LLaMA-MoE v2: Exploring Sparsity of LLaMA from Perspective of Mixture-of-Experts with Post-Training

Xiaoye Qu¹, Daize Dong¹, Xuyang Hu¹, Tong Zhu², Weigao Sun¹, Yu Cheng³

¹Shanghai AI Laboratory ²Soochow University

³The Chinese University of Hong Kong

{quxiaoye,dongdaize.d,huxuyang,sunweigao}@pjlab.org.cn;

tzhu7@stu.suda.edu.cn; chengyu@cse.cuhk.edu.hk

Abstract

Recently, inspired by the concept of sparsity, Mixture-of-Experts (MoE) models have gained increasing popularity for scaling model size while keeping the number of activated parameters constant. In this study, we thoroughly investigate the sparsity of the dense LLaMA model by constructing MoE for both the attention (i.e., Attention MoE) and MLP (i.e., MLP MoE) modules in the transformer blocks. Specifically, we investigate different expert construction methods and granularities under the same activation conditions to analyze the impact of sparsifying the model. Additionally, to comprehensively evaluate the model's capabilities across various domains (e.g., conversation, code, math) after sparsification, we apply sparsity to the instructed large language models (LLMs) and construct instructed MoE models. To counteract the performance degradation resulting from increased sparsity, we design a two-stage post-training strategy to enhance model performance. Experiments on the LLaMA3 model demonstrate the potential effectiveness of this approach for future developments of instructed MoE models. The source codes and models are available at: https://github.com/OpenSparseLLMs/ LLaMA-MoE-v2.

1 Introduction

Since the introduction of Mixtral (Jiang et al., 2024), Deepseek (DeepSeek-AI, 2024), and Gemini (Reid et al., 2024), Mixture-of-Experts (MoE) have surged in popularity across the academic and industrial spheres. It contains multiple experts but only activates a small part of experts, thus effectively scaling the model parameter while keeping the activation constant.

In this paper, we aim to explore the sparsity of the large language model by converting it to the MoE model. Previous works (Komatsuzaki et al., 2022; He et al., 2024; Zhu et al., 2024b; Team,



Figure 1: (a) Previous works construct MLP MoE models based on pre-trained LLMs and rely on continual pre-training to recover model performance. (b) In contrast, our work builds sparse Attention MoE and MLP MoE models by applying sparsification to the instructed LLM. Furthermore, we utilize post-training to refine the instructed MoE models.

2024; Wei et al., 2024) construct the MoE models from the dense pre-trained LLMs by converting the Multi-Layer Perceptron (MLP) parameters into experts. Subsequently, these MoE models need continual pre-training to improve their performance which consumes huge computation resources. However, such paradigms lead to two significant concerns. First, these works do not take into account the sparsity present in the attention module, and not all attention heads hold equal significance. Second, as shown in Figure 1(a), previous constructed MoE models need two-stage training including both continual pre-training and posttraining to build the instructed MoE, which is both resource-consuming and complex.

In this paper, we aim to study the above two issues. Firstly, we comprehensively study the expert construction strategies for both MLP and attention modules in the Transformer block as shown in Figure 1(b). Considering that the attention module naturally possesses a sparsification property, where different attention heads in LLMs exhibit heterogeneous attention patterns (Fu et al., 2024), therefore we integrate multiple attention heads to form a single expert conceptually. To group attention heads as experts, we take into account the characteristics of grouped query attention (Ainslie et al., 2023) and the expert granularity. Instead, the knowledge stored in the MLP is highly mixed. An intuitive approach to building experts is directly dividing the MLP into multiple experts (Zhu et al., 2024b). Considering there is shared knowledge between different downstream tasks, in this work, we also explore the residual version of MLP MoE (DeepSeek-AI, 2024; Rajbhandari et al., 2022), which extracts the common knowledge from the MLP layers to serve as shared experts, while the remaining parts of the MLP will activate a portion.

With the above sparsity scheme, we can construct both Attention MoE and MLP MoE models. To thoroughly explore the relationship between model performance and sparsity, as shown in Figure 1(b), we make the first attempt to apply this sparsification strategy to the instructed dense LLM, thereby building an instructed MoE model. However, a significant performance drop is observed between the MoE models and the original dense LLM, due to the reduced number of activated parameters and the introduction of gate networks for expert routing. As a result, the newly obtained MoE models require further training to recover performance. Instead of relying on the costly process of continual pre-training, we utilize post-training techniques, such as instruction tuning (IT), to enhance the performance of the instructed MoE models. Specifically, we devise a two-stage training paradigm to improve the model's performance across conversational, coding, and mathematical tasks. To validate the effectiveness of our approach, we sparsify the LLaMA-3 8B model into both MLP-MoE and Attention-MoE models. Experimental results on multiple benchmarks demonstrate the effectiveness and efficiency of our framework.

To sum up, our main contributions are summarized as follows:

- We comprehensively explore the sparsity of the LLaMA model from both the attention and MLP modules by building corresponding MoE models, considering different expert construction strategies and expert granularity.
- We make the first attempt to build MoE models from the instructed dense LLM and recover model performance from the post-training data. Moreover, we devise a two-stage posttraining pipeline to imporve the model's capabilities across various aspects.

 To verify the effectiveness of our framework, we sparsify the LLaMA3-8B model into MoE models. The performance on ten benchmarks demonstrates the effectiveness of our framework for building instructed MoE models.

