Mixture-of-Experts with Expert Choice Routing

Anonymous Author(s)
Affiliation
Address
email

Abstract

Sparsely-activated Mixture-of-experts (MoE) models allow the number of parameters to greatly increase while keeping the amount of computation for a given token or a given sample unchanged. However, a poor expert routing strategy can cause certain experts to be under-trained, leading to an expert being under or over-specialized. Prior work allocates a fixed number of experts to each token using a top-k function regardless of the relative importance of different tokens. To address this, we propose a heterogeneous mixture-of-experts employing an expert choice method. Instead of letting tokens select the top-k experts, we have experts selecting the top-k tokens. As a result, each token can be routed to a variable number of experts and each expert can have a fixed bucket size. We systematically study pre-training speedups using the same computational resources of the Switch Transformer top-1 and GShard top-2 gating of prior work and find that our method improves training convergence time by more than $2\times$. For the same computational cost, our method demonstrates higher performance in fine-tuning 11 selected tasks in the GLUE and SuperGLUE benchmarks. For a smaller activation cost, our method outperforms the T5 dense model in 7 out of the 11 tasks.

1 Introduction

Scaling up model capacity, dataset size, and training time has demonstrated huge success in enhancing the performance of computer vision architectures [4, 11, 13, 14] as well as neural language models [2, 20, 26, 27]. The final model quality has been found to have a power-law relationship with the amount of data, model size, and compute time [16, 20]. However, training efficiency, which is defined as the total amount of computation used to achieve superior model quality than the state of the art system [21], should receive greater attention as we increase our efforts towards green AI [29].

Sparsely gated mixture-of-experts [31] (MoE) provides an effective way to scale model capacity given a fixed computational cost, and has recently played an important role in increasing the training efficiency of large-scale language models [10, 21]. MoE operate by adopting a number of experts, each as a sub-network, and by activating only one or a few experts for each input token. A gating network must be chosen and optimized in order to route each token to the most suited expert(s). For example, recent work has implemented sparse routing via k-means clustering [12], linear assignment to maximize token-expert affinities [22], or hashing [8, 28]. Many of the prior work use a routing strategy concerning the *token choice*, where each token selects the best one or two experts.

We argue that the independent token choice of prior work often leads to an imbalanced load of experts, which causes training inefficiency and sub-optimal training of the model. In order to mitigate this issue, previous sparsely gated networks introduce additional auxiliary losses as regularization to prevent too many tokens being routed to a single expert, but the effectiveness is still limited. Recent approaches [8, 22, 28] explore alternative strategies for routing, but they focus on pre-training only and do not demonstrate performance gain on downstream tasks. Moreover, none of the previous

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

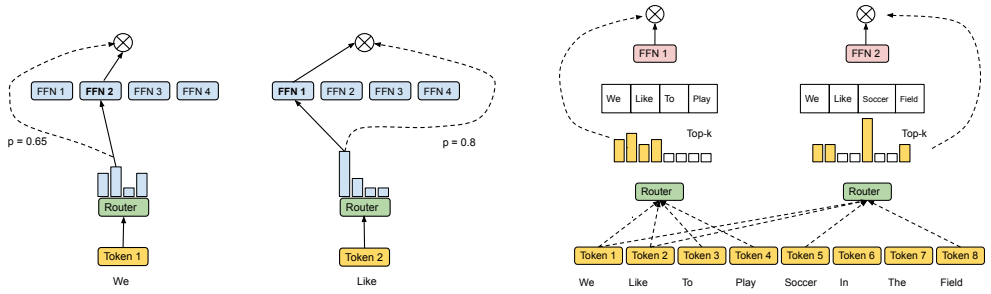


Figure 1: High-level Comparison Between Conventional MoE and expert choice MoE.

methods consider allocating a variable number of experts to each token based on importance, which can be beneficial.

We propose a very simple yet effective routing method we are calling *expert choice*. Unlike conventional MoE where tokens select one or two top-scoring experts, our method lets each *expert* pick the top-k tokens. Our method guarantees perfect load balancing, allows a variable number of experts for each token, and achieves substantial gains in training efficiency and downstream performance as demonstrated in our experiments. Our major contributions include:

- We identify common pitfalls in conventional MoE such as load imbalance as described in Section 3.1. We then propose a heterogeneous, expert choice method to provide a fluid allocation of model parameters based on a learnt token-to-expert importance. This method intrinsically guarantees load balance without imposing an auxiliary loss.
- We show our method provides over $2\times$ faster training convergence in a 8B/64E (8 billion activated parameters, 64 experts) model, compared to the top-1 and top-2 gating counterparts in Switch Transformer [10] and GShard [21].
- We show our method demonstrates strong scaling when increasing the number of experts from 16 to 128, evaluated in training perplexity.
- We show our method demonstrates strong performance on downstream tasks selected from GLUE and SuperGLUE at all the evaluated scales. More specifically, our 8B/64E model outperforms a T5 11B dense model in 7 out of 11 tasks evaluated.

