StructMoE : Augmenting MoEs with Hierarchically Routed Low Rank Experts

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Abstract

We introduce *StructMoE*, a method to scale MoEs by augmenting experts with dynamic capacity using structured matrices we call Low Rank Experts (*LoRE*). These *LoREs* are selected on a per-expert and per-token basis using a secondary router specific to every expert and are entangled with the main expert in the up-projection phase of the expert before the activation function. Empirically, we find this approach to outperform a parameter matched MoE baseline in terms of loss on a held out validation set.

1 Introduction

Transformers [17] are now the dominant architecture in NLP, Vision and Audio. Model performance is a function of model size and compute and has well understood scaling laws [8]. However, current models are now pushing the limits of existing hardware. As such, researchers have become interested in alternative ways to scale up models which do not require an increase in compute with model scaling. In this regard, the Mixture of Experts (MoE) [5, 14] approach has become extremely popular as evidenced by the fact that the current generation of foundation models like Gemini [15], DeepSeek [3], Mixtral [10] etc. are all MoEs. MoEs are sparse models as only part of a model is activated to process every input. This has provided researchers with another dimension to scale models along - one where model parameters can be increased without incurring an increase in the total amount of compute.

While MoEs offer scaling advantages over traditional dense models, they still face numerous challeneges in terms of model serving, training instabillity and expert load imbalance. In this paper, we introduce a technique to scale up MoEs by augmenting experts with dynamic capacity using routed *LoREs*. *LoREs* learn further fine-grained features and can provide even more specialized compute for every token thus improving token representations. We evaluate our technique on MoEs with upto 2B total parameters and find that it outperforms a parameter matched standard MoE model in terms of validation set loss[1].

2 Background & Related Works

2.1 Mixture of Experts

At a high level, MoEs are constructed by replacing the feedforward networks (FFNs) in the standard Transformer by an MoE layer. The MoE layer comprises of two components.

[1]Anonymized code is available at https://anonymous.4open.science/r/StructuredMoE-F419/

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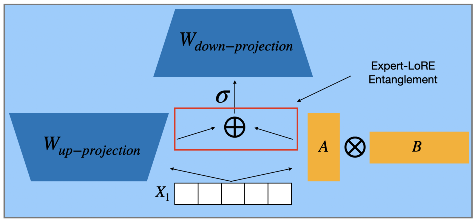
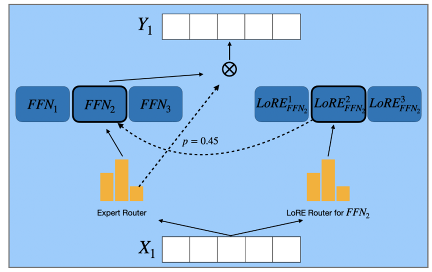


(a) Interaction mechanism between a selected expert and a *LoRE*. The outputs of the *up-projection* from the expert and the *LoRE* get summed before the activation is applied.



(b) Overall scheme for *StructMoE*. Each token gets routed to an expert and then through its corresponding *LoRE* router.

It has N parallel FFNs which are referred to as experts. For every token, only k of these experts will be used to process it. Thus no matter how many experts there are, the total compute will be constant with respect to the choice of k and this allows MoEs to operate as sparse models. The second component is called a router network and is responsible for token-to-expert assignment. For each token in the batch, it produces a distribution over the N experts which represents the suitability of processing that token using that expert. Higher scores for an expert relate to higher suitability. The dominant expert selection strategy to select the k experts to process a token is known as top-k routing [14], where the k experts with the highest expert scores are used to process that token. The router is a learnable component which consists of a linear transformation from the hidden dimension of the token to the number of experts followed by a softmax operation which produces a probability distribution.

2.2 Related Works

LoRa [9] was proposed as a parameter-efficient fine-tuning (PEFT) technique for deep models. It is inspired by the idea that the weight updates during fine tuning are ineherently low rank and thus the benefits of fine tuning can be achieved by explicitly constraining the weight updates to be of low rank. These low rank adapters are learnt during fine tuning and added to the original weight matrices which are frozen. After training LoRas for a particular task, the weight matrices can simply be added to the original weight matrices and thus this technique incurs no additional latency during inference.

Combining multiple LoRas has been an avenue of research but researchers have found that the simple approach of linearly combining mulitple LoRas impairs model performance. Mixture of LoRa experts [18] addresses this issue by learning a gating function over the LoRas and dynamically composing LoRas using the weights provided by the gating function. They find that different LoRas have unique characteristics and this dynamic composition preserves these characteristics even when a large number of LoRas are composed together.

3 Structured Mixture of Experts Using Hierarchical Routing

At a high level, *StructMoE* introduces an alternate way to scale Mixture of Experts. Instead of scaling by adding more experts, we develop a method to augment existing experts with additional dynamic capacity using modules composed of low rank matrices. In doing so, we attempt to introduce techniques used for finetuning into the pretraining stage.