2 Related Work

Mixture-of-Experts (MoE). Recently, Mixture-of-Experts (MoE) (Zhang et al., 2024; Lu et al., 2024; Zhu et al., 2024a) have surged in popularity across the academic and industrial spheres. MoE (Fedus et al., 2022; Rajbhandari et al., 2022; Lepikhin et al., 2020) is designed to enhance the capacity of deep neural networks while keeping computational costs low. In this paradigm, only a selected subset of parameters, referred to as experts, is activated for each input. Shazeer et al. (2017) are the first to integrate an MoE layer between LSTM layers. The Switch Transformer (Fedus et al., 2022) enhances this by simplifying the gating mechanism to select only the top-1 expert for each token. Gshard (Lepikhin et al., 2020) advances this by refining the top-2 expert routing strategy. Recently, a large number of MoE models have been designed (Jiang et al., 2024; DeepSeek-AI, 2024; Shen et al., 2024; Team, 2024). Among them, Deepseek-MoE (DeepSeek-AI, 2024) introduces shared experts which are dedicated to capturing and consolidating common knowledge across varying contexts. Meanwhile, it designs fine-grained experts and substantially enhances the combinatorial flexibility of activated experts. JetMoE (Shen et al., 2024) is composed of sparse attention and feedforward experts.

Expert Construction from Dense Models. Previous work on obtaining an MoE model from a dense model typically employs duplication or partitioning methods. One intuitive method is to build an MoE by replicating the MLP layer. Sparse upcycling (Komatsuzaki et al., 2022) first explores this idea based on the T5 model. Recently, following this line, Wei et al. (2024) experiment on the decoder-only models and copy the MLP of the original dense model, forming a 16-expert MoE and selecting the top-2 experts. Within this paradigm, the MoE model's total parameters become much larger than those of the dense model, and there is also an increase in the number of parameters being activated. There is another line of work that splits the parameters of the FFNs. Zhu et al. (2024b)



Figure 2: (a) We explore the sparsity of LLaMA by building MoE layers for both the attention and MLP modules. (b) For attention MoE, the attention heads are grouped as experts. (c) For MLP MoE, we extract the shared knowledge as a residual expert and then divide the other parts into multiple independent experts.

splits the parameters of MLP modules and then continues pretraining this converted MoE model. It explores different splitting strategies for the MLP layer. More recently, some work (Team, 2024; He et al., 2024) involves splitting the MLP first and then duplicating it to create fine-grained experts.

3 Methodology

In this paper, we explore the sparsity of the LLaMA model by building MoE models based on it, which construct experts for both the attention and MLP modules. The overall framework is illustrated in Figure 2. After converting to MoE models, only a part of the model parameters will be activated during the training and inference stage. Subsequently, we devise a two-stage post-training strategy to further improve the model performance. Finally, the constructed MoE models can handle different tasks.

3.1 Expert Construction of Attention

Before introducing our expert construction method for attention, we first review the standard multihead self-attention mechanism (Vaswani, 2017). For an input token $X \in \mathbb{R}^{d_h}$, the self-attention is as follows:

$$\operatorname{Attn}(Q, K, V) = \operatorname{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad (1)$$

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V, \quad (2)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{d_h \times d_k}$ are projection matrics, d_h is the hidden size, and d_k is the projected dimension in attention.

To improve the representation capability of the self-attention layer, the multi-head attention (MHA) calculates h distinct low-dimensional projections of (Q, K, V) and concatenates the outputs of them, and finally performs a projection on the concatenated result. The concatenated form of multi-head attention can be represented as:

$$MHA(X) = Concat(H^1, \dots, H^h)W_O, \quad (3)$$

$$H^{i} = \operatorname{Attn}(Q_{i}, K_{i}, V_{i}), \qquad (4)$$

$$Q_i = XW_Q^i, \quad K_i = XW_K^i, \quad V_i = XW_V^i, \quad (5)$$

where we have $W_Q^i, W_K^i, W_V^i \in \mathbb{R}^{d_h \times \frac{d_k}{h}}$ and $W_O \in \mathbb{R}^{d_k \times d_h}$. By considering W_O as a matrix aggregated from h heads W_O^i , there exists a one-to-one correspondence between the query, key, value, and output heads, respectively.

Recently, the grouped query attention (GQA) (Ainslie et al., 2023) has been widely used in large language models, e.g. LLaMA3 (AI@Meta, 2024) and LLaMA2 (Touvron et al., 2023), to replace the standard MHA, which can effectively reduce the size of the KV cache during inference. In GQA, multiple query heads correspond to a single key head in Eq. 4. For instance, in the LLaMA3-8B model, there are 32 query heads but only 8 key

and value heads. Thus, the query heads in GQA have stronger constraints compared to MHA, as consecutive query heads in GQA compute with the same key and value head.

In this work, we convert the attention module into multiple experts to explore the sparsity of the attention module. For an attention module $H = \{H_1, \ldots, H_h\}$ containing h heads, we group these heads into multiple experts E_i in order, each containing several heads. Finally, a router network will activate the top-K experts. Thus, given the input tokens X, the output of the attention MoE is the weighted sum of the outputs from the selected experts:

$$\operatorname{Attn}_{\operatorname{MoE}}(X) = \sum_{i=1}^{h} g_i H_i W_O^i, \qquad (6)$$

where g_i denotes the importance score of the router assigned to a specific attention expert.

3.2 Expert Construction of MLP

Different from the attention module, which is composed of structured heads, the MLP module is more flexible and fine-grained. Formally, the MLP in LLaMA consists of three parts: an up projection $W_{\rm up} \in \mathbb{R}^{d_h \times n}$, a gate projection $W_{\rm gate} \in$ $\mathbb{R}^{d_h \times n}$, and a down projection $W_{\text{down}} \in \mathbb{R}^{n \times d_h}$, where d_h is the hidden size, and n is the number of intermediate neurons in MLP. Therefore, each MLP module can be formulated as a set of neurons $\mathbf{S} = {\mathbf{n}_1, \dots, \mathbf{n}_n}$, and each neuron corresponds to a series of parameter vectors $\mathbf{n}_i := \{W_{\mathrm{up}_{:,i}}, W_{\mathrm{gate}_{:,i}}, W_{\mathrm{down}_{i,:}}\}$. In this paper, we treat the expert construction in MLP as a partition problem of its intermediate neurons. Given the neurons set S and the number of experts $N_{\rm E}$, we aim to obtain a series of subsets $\mathbf{S}_1, \ldots, \mathbf{S}_{N_{\rm E}} \in \mathbf{S}$, with each forming an individual expert.