2 Related Work

Scaling: Various approaches have been proposed to scale up neural network capacity to improve performance. Recent works have successfully scaled models to billions of parameters via various forms of model parallelism [2, 21, 26, 27, 33]. Model parallelism [30] splits weights and tensors across multiple cores while pipeline parallelism [18, 24] splits different layers across devices with micro-batches pipelined to the different layers. To enable continued scaling of neural networks, improving model training and serving efficiency has become a critical research area.

Conditional Computation: Computation decisions can be made dynamically based on the input [23, 25]. Conditional computation has been proposed as a way to increase the capacity of a deep neural network without increasing the amount of computation, by activating certain parameters and computation on demand, on a per-example or per-token basis [3]. Conditional convolution layers [1] with task-specific gating has been used to combat catastrophic forgetting when a sequence of learning problems are optimized. The gating decisions may be binary or sparse and continuous, stochastic or deterministic.

Mixture of Experts: Sparsely-gated MoE [31] is the first model to demonstrate massive improvements in model capacity, training time, or model quality with gating. Switch Transformer [10] simplifies the gating by selecting only the top expert per token using a softmax over the hidden state and demonstrates better scaling than previous work. All the prior work requires an auxiliary loss to explicitly encourage balancing. This loss term has to be carefully weighted to not overwhelm the

primary loss. However, auxiliary loss does not guarantee balancing and a hard capacity factor has to be imposed. As a result, many tokens can still be unprocessed by the MoE layer. Hard MoE [12] with a single decoding layer can be efficiently trained to good effect on large scale hashtag prediction tasks. Base Layers [22] formulate a linear assignment that maximizes token-expert affinities while ensuring each expert receives an equal number of tokens. Hash layers [8, 28] devise hashing techniques on input tokens. However, the evaluations are limited to pre-training perplexity. THOR [37] randomly activates experts during training and inference and is trained with a consistency regularization loss. THOR has demonstrated strong performance on translation tasks. Different from these prior works, our method is a learnt method that enables heterogeneous MoE and effectively improves downstream fine-tuning performance.

3 Method

We first identify a few pitfalls in the routing method of conventional mixture-of-experts (MoE) models and then present our method using expert choice to tackle these problems.

3.1 Pitfalls of Token-Choice Routing

MoE can be computationally advantageous compared to a dense model, a routing strategy must be used to assign each token to the most-suited experts. Conventional MoE models employ *token-choice* routing which independently selects the top-k experts for each token [10, 21, 31]. We argue that this strategy has a few pitfalls that lead to sub-optimal training.

Load Imbalance: Token-choice routing often lead to poor load balancing across experts. That is, some experts may be trained with most tokens, leaving the remaining experts under-utilized. Experts can be under specialized because a lot of model capacity in the under-utilized experts are wasted. On the other side, some tokens will not be processed, since over-utilized experts can only take a maximum number of tokens at each step in order to avoid running out of memory. Load imbalance can also hurt step latency, thus inference time, as the step latency can be determined by the most loaded expert. Previous methods add an auxiliary loss on load balancing to mitigate the issue. However, this auxiliary loss does not guarantee a balanced load, especially during the important early stages of training. Indeed, **we empirically observe that the over-capacity ratio can reach 20%–40% for some experts in token choice routing**, indicating that a significant portion of the tokens routed to these experts will be dropped.

Under Specialization: Each MoE layer uses a gating network to learn token-to-expert affinity. Ideally, the learnt gating network should produce the affinity such that similar or relevant tokens are routed to the same expert. A sub-optimal strategy can produce redundant experts and/or experts that are not sufficiently specialized. Under specialization may result by imposing an large auxiliary loss which favors more load balanced but less effective routing. Finding the right balance on the auxiliary loss to promote both load balancing and specialization is challenging for token-choice routing.

Same Compute for Every Token: Finally, in a token-choice strategy each token receives exactly k experts and therefore occupies the same amount of compute. We hypothesize that this is not necessary nor desired. Instead, a MoE model should flexibly allocate its compute resource based on the complexity of the input. Motivated by the aforementioned observations, we next describe a simple yet effective method which produces load balanced assignments based on *expert choice*.

3.2 Heterogeneous MoE via Expert Choice

Different from conventional routing, an expert choice method independently selects top-k tokens for each expert, where k is a fixed expert capacity (i.e. the number of tokens each expert can take). Despite its simplicity, expert choice achieves perfect load balancing by design. It also enables more flexible allocation of model compute since tokens can be received by a variable number of experts.

In our experiments, we set k as

$$k = \frac{n \times c}{e} \tag{1}$$

where n is the total number of tokens in the input batch (such as batch size $\times$ sequence length), c is the capacity factor, and e is the number of experts. The capacity factor c denotes on average how

many experts are utilized by a token. Given input token representations $X \in \mathbb{R}^{n \times d}$ where d is the model hidden dimension, our method produces a token-to-expert assignment denoted by three output matrices I, G and P. The matrix I is an index matrix where $I[i, j]$ specifies j-th selected token of the i-th expert. The gating matrix $G \in \mathbb{R}^{e \times k}$ denotes the weight of expert for the selected token, and $P \in \mathbb{R}^{e \times k \times n}$ refers to an one-hot version of I that will be used to gather tokens for each expert. These matrices are computed using a gating function,

$$\begin{aligned} S &= \mathrm{Softmax}(X \cdot W_g), \quad S \in \mathbb{R}^{n \times e} \\ G, I &= \mathrm{TopK}(S^\top, k), P = \mathrm{Onehot}(I) \end{aligned} \tag{2}$$

where S denotes the token-to-expert affinity scores, $W_g \in \mathbb{R}^{d \times e}$ denotes the expert embeddings, and $TopK()$ selects the k largest entries for each row of $S^\top$.

