
Scaling Diffusion Transformers to 16 Billion Parameters

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Abstract

In this paper, we present DiT-MoE, a sparse version of the diffusion Transformer, that is scalable and competitive with dense networks while exhibiting highly optimized inference. The DiT-MoE includes two simple designs: shared expert routing and expert-level balance loss, thereby capturing common knowledge and reducing redundancy among the different routed experts. When applied to conditional image generation, a deep analysis of experts specialization gains some interesting observations: (i) Expert selection shows preference with spatial position and denoising time step, while insensitive with different class-conditional information; (ii) As the MoE layers go deeper, the selection of experts gradually shifts from specific spacial position to dispersion and balance. (iii) Expert specialization tends to be more concentrated at the early time step and then gradually uniform after half. We attribute it to the diffusion process that first models the low-frequency spatial information and then high-frequency complex information. Based on the above guidance, a series of DiT-MoE experimentally achieves performance on par with dense networks yet requires much less computational load during inference. More encouragingly, we demonstrate the potential of DiT-MoE with synthesized image data, scaling diffusion model at a 16.5B parameter that attains a new SoTA FID-50K score of 1.80 in 512×512 resolution settings. The project page: <https://github.com/feizc/DiT-MoE>.

1 Introduction

Recently, diffusion models [42, 88, 89, 9] have emerged as powerful deep generative models in various domains, such as image [19, 44, 78], video [45, 62, 87, 43, 60], 3D object [58, 70, 71] and so on [94]. This advancement is attributed to diffusion models' ability to learn denoising tasks over diverse noise distributions, effectively transforming random noise into a target data distribution through iterative denoising processes. In particular, Transformer-based structure shows that increasing network capacity with additional parameters generally boosts performance [10, 68, 30, 32]. For example, Stable Diffusion 3 [24] as the competitive diffusion models to date, some with over 8B parameters. However, training and serving such models is expensive [66]. This is partially because these deep networks are typically dense, *i.e.*, every example is processed using every parameter, thereby, scale comes at a high computational cost.

Conditional computation [4, 3] is a promising scaling technique, which aims to enhance model capacity while maintaining relatively constant training and inference cost by applying only a subset of parameters to each example. In fields of NLP, sparse mixture of experts (MoE) are becoming increasingly popular [85, 14, 15] as a practical implementation that employs a routing mechanism to

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Figure 1: **DiT-MoE model achieve state-of-the-art image quality.** We show selected samples generated from our class-conditional XL/2-8E2A (left) and G/2-16E2A (right) models trained on ImageNet at 512×512 and 256×256 resolution, respectively.

control computational costs [61]. Moreover, the applications of MoE architectures in Transformers have yielded successful attempts at scaling language models to a substantial size with remarkable performance [21, 25, 55, 100]. Conventional MoE architectures in Transformers typically substitute the Feed-Forward Network (FFN) with MoE layers, each consisting of multiple experts that are structurally identical to a standard FFN. We along with a similar sparse design and investigate its effectiveness in diffusion Transformers [68, 59].

In this work, we explore conditional computation tailored specifically for Diffusion Tranformers (DiT) [68] at scale. We propose DiT-MoE, a sparse variant of the DiT architecture for image generation. The DiT-MoE replaces a subset of the dense feedforward layers in DiT with sparse MoE layers, where each token of image patch is routed to a subset of experts, *i.e.*, MLP layers. Moreover, our architecture involves two principal designs: shared part of experts to capture common knowledge and balance expert loss to reduce redundancy in different routed experts. We also provide a comprehensive analysis to demonstrate that these designs offer opportunities to train a parameter-efficient MoE diffusion model while some interesting phenomena about expert routing from different perspectives are observed.