To study the sparsity of the MLP module, we investigate two kinds of MLP MoE models, namely standard MLP MoE and residual MLP MoE. To build the standard MLP MoE, we evenly divide the parameters of the MLP into multiple experts. The following section describes the process of building the residual MLP MoE, which includes router initialization and importance-based neuron partition.

Router Initialization. The performance of MoE models significantly lies in the router representation (Li and Zhou, 2024). To this end, we propose a clustering method to initialize the router

weights $W_{\rm R} \in \mathbb{R}^{d_h \times N_{\rm E}}$ using hidden features extracted from the original dense model. Specifically, we prepare a validation data set D^{val} and feed the data into the dense model, obtaining sets of hidden features input to the MLP modules for all layers, i.e., $\mathbf{F}_1, \ldots, \mathbf{F}_l$ and $\mathbf{f} \in \mathbb{R}^{d_h}, \forall \mathbf{f} \in \mathbf{F}_{i \in [1,l]}$, where l is the number of layers. Then, we perform a balanced k-means clustering (Malinen and Fränti, 2014) using the L2 distance metric with $N_{\rm E}$ centroids on each \mathbf{F}_i and get corresponding centroid vectors $\mathbf{C}_i = {\mathbf{c}_{1,i}, \ldots, \mathbf{c}_{N_{\mathrm{E}},i} \in \mathbb{R}^{d_h}}.$ The obtained centroid vectors are subsequently initialized as the router weights, denoted as $W_{\mathbf{R}i} \leftarrow \mathbf{C}_i$. This design ensures that all router weights are both representative as each stands for a set of nearest hidden features, and balanced as all clustered sets are of equal size.

Importance-Based Neuron Partition. Following Zhu et al. (2024b), we retain N_E functionally similar neuron sets to form the routed experts $E_{R_1}, \ldots, E_{R_{N_E}}$, and set aside the most-shared neurons to form an always-activated shared expert E_S . The total number of experts is $N_E + 1$. The main adjustments we make to the partitioning strategy are two-fold. First, the token labels are assigned by the classification result from routers instead of pre-clustered data clusters. Second, all neurons are independent, i.e., there are no overlapped neurons across different experts.

To be specific, we maintain a set of score vectors $\mathbf{V} = {\{\mathbf{v}_1, \dots, \mathbf{v}_{N_{\rm E}} \in \mathbb{R}^n\}}$ initialized as zeros for each layer, recording the importance of the intermediate neurons for all experts. Here we neglect the layer index for simplicity. Given a hidden feature f, we calculate its importance $\mathbf{s}_f \in \mathbb{R}^n$ for all neurons **S** by $\mathbf{s}_f := |f \odot \nabla_f L(f)|$, which measures the loss change ΔL for each intermediate neuron when it gets pruned (Lee et al., 2018; Zuo et al., 2022). We then update the corresponding score vector \mathbf{v}_I by $\mathbf{v}_I := \frac{N_I}{N_I+1} \mathbf{v}_I + \frac{1}{N_I+1} \mathbf{s}_f$, where *I* is the index of the nearest expert for *f* determined by router weights $W_{\rm R}$, and N_I is the total number of features assigned to expert I. This process assigns the token to the expert with the highest routing score, which is denoted as $I \leftarrow \arg \max(f \cdot W_{\rm R})$. We forward the whole validation set D^{val} to improve the estimation precision.

After obtaining the importance of neurons for experts, we treat the partition of neurons as a balanced assignment problem and follow the implementation of Zhu et al. (2024b) to get the neuron subsets for

routed experts $E_{R_i} \leftarrow S_i, i \in [1, N_E]$, as well as for the shared expert $E_S \leftarrow (S - \bigcup S_{i \in [1, N_E]})$.

3.3 Load Balance and Total Training Objective

Directly training an MoE model may face load imbalance issues (Muennighoff et al., 2024), namely, there is the risk of routing collapse, where the model consistently chooses only a limited number of experts, thereby hindering the adequate training of other experts and limiting the overall performance of the model.

Following previous works (Fedus et al., 2022), we utilize load balancing loss to penalize the model if it is unbalanced. To calculate it, we multiply the fraction of tokens f_i routed to a specific expert E_i by the total routing probability P_i assigned to E_i for a single batch, and then sum this across all experts N_E .

$$\mathcal{L}_{LB} = N_E \cdot \sum_{i=1}^{N_E} f_i \cdot P_i \tag{7}$$

Thus, the total training objective for our MoE models is balancing loss \mathcal{L}_{LB} and traditional crossentropy loss for language modeling \mathcal{L}_{LM} . Here, we omit the specific loss of the cross-entropy loss. Furthermore, we adopt a hyper-parameter α to balance these two losses when training the MoE models. For all experiments and all MoE models, we set the hyper-parameter α to 0.01 (Zhu et al., 2024b; Muennighoff et al., 2024).

$$\mathcal{L}_{all} = \mathcal{L}_{LM} + \alpha \mathcal{L}_{LB} \tag{8}$$

3.4 Two-Stage Post-Training

After constructing the MoE models, we utilize instruction tuning to recover the model's performance. To prompt the model to deal with different abilities, we collect open-source datasets that encompass a diverse range of topics, including general conversation, mathematical problems, and code generation. Inspired by (Dong et al., 2023), we adopt a two-stage training pipeline for instruction tuning. Specifically, in the first stage, we train the constructed MoE models with general abilities such as conversation and email writing. Subsequently, in the second stage, we equip the model with math and coding abilities. It is worth noting that during the second stage of training, we also incorporate some general ability data. This prevents the model from losing its broader, more general

skills as it becomes more specialized in math and code tasks.