Similar to Switch Transformer [10] and GShard [21], we apply mixture of experts and the gating function in the dense feed-forward (FFN) layer, as it is the most computationally expensive part in a Transformer-based network. The input to the gated FFN, denoted by $X_{\text{in}} \in \mathbb{R}^{e \times k \times d}$, is produced using the permutation matrix P. Here $X_{\text{in}}[i] \in \mathbb{R}^{k \times d}$ denotes the input of the i-th expert. Similarly, let W_1 and W_2 denote the parameters of gated FFN in which $W_1[i]$ and $W_2[i] \in \mathbb{R}^{d \times d'}$ denote the parameter matrices of the i-th expert. We compute the output of each expert $X_e[i]$ as follows,

$$\begin{aligned} X_{in} &= P \cdot X \\ \forall i: \quad X_e[i] &= \mathrm{GeLU}(X_{in}[i] \cdot W_1[i]) \cdot W_2[i]^\top \end{aligned} \tag{3}$$

We omit the bias terms here for brevity. The finally output of the gated FFN layer $X_{\text{out}} \in \mathbb{R}^{n \times d}$ can be obtained given X_e, the permutation and gating matrices P and G,

$$X_{\text{out}}[l, d] = \sum_{i,j} P[i, j, l]\, G[i, j]\, X_e[i, j, d] \tag{4}$$

Both X_e and X_{out} can be efficiently computed using Einstein summation (einsum) operations.

3.3 Expert Choice with Additional Constraint

We also consider regularizing our expert choice routing by limiting the maximum number of experts for each token. We are interested in whether adding this constraint improves pre-training and fine-tuning results. More importantly, it helps analyzing to what degree using a variable number of experts per token affects the model performance.

Let $A \in \mathbb{R}^{e \times n}$ be a positive matrix where $A[i, j]$ represents whether the i-th expert selects j-th token. We solve the following entropy-regularized linear programming problem

$$\begin{aligned} &\max_A \ \langle S^\top, A \rangle + \lambda H(A) \\ \text{s.t.} \quad &\forall i: \sum_{j'} A[i, j'] = k; \ \ \forall j: \sum_{i'} A[i', j] \leq b; \ \ \forall i, j: \ 0 \leq A[i, j] \leq 1 \end{aligned}$$

where $< S^\top, A >$ denotes the inner product, $H(A)$ is the sum of element-wise entropy[1], and $b > 0$ is an integer that upper bounds the selection for each token. Adding a small entropy term gives a near-integer solution while enabling a fast iterative solver we can run on TPUs. Specifically, the solution space is the intersection of three convex sets each satisfying one of the linear constraints. We use Dykstra's algorithm [9] that alternatively projects the intermediate solution onto one of the convex sets.[2] After A is computed, the routing indices I is selected using $TopK(A, k)$ instead.

3.4 Model Architecture

At the high level, we adopt the idea of sparsely activated Mixture-of-Experts (MoE) [31]. We use a Transformer architecture and replace the feed-forward component of every other Transformer

[1] $H(A) = \sum_{ij} -A[i, j] \log A[i, j]$

[2] We use $\lambda = 0.001$ and a maximum of 100 iterations.

Model	Type	n_{params}	$n_{\text{act-params}}$	L	M	H	n_{heads}	d_{head}	E
0.1B	Dense	130M	130M	12	768	3,072	12	64	-
0.1B/16E	MoE	548M	145M						16
0.1B/32E	MoE	1.0B	145M						32
0.1B/64E	MoE	1.9B	145M						64
0.1B/128E	MoE	3.7B	145M						128
8B	Dense	8.7B	8.7B	32	4,096	16,384	32	128	-
8B/64E	MoE	143B	9.8B						64

Table 1: Sizes and architectures of both MoE and dense models that were trained in our experiments. Models are grouped by the number of activated parameters per token. All trained models share the same learning hyperparameters described in Section 4.1.

layer with a MoE layer, following recent practice [10, 21]. Interleaving regular Transformer layers and MoE layers empirically improves model performance and training efficiency, probably because forcing some shared components in between MoE layers can mitigate the negative effects of skipping tokens. Several additional modifications adopted in recent work have been applied in our experiments. For example, we replace the standard positional embedding with per-layer relative positional bias [5]. In the non-MoE feed-forward sub-layers (only every other layers are MoE layers), we replace the first linear projection and the activation function with the Gated Linear Unit [6], which computes the component-wise product of two linear transformation of the input, followed by a Gaussian Error Linear Unit [15] activation function.