Starting from a small-scale model, we validate the benefits of DiT-MoE architecture and present an effective recipe for the scale training of DiT-MoE. We then conduct an evaluation of class-based

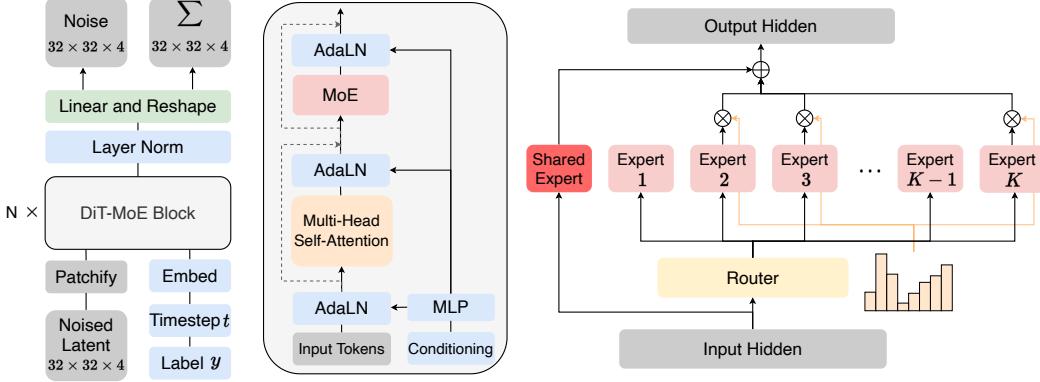


Figure 2: **Overview of the DiT-MoE architecture.** Generally, DiT-MoE is built upon the DiT and composed of MoE-inserted Transformer blocks. In between, we replace the MLP with a sparsely activated mixture of MLPs. The right subfigure demonstrates the details of MoE layer integration of the shared expert strategy.

image generation in the ImageNet benchmarks. Experiment results indicate that DiT-MoE matches the performance of state-of-the-art dense models, while requiring less time to inference. Alternatively, DiT-MoE-S can match the cost of DiT-B while achieving better performance. Leveraging with additional synthesis data, we subsequently scale up the model parameters to 16.5B while only activating 3.1B parameters, which attains a new state-of-the-art FID-50K score of 1.80 in 512×512 resolution. Our contributions can be summarized as follows:

- **MoE for diffusion transformers.** We present DiT-MoE, a sparsely-activated diffusion Transformer model for image synthesis. In between, it incorporates simple and effective designs, including shared components of experts to capture common knowledge, and an auxiliary expert-level balance loss to minimize redundancy among routed experts.
- **Expert routing analysis.** We have conducted statistics on the selection of experts in different scenarios and found interesting observations about expert selection preference with spatial position and denoising time step at different MoE layers, which can effectively guide future network design and interpretability.
- **Model parameters at scale.** We introduce a series of DiT-MoE models and show that these models can be stably trained, and seamlessly used for efficient inference. More encouragingly, we further undertake a preliminary endeavor that DiT-MoE can be performed and scale beyond 16B with well-selected synthesised data.
- **Performance and inference.** We show that DiT-MoEs strongly outperform their dense counterparts on conditional image generation tasks at the ImageNet benchmark. At inference time, the DiT-MoE models can be flexible to match the performance of the largest dense model while using as little as half of the amount of computation. Finally, we publicly release the code and trained model checkpoint.

2 Methodology

We first briefly describe diffusion models and network conditional computation with MoEs. We then present how we apply this methodology to diffusion transformers, and explain our design choices for optimizing expert routing algorithms. Finally, we provide computation analysis with different parameter scaling settings.

2.1 Preliminaries

Diffusion models. Diffusion models [42, 88] constitute a class of generative models that simulate a gradual noising and denoising process through a series of latent variables. They are characterized by a Markovian forward process and a learned reverse process. Specifically, the forward diffusion

process incrementally adds noise to an input image x_0 , transitioning it through a sequence of states x_1, \dots, x_T according to a predetermined variance schedule β_1, \dots, β_T . The reverse process, learned during training, aims to recover the original data from its noised version. The forward noising process is defined as:

$$q(x_t|x_0) = \mathcal{N}(\sqrt{\alpha_t}, (1 - \alpha_t)I) = \sqrt{\alpha_t}x_0 + \sqrt{(1 - \alpha_t)}\epsilon, \quad (1)$$

where $\alpha_t + \beta_t = 1$ and $\epsilon \sim \mathcal{N}(0, I)$ is the Gaussian noise. Diffusion models are trained to estimate the reverse process, $p_\theta(x_{t-1}|x_t)$, by approximating the variational lower bound of $\int p_\theta(x_{0:T}|x_t) d(x_{0:T})$ as computed by [88]. In practice, this reverse process is generally conditioned on the timestep t and aims to either predict the noise ϵ or reconstruct the original image x_0 . Formally, a noise prediction network $\epsilon_\theta(x_t, t)$ is incorporated by minimizing a noise prediction objective, *i.e.*, $\min_\theta \mathbb{E}_{t,x_0,\epsilon} \|\epsilon - \epsilon_\theta(x_t, t)\|_2^2$, where t is uniformly distributed between 1 and T . To learn conditional diffusion models, *e.g.*, class-conditional [19] or text-to-image [75, 6] models, additional condition information is integrated into the noise prediction objective as:

