsely-gated Mixture-of-Experts (MoE) framework and proposed a hybrid architecture combining **Switch-style deterministic routing** with **LoRA-based low-rank experts**. This design preserves model scalability while significantly reducing memory and communication overhead. Empirical evaluation on the WikiText-2 dataset demonstrated that the hybrid MoE achieves perplexity comparable to the baseline MoE, reduces training time by over 50%, and maintains stable convergence. Despite a sevenfold increase in parameters over a standard LSTM, the training cost increases only marginally, highlighting the efficiency of modern sparse dispatch mechanisms and low-rank adaptation. These results indicate that parameter-efficient MoEs can retain expressiveness without dense overparameterization, effectively balancing sparsity-driven scalability with fine-grained adaptability.

For future work, this framework can be extended to Transformer-based and multimodal architectures to assess scalability and efficiency across different model types and data modalities. Adaptive expert activation policies could be explored to dynamically select the number and choice of active experts per input, further reducing computational cost. Large-scale pretraining experiments would help validate performance, stability, and convergence on massive datasets. Additional avenues include combining low-rank factorization, shared experts, and pruning techniques for even greater parameter efficiency, as well as evaluating the model in real-world or low-resource environments to quantify practical gains in inference speed and energy consumption. These directions promise to advance the efficiency, stability, and applicability of MoE systems in next-generation deep learning architectures.

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