4 Experiment

4.1 Training Datasets

In this paper, we propose a two-stage instruction tuning process to recover the performance of our partitioned MoE models. Our training dataset is divided into two parts. The first part primarily includes conversation data from sources such as LIMA (Zhou et al., 2024), OpenHermes (Teknium, 2023), ShareGPT (Wang et al., 2023), BAAI Infinity Instruct (BAAI, 2024), and Magpie (Xu et al., 2024). In the second stage, we conduct experiments using code and data from BAAI and MetaMathQA (Yu et al., 2023), along with a small portion of conversation data from the first stage. The composition of the dataset and the number of training tokens are detailed in Table 2. Notably, we construct three versions of the dataset for first-stage instruction tuning, ranging from 0.40B, 1.28B, to 2.50B tokens.

4.2 Benchmarks and Comparing Models

To comprehensively assess our model's performance under various criteria, we evaluate the following benchmarks: 32-shot BoolQ, 0-shot PIQA (Bisk et al., 2020), 0-shot SciQ (Welbl et al., 2017), 5-shot MMLU (Hendrycks et al., 2020), 5-shot Winogrande (Sakaguchi et al., 2021), 25-shot ARC-Challenge (Clark et al., 2018), 10-shot HellaSwag (Zellers et al., 2019), 8-shot GSM8K (Cobbe et al., 2021), and the Pass@10 score for HumanEval (Chen et al., 2021). We evaluate the results on common benchmarks from the LM Evaluation Harness¹ (Gao et al., 2024). Moreover, as our framework is applied to instructed models, we also utilize the Instruction-Following Eval (IFEval) (Zhou et al., 2023). In appendix, we present several generation samples from our MoE model in Tables 3 and 4.

4.3 Implementation Details

In this paper, we conduct experiments on the LLaMA3-8B model (AI@Meta, 2024) to investigate the sparsity of both the attention and MLP modules by converting them to MoE. All models are trained on 32 NVIDIA-A100 (80G) GPUs. We train for two epochs during both the first-stage and second-stage instruction tuning. Therefore, the

¹For fair comparison and re-implementation, we use the commit id d14b36e81aea4cef.



Figure 3: (a) The performance of Attention MoE with different numbers of activated experts. (b) The performance of Attention MoE with varying granularities while keeping the activation ratio to 50%. (c) The performance of the MLP MoE model with different numbers of activated experts and varying expert types.

training budget is 5.0B tokens for the first-stage instruction tuning and 2.0B for the second stage. The context length is 4096. To speed up training, we pack multiple instances into one sample. The maximum learning rate is set to 2e-5 with a 0.03 warmup ratio, and the final learning rate decays to 2e-6 using cosine scheduling. For both attention MoE and MLP MoE, we apply a balance loss to promote an even distribution of experts, with a coefficient of 0.01. Since our model is based on LLaMA3, we adopt the same chat format² to ensure versatile task representation. More details on the implementation can be found in our open-source code.

5 Analysis

In this section, we comprehensively investigate the sparsity of the LLaMA model, specifically the (i) attention and (ii) MLP module, and (iii) compare the sparsity between them.

5.1 Exploring Sparsity of Attention

Takeaway: • Activating less than half of the parameters in Attention leads to a significant performance decline. • Increasing the expert granularity leads to performance improvement but too large granularity damages.

In this section, we explore the sparsity of the attention module by comparing different approaches to building experts for Attention MoE. The experiments in this study are limited to the first-stage instruction tuning, where we assess the language ability. All experiments are conducted with 0.40B instruction tokens, as shown in Table 2. As shown in Figure 3(a), we begin by splitting the attention heads into 8 experts and activating different numbers of experts. For example, when two experts are activated, we denote this configuration as "8top2". When more than half of the heads are activated, the model's performance rapidly approaches that of the dense LLaMA-3 model. In contrast, activating only a few heads results in a notable performance degradation.

Additionally, we explore the performance of finegrained experts, as shown in Figure 3(b). We observe that as the granularity of the experts increases from 8 to 16, the model's performance improves. However, when the granularity becomes too large (e.g., 32 experts), performance starts to decline.

To further validate the effectiveness of our "16top8" variant, we scale the training data from 0.4B to 1.28B tokens, as shown in Figure 4(a). Here, we present results from five benchmarks, including Hellaswag and MMLU, for a comprehensive evaluation of our Attention MoE. The results demonstrate favorable scaling properties, with performance improving as the dataset size increases. Notably, the performance on SciQ, Hellaswag, and MMLU shows significant improvement.

5.2 Exploring Sparsity of MLP

Takeaway: • Activating half of the parameters in MLP already achieves moderate performance. • Different MLP MoE construction methods present diverse characteristics, but both share favorable scaling properties.

Building on the previous study of Attention MoE, in this section, we explore the sparsity of the MLP module. The experiments are conducted using the same 0.40B instruction data as in the previous section. First, we investigate the impact of different numbers of activated experts when splitting the MLP into 8 experts. As shown in Figure 3(c), activating half of the experts (i.e., 4 experts) achieves moderate performance.

We also compare different types of MLP MoE, including the standard MoE, which evenly splits the MLP into 8 experts and activates 2 experts,

²https://llama.meta.com/docs/model-cards-and-promptformats/meta-llama-3/

Table 1: Comparison of our MoE model with open-source dense and MoE models. All models in this table are **instructed versions** from their official repository. The detailed settings of benchmarks are described in Section 4.2. As our MoE models are from the LLaMA3-8B model, we place the result of this model in the first line for reference. We only highlight the **best performance** among our MoE models and competitive methods except for LLaMA3-8B. Here we further report the training budgets (#Tokens) for each model in the table.