As described earlier, each MoE layer consists of a group of independent feed-forward networks as denoted as "experts". The gating function in Eq. (2) uses a softmax activation function to model a probability distribution over these experts. This distribution denotes the preference over experts of each incoming token, which is computed similarly in a conventional gating network [10, 21, 31]. During training, each MoE layer's learnable gating network described in Eq. (2) is trained to use the input to activate the best subset of experts using a top-k function along the token dimension. An "shuffle" stage and an "unshuffle" stage are inserted to the MoE layer, where the first stage gathers the tokens to their designated experts while the second stage permutes the tokens back to their original order in the input batch. This step is formulated in Eq. (3) and Eq. (4).

Similar to conventional MoE method, there are more parameters in the MoE layer. However, the activated model size per token can be comparable to a dense layer because during training or inference, only a limited subset of experts is activated for any given token. For instance, Switch Transformer [10] has only one activated expert while GShard [21] uses two experts per token. In our method, the number of activated experts can vary for each token but the overall computation is kept the same as the baseline architectures by fixing the capacity factor c in Eq. (1). Unless otherwise specified, we set $c = 2$ such that our method can be directly compared to the top-2 token-choice gating in GShard.

We train several variants of our architecture at the 100M scale (i.e. 100M expert size) by increasing the number of experts to understand the scaling effects of our method. We also train a 8B scale MoE model. The large MoE model is partitioned with a 2D sharding algorithm as presented in GSPMD [36], which fully exploits the 2D topology of the TPU cluster [19]. Across different scales and setups, our method outperforms related work and demonstrates strong downstream task performance on selected tasks in GLUE and SuperGLUE.

4 Experiments

4.1 Setup

Table 1 summarizes the hyperparameter settings of different MoE models. As a reference point, we also include the respective dense model configurations with comparable numbers of activated parameters per-token during inference. To study of the effect of scaling the number of experts, we studied varying the number of experts but fixing the per expert size to 100M parameters. For example, 0.1B/64E represents the architecture of an approximately 100M parameter dense model with every other layer replaced by a 64-expert MoE layer. The MoE model degenerates into a dense transformer architecture when each MoE layer only has one expert. While n_{params} is the total number of trainable parameters, $n_{act-params}$ represents the number of activated parameters per token. L is the total

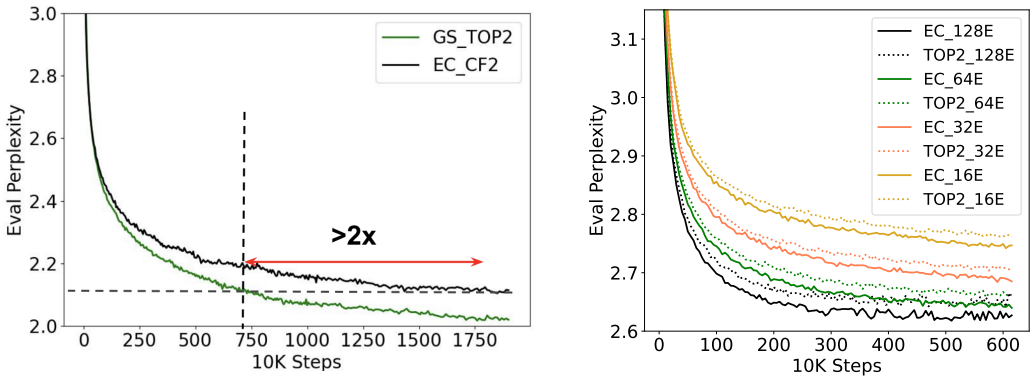
number of Transformer layers, M is the model dimension, H is the hidden dimension after the projection in each transformer layer, n_{heads} is the number of attention heads, and d_{head} is the hidden dimension of each attention head.

Dataset: We use the high-quality dataset from GLaM [7] of 1.6 trillion tokens that are representative of a wide range of natural language use cases. An in-house classifier is trained to classify between a collection of curated text and other webpages and estimate the content quality of a webpage. A high-quality filtered subset of webpages are combined with books, Wikipedia pages, conversations, forums, and news to create the final dataset. The data and mixture weights can be found in Table 3 in the GLaM paper.

Model Training: Our model training follows the setups of GLaM [7] where a maximum sequence length of 1024 tokens is adopted. We use an Adafactor optimizer [32] with first-moment decay $\beta_1 = 0$ and second-moment decay $\beta_2 = 0.99$. We keep the learning rate constant for the first 10K training steps, and then decay it with an inverse square root schedule. Unlike most related works, we do not impose any auxiliary loss for load balance, such as described in Switch Transformer [10] and GShard [21]. We use the SentencePiece subword tokenizer with a vocabulary of size of 256K. The largest model (8B/64E) is trained on 512 TPU V4 chips. We use a dropout rate of 0 during training as the number of tokens in the training data corpus is much greater than the total number of tokens during training.

Model Evaluation: We mainly focus on evaluating the finetuning performance on the 11 selected tasks from GLUE and SuperGLUE benchmarks [34, 35].

4.2 Training Efficiency



(a) (b)

Figure 2: (a) Training convergence is more than 2x faster using our method compared to GShard top-2 gating. (b) Training perplexity scales strongly with the number of experts while keeping the expert size fixed. EC consistently outperforms GShard top-2 gating.