$$\min_\theta \mathbb{E}_{t,x_0,c,\epsilon} \|\epsilon - \epsilon_\theta(x_t, t, c)\|_2^2, \quad (2)$$

where c can be the condition index or its continuous embedding.

Conditional computation with MoEs. Conditional computation seeks to activate subsets of a neural network depending on the input [4, 3]. A mixture-of-experts model exemplifies this concept by assigning different model experts to various regions of the input space [48]. We follow the framework of [85], who present a mixture of experts layer in deep learning, comprising E experts, defined as:

$$\text{MoE}(x) = \sum_{i=1}^E g(x)_i e_i(x), \quad (3)$$

where $x \in \mathbb{R}^D$ is the input to the layer, $e_i : \mathbb{R}^D \rightarrow \mathbb{R}^D$ denotes the function computed by expert i , and $g : \mathbb{R}^D \rightarrow \mathbb{R}^E$ is the routing function that determines the input-conditioned weights for the experts. Both e_i and g are parameterized by neural networks. As originally defined, this structure remains a dense network. However, if g is sparse, *i.e.*, restricted to assign only $k \ll E$ non-zero weights, then unused experts need not be computed. This approach enables super-linear scaling of the number of model parameters relative to the computational cost of inference and training.

2.2 MoEs for Diffusion Transformers

Here we explore the application of sparsity to diffusion models within the context of the Diffusion Transformers (DiT) [68]. DiT has demonstrated superior scalability across various parameter settings, achieving enhanced generative performance compared to CNN-based U-Net architectures [79, 23] with higher training computation efficiency. Similar to vision transformers [20], DiT processes images as a sequence of patches. An input image is first divided into a grid of equal-sized patches. These are linearly projected to features identical to the model’s hidden dimension. After adding positional embeddings, the patch embeddings, *i.e.*, image patch tokens, are processed by a sequence of Transformer blocks, which consists predominately of alternating self-attention and MLP layers. The standard MLPs consist of two layers and a GeLU [39] non-linearity:

$$\text{MLP}(x) = W_2 \sigma_{\text{gelu}}(W_1 x), \quad (4)$$

For DiT-MoE, we replace a subset of these with MoE layers, where each expert is an MLP; see Figure 2 for viewing. The experts share the same architecture and it follows a similar design pattern as [77, 15, 21].

On top of the generic MoE architecture, we introduce extra designs to exploit the potential of expert specialization. As illustrated in the right subfigure 2, our architecture incorporates two principal strategies: shared expert routing and expert load balance loss. Both of these strategies are designed to optimize the level of expert specialization and introduction as below:

Shared expert routing. Under conventional routing strategies, tokens assigned to different experts may require access to overlapping knowledge or information. Consequently, multiple experts may converge in acquiring this shared knowledge within their respective parameters, leading to parameter redundancy. Referring to [15, 74], we incorporate additional n_s experts to serve as shared experts. That is, regardless of the original router module, each image patch token will be deterministically assigned to these shared experts.

Table 1: **Scaling law model size.** The model sizes, detailed hyperparameters settings, and inference burden for MoE scaling experiments.

	Total param.	Activate param.	#Blocks L	Hidden dim. D	#Head n	Gflops
S/2-8E2A	199M	71M	12	384	6	3.66
S/2-16E2A	369M	71M	12	384	6	3.66
B/2-8E2A	795M	286M	12	768	12	14.62
L/2-8E2A	2.8B	1.0B	24	1024	16	51.92
XL/2-8E2A	4.1B	1.5B	28	1152	16	76.65
G/2-16E2A	16.5B	3.1B	40	1408	16	163.51

Expert-level balance loss. Directly learned routing strategies often encounter the issue of load imbalance, leading to significant performance defects [84]. To address this, we introduce an expert-level balance loss, calculated as follows:

$$L_{balance} = \alpha \sum_{i=1}^n \frac{n}{KT} \sum_{t=1}^T \mathcal{I}(t, i) \frac{1}{T} \sum_{t=1}^1 \mathcal{P}(t, i), \quad (5)$$

where α is expert-level balance factor, T is the length of image patch sequence, $\mathcal{I}(t, i)$ denotes the indicator function that image token t selects expert i and $\mathcal{P}(t, i)$ is the probability distribution of token t for expert.