	# Tokens	BoolQ	SciQ	PIQA	ARC-C	TruthfulQA	HellaSwag	MMLU	GSM8K	HumanEval	IFEval
LLaMA3-8B	15T	83.00	93.20	78.51	61.86	51.71	78.79	67.22	76.50	71.38	76.53
INCITE-3B	1T	66.54	94.70	74.43	40.19	36.40	65.61	25.10	2.12	6.92	30.13
Sheared-LLaMA-2.7B	50B	67.58	76.80	75.84	41.13	47.65	71.28	28.28	1.90	3.29	28.84
Gemma-2-2b	2T	72.29	75.80	67.46	52.56	50.79	68.97	52.99	26.31	46.12	34.94
Salamandra-2b	7.8T	67.98	89.80	74.65	46.25	43.39	62.27	25.13	1.90	5.82	27.72
SmolLM2-1.7B	11T	68.23	84.30	75.95	53.24	39.89	72.55	50.42	38.51	39.05	29.02
OpenMoE-3B-9B	1T	61.71	68.40	65.67	33.28	40.49	56.45	26.46	1.36	1.01	31.24
LLaMA-MoE-3B-7B	200B	68.10	88.80	77.91	44.03	33.29	73.23	28.24	4.62	12.02	28.10
OLMoE-1B-7B	1T	80.89	94.90	80.09	55.63	43.26	79.58	53.79	40.94	40.48	35.49
MLP-MoE (8top2)	7B	74.62	90.60	69.26	42.83	45.62	58.95	37.41	53.07	53.53	32.72
MLP-MoE (1+7top1)	7B	76.88	88.80	67.90	40.19	46.85	53.67	40.89	55.04	51.21	36.04



Figure 4: (a) Scaling the training data for Attention MoE. (b) Scaling the training data for MLP MoE with uniform expert partition. (c) Scaling the training data for MLP MoE with a shared expert. (d) The performance comparison of the second-stage instruction tuning data ratio.

and the residual MoE, which has 1 shared expert and 7 distinct experts. Both MoE models have the same number of activated parameters. Notably, the residual MoE outperforms the standard MoE in the SciQ benchmark, with only 25% activation, surpassing the standard MoE with 50% activation.

Furthermore, similar to the Attention MoE, we scale the training instruction data to 1.28B and 2.50B tokens and evaluate the performance of both MLP MoE models. As shown in Figure 4(a) and Figure 4(b), our MLP MoE demonstrates favorable scaling properties across benchmarks. However, we observe that the Hellaswag metric remains relatively low due to the splitting of the MLP and limited training data, suggesting that additional data is needed to improve language ability. Additionally, when comparing the two MoE models, we find that the standard MoE performs significantly better on the Hellaswag metric, while the residual MoE slightly outperforms it on the MMLU benchmark. We attribute this discrepancy to the fact that the residual MoE relies on a stronger prior, which enhances its knowledgeability but reduces flexibility.

5.3 Sparsity Comparison of Attention and MLP

After investigating the variants of Attention MoE and MLP MoE in the above two sections, in this section, we compare the sparsity of these two kinds of modules. As depicted in Figure 3 (a) and (c), "8top2" in MLP MoE already performs better than "8top4" in Attention MoE, suggesting that MLP has more sparsity than the Attention module. For instance, "8top4" Attention MoE achieves 0.54 on PIQA, but "8top2" MLP MoE obtains 0.66. This trend remains when we increase the granularity of the Attention MoE, but the divergence has narrowed. Intriguingly, when scaling the training data, as shown in Figure 4 (a) and (b), we observe that "16top8" Attention MoE presents varying levels of ability. For instance, it performs worse than "8top2" MLP on BoolQ, PIQA, SciQ, but achieves better results on HellaSwag and MMLU.

5.4 Two-Stage Post-Training

In this study, we devise a two-stage instruction tuning to improve the model performance. Specif-



Figure 5: The router distribution of MLP MoE model (8top2). We demonstrate the distribution of the first layer and last layer for four different benchmark datasets.

ically, we first train our moe model with single conversation data to improve the model's language ability. Subsequently, we train the math and code instruction data to prompt the model to handle corresponding tasks. Notably, in this stage, we will also incorporate some conversation data to ensure that the model does not lose its conversational abilities. The conversation data is sampled from the first phase, and we control the relative proportion of conversation data to math and code data. As shown in Figure 4(d), based on the standard MLP MoE, which contains 8 experts and activates two, we incorporate different ratios of conversation in the second-stage training. The baseline indicates the result after training in the first stage, and it performs especially poorly on the HumanEval benchmark. Moreover, we compare three different settings for second-stage training by incorporating 5%, 10%, and 50% training data from the first stage. We can observe that 10% of conversation data leads to the best performance among all variants. Especially on the HumanEval, it achieves 53.53, significantly better than other variants.

5.5 Performance Scaling

As shown in Table 1, in order to demonstrate the effectiveness of our framework, we present the results of our two variants of MLP-MoE, which possess the same parameters 8.0B with LLaMA3-8B but only activate 3.8B parameters. In this table, we compare different abilities covering language ability, math, code, and instruction following. Specifically, we first compare our MLP-MoE models with the original LLaMA3-8B model, and our MLP-MoE significantly recovers the performance with only a small amount of post-training data. Further-

more, we compare our MLP-MoE with recent opensource large language models with similar activation parameters, including both dense models and MoE models. From the results, we can observe that our model achieves comparable performance with these models but obtains better math and code ability. For instance, our MLP-MoE (8top2) achieves 53.07 on the GSM8K benchmark, while previous dense gemma-2-2b only reaches 26.31. Moreover, OpenMoE and LLaMA-MoE demonstrate significantly worse results than our model on MMLU, GSM8K, and HumanEval.