We first study training efficiency and convergence. We use expert choice with a capacity factor of 2 (EC-CF2) to match the activated model size and computational cost on a per token basis in GShard top-2 gating and run both for a fixed number of steps. The results are shown in Fig. 2 (a). Comparing to GShard top-2 gating, which showed stronger performance in both perplexity in the evaluation dataset and finetuning on downstream tasks compared to Switch Transformer top-1 gating, EC-CF2 converges more than 2x faster during training. More specifically, EC-CF2 reaches the same perplexity as GShard top-2 in less than half the steps, and with each GShard top-2 step being 20% slower than our method. As explained in Section 3.1, the slower step time in top-2 gating can be explained by the large over capacity factor (e.g. can be as large as 8 in 8B64E setting) used due to load imbalance. The step latency can be determined by the most loaded expert.

4.3 Scaling the Number of Experts

As presented in Table 1, increasing the number of experts effectively increases model capacity without increasing activated model size. We scale the number of experts while fixing the expert size to 100M

			100M/128E			100M/64E		
Name	Metric	Split	ST Top-1	GS Top-2	EC-CF2	ST Top-1	GS Top-2	EC-CF2
BoolQ	acc	dev	77.4	76.5	**76.9**	73.2	77.5	**79.7**
CB	acc	dev	87.5	80.9	**89.1**	85.9	84.4	**89.1**
CoLA	acc	dev	78.9	84.0	**86.7**	64.1	85.2	**88.3**
MNLI	acc	dev	82.3	83.6	**84.9**	80.8	85.2	**86.7**
MRPC	acc	dev	82.6	81.0	**83.1**	81.3	81.3	**84.4**
QNLI	acc	dev	**89.5**	88.6	89.0	89.4	89.7	**91.3**
QQP	acc	dev	**90.6**	90.3	90.4	88.9	90.5	**91.0**
RTE	acc	dev	77.0	**78.9**	78.5	74.1	79.3	**81.6**
SST2	acc	dev	92.0	94.5	**94.6**	91.8	95.1	**95.1**
WiC	acc	dev	67.8	65.5	**68.1**	64.4	**67.8**	65.6
WNLI	acc	dev	65.6	**70.3**	67.2	68.8	68.8	**71.7**
Avg	-	-	81.0	81.3	**82.6**	78.4	82.2	**84.0**

			100M/32E			8B/64E		
Name	Metric	Split	ST Top-1	GS Top-2	EC-CF2	ST Top-1	GS Top-2	EC-CF2
BoolQ	acc	dev	74.5	79.0	**79.3**	89.1	**89.5**	89.2
CB	acc	dev	80.6	81.3	**92.2**	93.8	96.7	**100**
CoLA	acc	dev	87.5	92.2	**93.8**	88.3	87.5	**89.1**
MNLI	acc	dev	83.1	87.8	**88.0**	90.7	**91.4**	91.1
MRPC	acc	dev	82.3	**85.2**	84.4	89.3	**91.7**	90.6
QNLI	acc	dev	91.6	91.9	**92.5**	94.5	94.9	**95.0**
QQP	acc	dev	90.1	91.5	**92.0**	92.1	92.5	**93.8**
RTE	acc	dev	75.0	**79.1**	78.1	91.0	92.2	**95.2**
SST2	acc	dev	93.3	94.4	**95.4**	97.1	**98.0**	97.7
WiC	acc	dev	62.5	65.9	**69.8**	74.5	76.4	**83.8**
WNLI	acc	dev	65.6	64.1	**68.8**	78.1	82.8	**92.8**
Avg	-	-	80.6	83.5	**85.0**	88.9	90.3	**92.6**

Table 2: Expert choice with capacity factor of 2 (EC-CF2) outperforms Top-1 gating in Switch Transformer (ST) and top-2 gating in GShard (GS) on GLUE and SuperGLUE tasks. Note that with an expert size of 100M parameters, 100M/32E works best for our method and Ghard Top-2 while 100M/128E works better for Switch Transformer Top-1. Our method consistently outperforms the others across all the scales.

parameters for both expert choice (EC) and GShard (Top-2) methods and find both methods scale well in terms of perplexity on the evaluation dataset during pre-training, as demonstrated in Fig. 2 (b). Having more experts consistently improves training perplexity, which often translates directly to better performance in downstream tasks.

4.4 Fine-tuning on GLUE and SuperGLUE

We perform fine-tuning on 11 selected tasks from GLUE and SuperGLUE on the pretrained models of three MoE methods, including Switch Transformer top-1 gating (ST Top-1), GShard top-2 gating (GS Top-2) and our method with a capacity factor of 2 (EC-CF2) to match the activation memory size and thus computational cost of GS Top-2. Indicated by the results in Table 2, our EC-CF2 method consistently outperforms the related methods and yields more than 2% average accuracy increase in a large 8B/64E setting. Comparing to the 8B dense counterpart, our 8B MoE model achieves stronger pre-training perplexity and stronger fine-tuning performance presented in Table 3. Our best sparse model outperforms the 8B dense model by 3.4 points on average.

Interestingly, we observe the 100M/32E model setting works the best for both GS Top-2 and EC-CF2, even though the effective model capacity is smaller than that of 100M/64E and 100M/128E. This result indicates that a good training perplexity does not always translate to better performance of downstream tasks.