2.3 Computation Analysis

In DiT-MoE, some of the MLPs are replaced by MoE layers, which helps increase the model capacity while keeping the activated number of parameters, and thus compute efficiency. Formally, the MoE modules are applied to MLPs every e layer. When using MoE, there are n possible experts per layer, with a router choosing the top K experts and shared n_s experts at each image patch token. This design allows DiT-MoE to optimize various properties by adjusting n , K , and e . Specifically, increasing n enhances model capacity at the cost of higher memory usage, while increasing K raises the number of active parameters and computational requirements. Conversely, increasing e reduces model capacity but also decreases both computation and memory requirements, along with communication dependencies. Various configurations of DiS are delineated in Table 1. They cover a wide range of total model sizes and flop allocations, from 199M to 16.5B, thus affording comprehensive insights into the scalability performance. Aligned with [68], Gflop metric is evaluated in 256×256 size image generation with patch size $p = 2$ with thop python package. We set $e = 1$ by default. The model is named according to their configs and patch size p ; for instance, DiT-MoE L/2-8E2A refers to the Large version config, $p = 2$, $n = 8$, and $K = 2$.

3 Experiments

In this section, we begin by outlining our experimental setups in Section 3.1. Next, we present the experimental results of different DiT-MoE design spaces in Section 3.2, and provide a detailed routing analysis. Then, we provide comparative results with diffusion models in Section 3.3. Finally, we explore further scaling model with synthesized data and show some impressive cases.

3.1 Experimental Settings

Datasets. Following settings [68] for class-conditional image generation task, we utilize ImageNet [17] dataset at resolutions of 256×256 and 512×512 , which comprises 1,281,167 training images across 1,000 different classes. The only data augmentation is horizontal flips. We train 500K, 1M, and 7M iterations at both resolutions, with a batch size of 1024, respectively. For the synthesis training data, we use open-source text-to-image models including SDXL [69] and SD3-Medium [24] to create approximately 5M different 512×512 images according to the given tag label. Specifically, we use the prompt template “[image class], in a natural and realistic style.” to create images with different seeds and filters with top CLIP similarity [72]. Finally, we construct a mixed training image set with a real-to-synthesis ratio of 1:5.

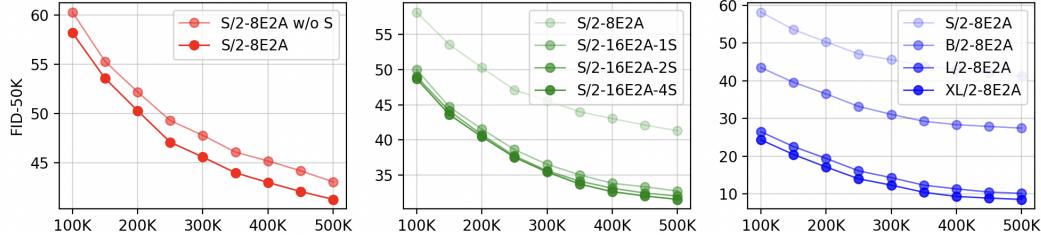


Figure 3: **Ablation experiments** on ImageNet dataset at 256×256 resolution. We report FID metrics on 50K generated samples without CFG. (a) Incorporation of **shared expert routing** can accelerate the training as well as optimize generated results. (b) **Number of experts** and (c) **model parameters scaling**. As we expected, increasing the expert number and the model size can consistently improve the generation performance. However, directly changing the share experts number influences the results marginally.



Figure 4: **Training loss curves for small version variants.** We can see that the incorporation of simple designs helps DiT-MoE training stably and consistently converge. On the other hand, increasing the expert number helps loss decrease while introducing more loss spikes.