5.6 What are the Experts Specializing in?

In this section, we visualize the routing distribution of the MLP MoE model after the second-stage training. As shown in Figure 5, we notice that the router has a different tendency for each layer. For the first layer, experts 1, 3, 7, and 8 handle a relatively large number of tokens. However, in the final layer, experts 1, 4, and 7 handle the most tokens. To further study this phenomenon, we count the total number of tokens handled by experts across all layers and find that the number of tokens processed by each expert is basically equal, indicating that our balance loss is functioning effectively.

5.7 Discussion

The key differences between our paper and previous work are as follows: (i) We explore sparsity in both the Attention and MLP modules, whereas other studies typically focus on one of these modules. (ii) Our work investigates the sparsity of the instruction-tuned model, rather than the pre-trained model, thus covering a more comprehensive range of capabilities including conversation, math, code. (iii) To enhance the performance of the MoE models, we propose a two-stage post-training method, avoiding the resource-intensive process of continual pre-training. The experiment results verify the effectiveness of our two-stage training for building an instructed MoE model.

6 Conclusion and Future Work

In this paper, we comprehensively explore the sparsity of the LLaMA model from both the attention and MLP modules by building corresponding MoE models. Specifically, we investigate different expert construction methods and granularities to analyze the impact of sparsifying the model. Furthermore, to have a comprehensive study of model ability, we make the first attempt to build instructed MoE models from the instructed dense LLM and recover model performance with a devised two-stage post-training stage. The experiments verify the effectiveness of our method to build an instructed MoE with a small amount of training tokens.

In the future, we plan to (i) explore sparsification techniques on additional LLaMA models, such as LLaMA 3.1, (ii) investigate more effective methods for splitting both Attention MoE and MLP MoE, and (iii) further collect instruction tuning data to train the instructed MoE models. Our experiments have demonstrated promising scaling performance, and we hope to leverage post-training to develop a highly effective instructed MoE model.

References

AI@Meta. 2024. Llama 3 model card.

- Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebrón, and Sumit Sanghai. 2023. Gqa: Training generalized multi-query transformer models from multi-head checkpoints. *arXiv preprint arXiv:2305.13245*.
- BAAI. 2024. Infinity instruct. arXiv preprint arXiv:2406.XXXX.
- Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. 2020. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 7432–7439.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*.

- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*.
- DeepSeek-AI. 2024. DeepSeek-v2: A strong, economical, and efficient mixture-of-experts language model. *Preprint*, arXiv:2405.04434.
- Guanting Dong, Hongyi Yuan, Keming Lu, Chengpeng Li, Mingfeng Xue, Dayiheng Liu, Wei Wang, Zheng Yuan, Chang Zhou, and Jingren Zhou. 2023. How abilities in large language models are affected by supervised fine-tuning data composition. *arXiv preprint arXiv:2310.05492*.
- William Fedus, Barret Zoph, and Noam Shazeer. 2022. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. *Journal of Machine Learning Research*, 23(120):1–39.
- Tianyu Fu, Haofeng Huang, Xuefei Ning, Genghan Zhang, Boju Chen, Tianqi Wu, Hongyi Wang, Zixiao Huang, Shiyao Li, Shengen Yan, et al. 2024. Moa: Mixture of sparse attention for automatic large language model compression. *arXiv preprint arXiv:2406.14909*.
- Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2024. A framework for few-shot language model evaluation.
- Ethan He, Abhinav Khattar, Ryan Prenger, Vijay Korthikanti, Zijie Yan, Tong Liu, Shiqing Fan, Ashwath Aithal, Mohammad Shoeybi, and Bryan Catanzaro. 2024. Upcycling large language models into mixture of experts. *arXiv preprint arXiv:2410.07524*.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. arXiv preprint arXiv:2009.03300.
- Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. 2024. Mixtral of experts. arXiv preprint arXiv:2401.04088.
- Aran Komatsuzaki, Joan Puigcerver, James Lee-Thorp, Carlos Riquelme Ruiz, Basil Mustafa, Joshua Ainslie, Yi Tay, Mostafa Dehghani, and Neil Houlsby.

2022. Sparse upcycling: Training mixture-ofexperts from dense checkpoints. *arXiv preprint arXiv:2212.05055*.

- Namhoon Lee, Thalaiyasingam Ajanthan, and Philip HS Torr. 2018. Snip: Single-shot network pruning based on connection sensitivity. *arXiv preprint arXiv:1810.02340*.
- Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. 2020. Gshard: Scaling giant models with conditional computation and automatic sharding. *arXiv preprint arXiv:2006.16668*.
- Ziyue Li and Tianyi Zhou. 2024. Your mixture-ofexperts llm is secretly an embedding model for free. *arXiv preprint arXiv:2410.10814*.
- Zhenyi Lu, Chenghao Fan, Wei Wei, Xiaoye Qu, Dangyang Chen, and Yu Cheng. 2024. Twin-merging: Dynamic integration of modular expertise in model merging. *arXiv preprint arXiv:2406.15479*.
- Mikko I. Malinen and Pasi Fränti. 2014. Balanced kmeans for clustering. In *Structural, Syntactic, and Statistical Pattern Recognition*, pages 32–41, Berlin, Heidelberg. Springer Berlin Heidelberg.
- Niklas Muennighoff, Luca Soldaini, Dirk Groeneveld, Kyle Lo, Jacob Morrison, Sewon Min, Weijia Shi, Pete Walsh, Oyvind Tafjord, Nathan Lambert, Yuling Gu, Shane Arora, Akshita Bhagia, Dustin Schwenk, David Wadden, Alexander Wettig, Binyuan Hui, Tim Dettmers, Douwe Kiela, Ali Farhadi, Noah A. Smith, Pang Wei Koh, Amanpreet Singh, and Hannaneh Hajishirzi. 2024. Olmoe: Open mixture-of-experts language models. *Preprint*, arXiv:2409.02060.
- Samyam Rajbhandari, Conglong Li, Zhewei Yao, Minjia Zhang, Reza Yazdani Aminabadi, Ammar Ahmad Awan, Jeff Rasley, and Yuxiong He. 2022. Deepspeed-moe: Advancing mixture-of-experts inference and training to power next-generation ai scale. In *International conference on machine learning*, pages 18332–18346. PMLR.
- Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy Lillicrap, Jean-baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. arXiv preprint arXiv:2403.05530.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2021. Winogrande: An adversarial winograd schema challenge at scale. *Communications of the ACM*, 64(9):99–106.
- Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, and Jeff Dean. 2017. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *arXiv preprint arXiv:1701.06538*.