4.5 Heterogeneity Matters

Capped Expert Choice: We regularized expert choice by limiting the maximum number of experts for each token, using the method described in Section 3.3. Table 4 reports the average accuracy on the 11 selected datasets. EC-CAP2 is the variant of our expert choice method by limiting the number of experts of each token to 2. This decreases the fine-tuning accuracy by 0.8 points on average. In addition, EC-CAP3 allows a maximum of 3 experts per token and achieves on par results compared

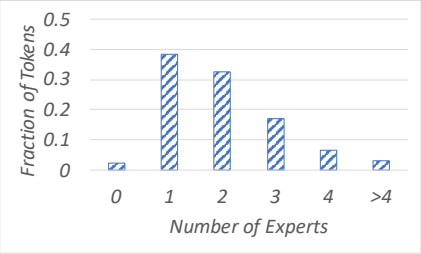
Model	BoolQ	CB	CoLA	MNLI	MRPC	QNLI	QQP	RTE	SST2	WiC	WNLI	Avg
Dense 8B	88.2	100	86.4	91.3	86.7	94.7	91.2	92.2	97.2	75.6	78.1	89.2
EC-CF2 8B/64E	89.2	100	89.1	91.1	90.6	95.0	93.8	95.2	97.7	83.8	92.8	**92.6**

Table 3: Comparison between Dense 8B and Expert Choice (EC-CF2) 8B/64E models: Our method significantly outperforms the dense model in downstream tasks.

Table 4: (a) Limiting the number of experts per token in expert choice method affects downstream accuracy. (b) Comparing to Hash Layer.

Method	Max # of Experts	Avg acc.
EC-CAP2	2	83.2 ± 0.4
EC-CAP3	3	84.0 ± 0.4
EC-CF2	-	84.0 ± 0.2
Hash Layer	-	81.3 ± 0.1

Figure 3: Distribution of the number of experts routed to per token in a 100M/64E model.



to the vanilla expert choice method. This ablation study confirms that **allowing variable number of experts per token is indeed helpful.** Additional results can be found in Supplementary Section C.

Variable Experts per Token: We compute statistics on token-to-expert routing, particularly on the ratio of tokens that have been routed to a certain number of experts. According to Fig. 3, a majority of tokens have been routed to one or two experts while 23% have been routed to three or four experts and only about 3% tokens have been routed to more than 4 experts. This plot verifies our hypothesis that our method learns to allocate a variable number experts to tokens, which can be beneficial for important tokens.

4.6 Comparison with Hash Layer

In this section, we compare our method with Hash Layers [28]. We use $\mod x$ to map a token ID to an expert ID. This ensures load balance and generates specialized experts. The fine-tuning results are presented in the last row in Table 4 and more detailed scores can be found in Supplementary Table 2. Hashing based routing performs much worse than expert choice in terms of average scores and variance. **This indicates that load balancing alone does not generate all the benefits**.

4.7 Ablation

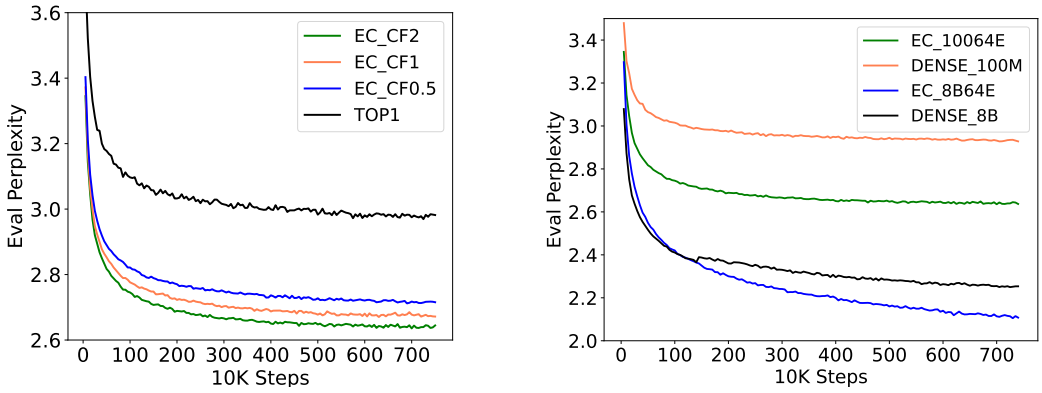


Figure 4: (a) Varying the capacity factor in our expert choice method: Decreasing the capacity factor from two to one degrades the perplexity but still outperforms the top-1 gating. (b) Training perplexity comparison with dense models.

Capacity Factor: We study the capacity factor in our expert choice method and compare the training perplexity with the baseline top-1 gating method used in Switch Transformer. As described in Eq. (1), the capacity factor determines how many experts on average each token can be routed to, thus the bucket size k of each expert. In all our previous experiments, we use a capacity factor of 2, which matches the computational footprint of the top-2 gating used in GShard method. To match the computation cost on a per-token basis fairly with top-1 gating used in Switch Transformer, we reduce the capacity factor to 1 and plot the training perplexity. Fig. 4 (a) demonstrates that our method with a capacity factor of 1 (EC_CF1) still significantly outperforms top-1 gating. We further push the capacity factor further down to 0.5, and find it only marginally hurts training perplexity, outperforming top-1 gating. Not surprisingly, using a larger capacity factor in expert choice yields better performance. More details on downstream tasks are presented in Supplementary Section B.