We augment experts by initializing a set of M structured matrices, called *LoREs*, for each expert. The structure is introduced similar to the LoRa technique where each matrix is composed by the outer product of two matrices A and B where $A \in \mathbb{R}^{d \times r}$ and $B \in \mathbb{R}^{r \times ed}$ where d is the hidden dimension, r is the rank of AB and $r \ll d$ and e is the expansion factor of the MLP. During training, a subset, l, of the M *LoREs* are used to update the weights of the up-projection matrix of its corresponding expert by adding the output of AB into the up-projection matrix. The selection of the *LoREs* is done using a secondary router which provides a distribution, π, over all the *LoREs* designated for an expert as illustrated in

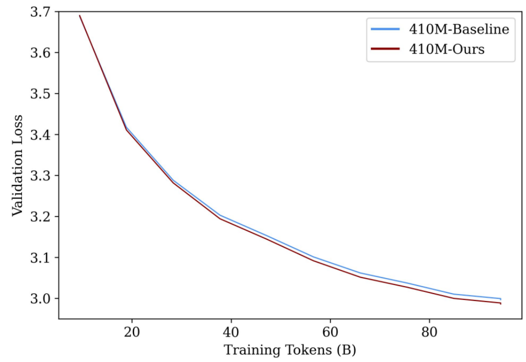


Figure 2: Validation loss curves for a 410M activated parameter model with *StructMoE* and a parameter matched baseline MoE with 13 experts showing *StructMoE* outperforms the baseline. Both models have approximately 2B total parameters and are trained for 100B tokens on Fineweb.

Figure 1b. We select l *LoREs* using the top-k selection scheme. We can represent this scheme using the following equation:

$$W'_{upproj} = W_{upproj} + \Sigma_i^l \pi_i A_i B_i \tag{1}$$

In practice, we use the following equivalent formulation which is more efficient as it does not require materializing the *LoREs*:

$$H = xW_{upproj} + \Sigma_i^l (x \pi_i A_i) B_i \tag{2}$$

where H is the intermediate representation of the MLP that will be passed to the activation function.

Thus, we propose a hierarchical routing scheme where each token, x, is first routed to k experts using the expert router. Then, the token is routed via each of the k expert's *LoRE* router to l of its respective *LoREs*. Finally, the expert and the *LoREs* are entangled together using Eq 2. We illustrate this scheme in Figure 1a. While each expert has a corresponding *LoRE* router to route tokens assigned to it to their respective *LoREs*, our implementation combines all *LoRE* routers such that the *LoREs* for all tokens over all the experts are chosen in parallel.

4 Evaluation

4.1 Experimental setup

Architecture. Our MoE model consists of 24 transformer layers with 16 attention heads and a hidden dimension of 1024. The total parameters in the model are 2B of which 410M are activated for every token as we set $k = 1$ for the top-k routing scheme as in [5]. We use standard MLP blocks as our experts which have an intermediate dimension of 4096 (4x expansion factor) and utilize the GELU [7] activation function. Our *StructMoE* implementation consists of 32 *LoREs* per expert each of which has a rank of 64. The router for the *StructMoE* component is similar to the router for the main experts. Our baseline is a parameter matched MoE with 13 experts.

Data. We train our models either using RedPajama [2] tokenized with the Llama2 [16] tokenizer (32k vocabulary size) or Fineweb [12] tokenized with the Llama3 [4] tokenizer (128K vocabulary size).

Hyperparameters. We use AdamW [11] as our choice of optimizer with a maximum learning rate of 6e$-$4 which is decayed to a minimum of 6e$-$5 using a cosine learning rate decay scheduler [8, 13]. We use a linear learning rate warmup for 1000 steps. Models trained with RedPajama have an effective token batch size of 2^{22} whereas those trained with Fineweb have a token batch size of 2^{21}. This difference is due to the bigger vocabulary size of the Llama3 tokenizer. We train all models for approximately 100B tokens. We set the coefficient for the load balancing loss [5] and z-loss [19] to 0.01. We do not add auxiliary losses to the *LoRE* routers as we observe that they are inherently quite load balanced.

Implementation. We utilize the GPT-NeoX [1] framework which has been integrated with Megablocks [6] for training our models. We train using 64 NVIDIA A100 GPUs split across 8 nodes for a total of approximately 4000 GPU hours per model.

4.2 Results

Main finding. We evaluate our technique by comparing it to a standard MoE model over loss on a held out validation set and plot the results in 2. We can see that *StructMoE* outperforms the baseline over the 100B training run and converges to a lower loss. Moreover, we observe that the gap between the baseline and *StructMoE* increases slightly as training progresses indicating the possibility of further improvement with longer training runs.