- Yikang Shen, Zhen Guo, Tianle Cai, and Zengyi Qin. 2024. Jetmoe: Reaching llama2 performance with 0.1 m dollars. *arXiv preprint arXiv:2404.07413*.
- Qwen Team. 2024. Qwen1.5-moe: Matching 7b model performance with 1/3 activated parameters".
- Teknium. 2023. Openhermes 2.5: An open dataset of synthetic data for generalist llm assistants.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv*:2307.09288.
- A Vaswani. 2017. Attention is all you need. Advances in Neural Information Processing Systems.
- Guan Wang, Sijie Cheng, Xianyuan Zhan, Xiangang Li, Sen Song, and Yang Liu. 2023. Openchat: Advancing open-source language models with mixed-quality data. *arXiv preprint arXiv:2309.11235*.
- Tianwen Wei, Bo Zhu, Liang Zhao, Cheng Cheng, Biye Li, Weiwei Lü, Peng Cheng, Jianhao Zhang, Xiaoyu Zhang, Liang Zeng, et al. 2024. Skyworkmoe: A deep dive into training techniques for mixture-of-experts language models. arXiv preprint arXiv:2406.06563.
- Johannes Welbl, Nelson F Liu, and Matt Gardner. 2017. Crowdsourcing multiple choice science questions. *arXiv preprint arXiv:1707.06209.*
- Zhangchen Xu, Fengqing Jiang, Luyao Niu, Yuntian Deng, Radha Poovendran, Yejin Choi, and Bill Yuchen Lin. 2024. Magpie: Alignment data synthesis from scratch by prompting aligned llms with nothing. *arXiv preprint arXiv:2406.08464*.
- Longhui Yu, Weisen Jiang, Han Shi, Jincheng Yu, Zhengying Liu, Yu Zhang, James T Kwok, Zhenguo Li, Adrian Weller, and Weiyang Liu. 2023. Metamath: Bootstrap your own mathematical questions for large language models. *arXiv preprint arXiv:2309.12284*.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. Hellaswag: Can a machine really finish your sentence? *arXiv preprint arXiv:1905.07830*.
- Jihai Zhang, Xiaoye Qu, Tong Zhu, and Yu Cheng. 2024. Clip-moe: Towards building mixture of experts for clip with diversified multiplet upcycling. *arXiv preprint arXiv:2409.19291*.
- Chunting Zhou, Pengfei Liu, Puxin Xu, Srinivasan Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. 2024. Lima: Less is more for alignment. *Advances in Neural Information Processing Systems*, 36.

- Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. 2023. Instruction-following evaluation for large language models. *arXiv preprint arXiv:2311.07911*.
- Tong Zhu, Daize Dong, Xiaoye Qu, Jiacheng Ruan, Wenliang Chen, and Yu Cheng. 2024a. Dynamic data mixing maximizes instruction tuning for mixture-ofexperts. *arXiv preprint arXiv:2406.11256*.
- Tong Zhu, Xiaoye Qu, Daize Dong, Jiacheng Ruan, Jingqi Tong, Conghui He, and Yu Cheng. 2024b. Llama-moe: Building mixture-of-experts from llama with continual pre-training. *arXiv preprint arXiv:2406.16554*.
- Simiao Zuo, Qingru Zhang, Chen Liang, Pengcheng He, Tuo Zhao, and Weizhu Chen. 2022. Moebert: from bert to mixture-of-experts via importance-guided adaptation. *arXiv preprint arXiv:2204.07675*.

A Dataset Information and Processing

In this section, we describe the composition of the dataset used in the two-stage Instruction tuning. As shown in Table 2, we construct three datasets of different sizes by combining open-source datasets, including OpenHermes-2.5³, Lima⁴, ShareGPT4⁵, SlimOrca⁶, BAAI/Infinity-Instruct⁷, and Llama-3-Magpie-Air-3M-v0.1⁸. When merging multiple datasets, we apply filtering to ensure the quality of the datasets. Subsequently, we adopt the MetaMathQA⁹ and the code and math part of the BAAI/Infinity-Instruct.

B Generation Cases

In this section, we present some examples from the IFEval and GSM8K benchmarks to demonstrate that our model exhibits good instruction-following and math capabilities.

anon8231489123/ShareGPT_Vicuna_unfiltered

⁸https://huggingface.co/datasets/Magpie-Align/ Llama-3-Magpie-Air-3M-v0.1

Table 2: Dataset Composition of the Instruction F	ollow
ing Training Stage.	