Comparison with Dense Models: We compare our method with dense models where no MoE are used. As shown in Fig. 4 (b), our method consistently outperforms the dense method in training perplexity and training convergence time. For a small expert size of 100M parameters, the benefit of sparse gating is even more significant. Orthogonal to results presented in Fig. 2 (b), where scaling the number of experts improves model performance, Fig. 4 (b) shows that increasing expert capacity also significantly increases model performance. We conduct fine-tuning on the selected 11 tasks described in Table 2 on a dense 8B model and report the average score of 89.2, which is 3.4% lower than 8B/64E EC-CF2 in our method. More details are in Supp. Section A.

5 Conclusion

We propose a new routing method for sparsely activated mixture-of-experts (MoE) models. This method addresses load imbalance and under-utilization of experts in conventional MoE methods, and enables selecting different numbers of experts for each token. Our model demonstrates more than 2x training efficiency improvements when compared to the state-of-the-art GShard and Switch Transformer models, and also achieves strong gains when finetuning on 11 datasets in the GLUE and SuperGLUE benchmark.

6 Limitations

The expert choice method might not immediately apply to auto-regressive text generation as our current implementation takes in the past and future tokens to perform the top-k selection. One possible solution is to collect a large batch of input sequences, dispatch tokens of the same sequence into separate groups, and perform expert choice routing for each group. Another scenario where the expert choice method does not immediately apply is when the batch size becomes very small during serving or inference. A global top-k can be selected instead and we can cap the number of times each expert or token gets selected. We leave these possible improvements for future work.

Another long-standing issue with MoE has been the large memory footprint. Even though computational cost can be reduced using sparsely gated networks, the total number of parameters increases linearly or sub-linearly with the number of experts. Increasing the number of experts requires reservation of a large number of hardware devices. Therefore, dynamic (used) power is saved while static (reserved) power is not. Power saving techniques such as the ability to put hardware devices into low power states while not in use [17] can help with reducing the reserved power requirements.

7 Checklist

(a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes**

(b) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes**

(c) Did you discuss any potential negative societal impacts of your work? **N/A. Not any.**

(d) Did you describe the limitations of your work? **Yes**

(a) Did you include the code, data, and instructions needed to reproduce the main experimental results? **Yes. We include details in the experiment setup to help reproduce the main results.**

(b) Did you specify all the training details? **Yes**

(c) Did you report error bars? **Yes**

(d) Did you include the amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **Yes**

(a) If your work uses existing assets, did you cite the creators? **Yes**

(b) Did you mention the license of the assets? **No. The used dataset is not released yet.**

(c) Did you include any new assets either in the supplemental material or as a URL? **No. The dataset is not released yet.**

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? **No. Not using persons' data.**

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **Yes. The dataset does not contain any personally identifiable information or offensive content.**

References

[1] Davide Abati, Jakub Tomczak, Tijmen Blankevoort, Simone Calderara, Rita Cucchiara, and Babak Ehteshami Bejnordi. Conditional channel gated networks for task-aware continual learning. In *CVPR*, pages 3930–3939. Computer Vision Foundation / IEEE, 2020.

[2] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*.

[3] Kyunghyun Cho and Yoshua Bengio. Exponentially increasing the capacity-to-computation ratio for conditional computation in deep learning, 2014.

[4] Zihang Dai, Hanxiao Liu, Quoc V. Le, and Mingxing Tan. CoAtNet: Marrying convolution and attention for all data sizes. In *Advances in Neural Information Processing Systems*, 2021.

[5] Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc Le, and Ruslan Salakhutdinov. Transformer-XL: Attentive language models beyond a fixed-length context. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, Florence, Italy, July 2019. Association for Computational Linguistics.

[6] Yann N. Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated convolutional networks. In *Proceedings of the 34th International Conference on Machine Learning - Volume 70*, ICML'17, page 933–941. JMLR.org, 2017.

[7] Nan Du, Yanping Huang, Andrew M. Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, Barret Zoph, Liam Fedus, Maarten Bosma, Zongwei Zhou, Tao Wang, Yu Emma Wang, Kellie Webster, Marie Pellat, Kevin Robinson, Kathy Meier-Hellstern, Toju Duke, Lucas Dixon, Kun Zhang, Quoc V Le, Yonghui Wu, Zhifeng Chen, and Claire Cui. Glam: Efficient scaling of language models with mixture-of-experts, 2021.

[8] Dheeru Dua, Shruti Bhosale, Vedanuj Goswami, James Cross, Mike Lewis, and Angela Fan. Tricks for training sparse translation models, 2021.

[9] Richard L Dykstra. An iterative procedure for obtaining i-projections onto the intersection of convex sets. *The annals of Probability*, pages 975–984, 1985.

[10] William Fedus, Barret Zoph, and Noam Shazeer. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity, 2021.