4.3 Ablating over design choices

Router free *StructMoE*. We explored the importance of routing in *StructMoE* by experimenting with a single *LoRE* per expert which has the the rank of all *LoREs* combined. This *LoRE* is always activated whenever its corresponding expert is selected, thus eliminating the need for a router for the *LoREs*. We find that the router is critical for the performance of *StructMoE* as we observe almost no performance gain over the standard baseline MoE as indicated in Figure 5 in the Appendix. This is inline with our hypothesis that each *LoRE* learns offsets to the expert which are best suited for that token and thus was selected by the router to process it.

Non-entangled *LoREs*. We also performed ablations where we treat the *LoREs* as standalone experts *i.e.* their outputs get added to the final output of the experts and found that this approach underperformed our entangled *LoREs* indicating the importance of entanglement. We plot the results in Figure 4 in the Appendix.

5 Limitations & Future Work

Limitations. While we show improved performance of *StructMoE* over a parameter matched standard MoE baseline, our performance metric is limited to validation loss. While lower validation loss generally leads to better performance on downstream tasks and benchmarks [5], we are yet to perform these evaluations. We also do not provide a thorough analysis of gains or degradation in hardware utilization due to our method. Moreover, our largest model has approximately 2B total parameters and it is unclear whether this method scales to much larger MoE models.

Future work. Future work involves figuring out the optimal way to scale *StructMoE* in terms of rank / number and deriving a scaling law for this method. It is also worth exploring how this method scales to multi-billion parameter LMs with different routing schemes *i.e.* top-textitk = 2 routing and types of experts *i.e.* fine-grained experts. Integrating *LoREs* with GLU and its variants is also a future avenue for research.

Conclusion. We introduce a new technique to scale MoEs which augments existing experts with additional capacity by way of adding several structured modules to the expert which are selected on a per-token and per-expert bases using a secondary router and are entangled with the main expert. Empirically, we observe that this is a more efficient method to scale MoEs as it leads to lower validation loss when compared to a standard parameter matched MoE baseline.

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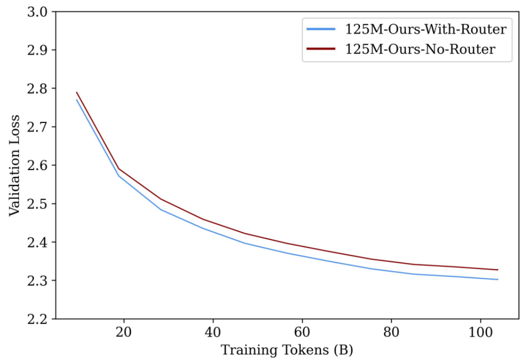

Figure 3: Validation loss curves for a 125M activated parameter model with *StructMoE* and a parameter matched baseline MoE with 10 experts showing *StructMoE* outperforms the baseline. Both models have approximately 710M, total parameters, out of which 125M are activated, and are trained for 100B tokens on RedPajama.

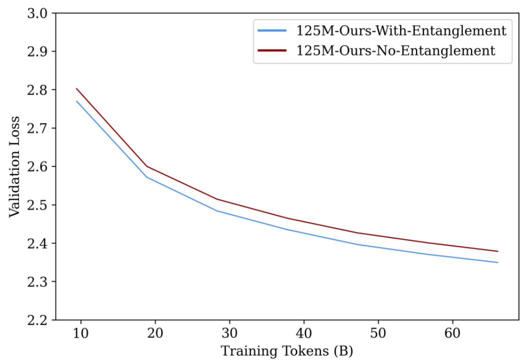

Figure 4: This plot shows the importance of entangling the *LoREs* with their corresponding experts. Using *LoREs* as standalone experts underperforms our entangled *LoRE* technique. Both models have approximately 710M total parameters, with 125M activated, and are trained for 80B tokens on RedPajama

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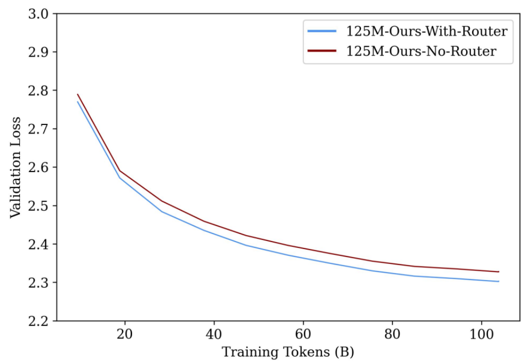

Figure 5: The impact of having routed *LoREs*. We observe that having a single *LoRE* with the capacity of all the routed *LoREs* performs worse than routed *LoREs* which highlights the importance of the dynamic selection of *LoREs*. Models have approximately 710M total parameters, with 125M activated, and are trained for 100B tokens on RedPajama

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