Dataset Composition	Tokens		
First-Stage Instruction Tuning			
OpenHermes-2.5	0.40B		
Lima			
ShareGPT4			
SlimOrca			
OpenHermes-2.5	1.28B		
Lima			
ShareGPT4			
SlimOrca			
BAAI/Infinity-Instruct			
OpenHermes-2.5	2.50B		
Lima			
ShareGPT4			
SlimOrca			
BAAI/Infinity-Instruct			
Llama-3-Magpie-Air-3M-			
v0.1			
Second-Stage Instruction	Funing		
MetaMathQA			
BAAI/Infinity-Instruct/code			
BAAI/Infinity-Instruct/math			
Conversation from First-stage	0.99B		

³https://huggingface.co/datasets/teknium/ OpenHermes-2.5

⁴https://huggingface.co/datasets/GAIR/lima
⁵https://huggingface.co/datasets/

⁶https://huggingface.co/datasets/Open-Orca/ SlimOrca

⁷https://huggingface.co/datasets/BAAI/ Infinity-Instruct/tree/main

⁹https://huggingface.co/datasets/meta-math/ MetaMathQA

Table 3. Examples from our	I I aMA-MoE v2 model	The examples are from	the IFEval benchmark
Tuble 5. Examples from our	LLuivin a mole v2 model.	The examples are nom	the fi Lvai benefiniark.

Query	Response
Query Who built the first artificial ice rink? Please include the keys (1) Name (2) Location and (3) Year. Use less than 150 words. Write a short essay about the updates of the latest episode of your favorite TV show. Use less than 300 words.	Response The first artificial ice rink was built by the French engineer, Pierre de Chambolle, in 1889. Chambolle's ice rink was located in Paris, France. The ice rink was made of a combination of ice and water, and it was heated by a steam engine. Chambolle's invention revolutionized the world of ice sports and paved the way for the development of modern artificial ice rinks. The latest episode of my favorite TV show, "The Walking Dead," has been a thrilling ride. The episode picks up where the previous one left off, with the survivors of the group dealing with the aftermath of the recent attack on the town. The group is now on their way to the nearby town of Woodbury, where they hope to find safety and a new beginning. As they journey through the post-apocalyptic landscape, they encounter a number of new characters, including a young girl who has been surviving on her own. The group is initially wary of her, but as they get to know her, they realize that she is a valuable asset to their group. The episode also introduces a number of new plot twists, includ- ing the revelation that the group's leader, Rick Grimes, has been secretly working with a group of survivors to take down the walkers. This adds a new layer of complexity to the story, and raises questions about the true nature of the group's mission. Overall, the latest episode of "The Walking Dead" is a gripping
	Overall, the latest episode of "The Walking Dead" is a gripping and intense ride, with plenty of action, suspense, and emotional moments. The characters are well-developed, and the plot is engaging and unpredictable. If you haven't already, I highly recommend checking it out.
Invent a funny tagline for a	"Laugh your way to the stars with us at the 'Laughing Llama'
local comedy show, and put	comedy show, where even the most awkward jokes are guaran-
your whole response in double quotes.	teed to make you giggle!"
What is another word for En-	carvings
gravings? Answer in lowercase	
ietters only, throughout your en-	
ure answer.	

Table 4: Examples from our LLaMA-MoE v2 model. The examples are from the GSM8K benchmark.

Query	Response
At a restaurant, Juice Box A is 4 dollars. Juice Box B is 5 dollars more than Juice Box A. Juice Box C is 7 dollars more than	Juice Box A is 4 dollars. Juice Box B is 5 dollars more than Juice Box A, so it is $4 + 5 = 9$ dollars. Juice Box C is 7 dollars more than Juice Box A, so it is $4 + 7 = 11$ dollars. To find out how much more Juice Box C is than Juice Box B, we subtract
Juice Box A. How much more is Juice box C than Juice Box B?	the price of Juice Box B from the price of Juice Box C: $11 - 9 = 2$. The answer is 2.
After Andrea saved some money, she then spent the rest of her money on an \$11 sweater and gave her brother \$4. If she had \$36 in the beginning, how much did Andrea save?	Andrea had \$36 in the beginning. She spent \$11 on a sweater and gave her brother \$4. So she spent $11 + 4 = 15$ dollars. $36 - 15 = 21$. The answer is 21.
Carver just turned 45 years old, which makes him 5 years less than twice the age of his son. How old is his son, in years?	Let's call Carver's son's age "S". According to the information, 5 years less than twice the age of his son is 45. So, $2S - 5 = 45$. Adding 5 to both sides, we get $2S = 50$. Dividing both sides by 2, we find $S = 25$. The answer is 25.
Michael is racing his horse and notices that for every mile the horse runs, he eats 1/2 a bail of hay. A bail of hay costs \$3. If his horse runs for 30 minutes at 32MPH, and Michael has six 5 dollar bills, how much change does he have after he buys the hay?	First, we need to find out how many miles the horse runs. 30 minutes is $30 / 60 = 0.5$ hours. At 32MPH, the horse runs $0.5 \times 32 = 16$ miles. For every mile, the horse eats $1/2$ a bail of hay. So the horse eats $16 \times 1/2 = 8$ bails of hay. A bail of hay costs \$3, so 8 bails cost $8 \times 33 = 24 . Michael has six 5 dollar bills, so he has $6 \times 55 = 30 . After buying the hay, he has $$30 - $24 = 6 left. The answer is 6.
Melissa works as a pet groomer. This week, she has 8 dogs that need to be bathed, 5 cats that need their nails clipped, 3 birds that need their wings trimmed, and 12 horses that need to be brushed. If she splits the groom- ing jobs evenly over the days, how many animals will she groom each day of the week?	Melissa has a total of $8 + 5 + 3 + 12 = 28$ animals to groom. If she splits them evenly over 7 days, she will groom $28 / 7 = 4$ animals each day. The answer is 4.
Mason is on his bike journey at a rate of 8 miles per hour. He travels for 4 hours, takes some rest, and then goes on for an- other 6 hours. How many miles has he traveled in total?	Mason travels for 4 hours at 8 miles per hour, so he covers 4 x $8 = 32$ miles. Then he goes for another 6 hours at 8 miles per hour, so he covers 6 x $8 = 48$ miles. In total, he has traveled $32 + 48 = 80$ miles. The answer is 80.