[11] Golnaz Ghiasi, Tsung-Yi Lin, and Quoc V. Le. NAS-FPN: learning scalable feature pyramid architecture for object detection. In *CVPR*, pages 7036–7045. Computer Vision Foundation / IEEE, 2019.

[12] Sam Gross, Marc'Aurelio Ranzato, and Arthur Szlam. Hard mixtures of experts for large scale weakly supervised vision, 2017.

[13] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Identity mappings in deep residual networks. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, *Computer Vision – ECCV 2016*, pages 630–645, Cham, 2016. Springer International Publishing.

[15] Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (GELUs), 2016.

[16] Joel Hestness, Sharan Narang, Newsha Ardalani, Gregory Diamos, Heewoo Jun, Hassan Kianinejad, Md. Mostofa Ali Patwary, Yang Yang, and Yanqi Zhou. Deep learning scaling is predictable, empirically, 2017.

[17] Ping Huang, Zuocheng Xing, Tianran Wang, Qiang Wei, Hongyan Wang, and Guitao Fu. A brief survey on power gating design. In *2010 10th IEEE International Conference on Solid-State and Integrated Circuit Technology*, pages 788–790, 2010.

[18] Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Dehao Chen, Mia Xu Chen, HyoukJoong Lee, Jiquan Ngiam, Quoc V. Le, Yonghui Wu, and Zhifeng Chen. Gpipe: Efficient training of giant neural networks using pipeline parallelism. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 103–112, 2019.

[19] Norman P. Jouppi, Doe Hyun Yoon, George Kurian, Sheng Li, Nishant Patil, James Laudon, Cliff Young, and David A. Patterson. A domain-specific supercomputer for training deep neural networks. *Commun. ACM*, 63(7):67–78, 2020.

[20] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models, 2020.

[21] Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. GShard: Scaling giant models with conditional computation and automatic sharding. In *International Conference on Learning Representations*, 2021.

[22] Mike Lewis, Shruti Bhosale, Tim Dettmers, Naman Goyal, and Luke Zettlemoyer. Base layers: Simplifying training of large, sparse models. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 6265–6274. PMLR, 18–24 Jul 2021.

[23] Min Lin, Jie Fu, and Yoshua Bengio. Conditional computation for continual learning, 2019.

[24] Deepak Narayanan, Aaron Harlap, Amar Phanishayee, Vivek Seshadri, Nikhil R. Devanur, Gregory R. Ganger, Phillip B. Gibbons, and Matei Zaharia. Pipedream: Generalized pipeline parallelism for dnn training. New York, NY, USA, 2019. Association for Computing Machinery.

[25] Joan Puigcerver, Carlos Riquelme Ruiz, Basil Mustafa, Cédric Renggli, André Susano Pinto, Sylvain Gelly, Daniel Keysers, and Neil Houlsby. Scalable transfer learning with expert models. In *ICLR*. OpenReview.net, 2021.

[26] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. 2018.

[27] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21:140:1–140:67, 2020.

[28] Stephen Roller, Sainbayar Sukhbaatar, Arthur Szlam, and Jason Weston. Hash layers for large sparse models, 2021.

[29] Roy Schwartz, Jesse Dodge, Noah A. Smith, and Oren Etzioni. Green ai, 2019.

[30] Noam Shazeer, Youlong Cheng, Niki Parmar, Dustin Tran, Ashish Vaswani, Penporn Koanantakool, Peter Hawkins, HyoukJoong Lee, Mingsheng Hong, Cliff Young, Ryan Sepassi, and Blake Hechtman. Mesh-tensorflow: Deep learning for supercomputers. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, NIPS'18, page 10435–10444, Red Hook, NY, USA, 2018. Curran Associates Inc.

[31] Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc V. Le, Geoffrey E. Hinton, and Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. In *ICLR (Poster)*. OpenReview.net, 2017.

[32] Noam Shazeer and Mitchell Stern. Adafactor: Adaptive learning rates with sublinear memory cost. In Jennifer Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning*, volume 80 of *Proceedings of Machine Learning Research*, pages 4596–4604. PMLR, 10–15 Jul 2018.

[33] Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. Megatron-lm: Training multi-billion parameter language models using model parallelism, 2020.

[34] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. In H. Wallach, H. Larochelle, A. Beygelzimer, F. dAlché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*. Curran Associates, Inc.

[35] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, Brussels, Belgium, November 2018. Association for Computational Linguistics.

[36] Yuanzhong Xu, HyoukJoong Lee, Dehao Chen, Blake A. Hechtman, Yanping Huang, Rahul Joshi, Maxim Krikun, Dmitry Lepikhin, Andy Ly, Marcello Maggioni, Ruoming Pang, Noam Shazeer, Shibo Wang, Tao Wang, Yonghui Wu, and Zhifeng Chen. GSPMD: general and scalable parallelization for ML computation graphs. *CoRR*, abs/2105.04663, 2021.

[37] Simiao Zuo, Xiaodong Liu, Jian Jiao, Young Jin Kim, Hany Hassan, Ruofei Zhang, Tuo Zhao, and Jianfeng Gao. Taming sparsely activated transformer with stochastic experts, 2021.