Implementation details. We use the AdamW optimizer [50] without weight decay across all datasets, maintaining a constant learning rate of $1e-4$. In line with [68], we utilize an exponential moving average of DiT-MoE weights over training with a decay of 0.9999. All results were reported using the EMA model. Our models are trained on Nvidia A100 GPU. When trained on ImageNet dataset at different resolutions, we adopt classifier-free guidance [41] following [78] and use an off-the-shelf pre-trained variational autoencoder (VAE) model [52] from Stable Diffusion [78] available in huggingface². The VAE encoder has a downsampling factor of 8. We retrain diffusion hyperparameters from [68], using a $t_{max} = 1000$ linear variance schedule ranging from 1×10^{-4} to 2×10^{-2} and parameterization of the covariance. We set the share experts number n_s to 2 and the expert-level balance factor α to 0.05 by default.

Evaluation metrics. We measure image generation performance with Fréchet Inception Distance (FID) [40], a widely adopted metric for assessing the quality of generated images. We follow convention when comparing against prior works and report FID-50K using 250 DDPM sampling steps [65] following the process of [19]. We additionally report Inception Score [82], sFID [63] and Precision/Recall [53] as secondary metrics.

3.2 Model Design Analysis

In this section, we ablate on the ImageNet dataset with a resolution of 256×256 , evaluate the FID score on 50K generated samples following [2, 30], and identify the optimal settings.

Effect of shared expert routing. To assess the impact of the shared expert routing strategy, we conducted an ablation study by removing the shared expert while maintaining the same number of activated parameters as in the conventional expert routing approach, and trained the model from

²<https://huggingface.co/stabilityai/sd-vae-ft-ema>

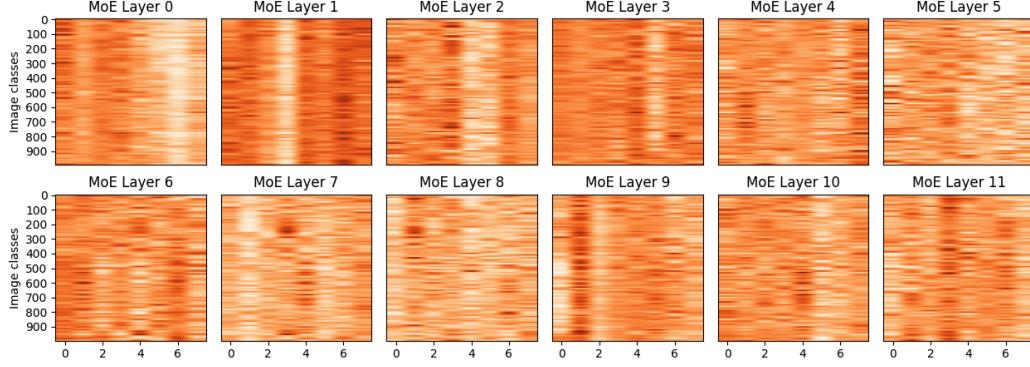


Figure 5: Frequency for selected experts per image class. We show the 12 MoE layers of DiT-MoE-S/2-8E2A. The x -axis corresponds to the 8 experts in a MoE layer. The y -axis is the 1000 ImageNet classes. For each pair (expert e , image class i), we show the average routing frequency for the patches corresponding to all generated images with class i that particular expert e . The darker the color, the higher the frequency of selection. The larger the layer number, the deeper the MoE layers.

scratch. As illustrated in Figure 3 (a), the results indicate that incorporating an additional shared expert enhances performance across most steps compared to conventional expert routing. These findings support the hypothesis that the shared expert strategy facilitates better knowledge disentangling and contributes to improved MoE model performance.

Optimal share expert number. We then examine the optimal number of shared experts at scale. Using the small version of MoE-DiT, which comprises 16 total experts, we maintain the number of activated experts at 2 and experimented with incorporating 1, 2, and 4 shared experts. As depicted in Figure 3 (b), we can find that varying the ratio of shared experts to routed experts does not significantly affect performance. Considering the trade-off between memory usage and performance, we standardize the number of shared experts to 2 when scaling up DiT-MoE.

Influence of increasing expert number. We directly increase the expert number from 8 to 16, while keeping the number of activated parameters fixed at 2. As reported in Figure 3 (b), the adjustment leads to consistently improved generative performance, albeit with a significant increase in GPU memory consumption. On the other hand, the loss curve in Figure 4 demonstrates that incorporation of MoE can achieve competitive performance and helps to faster loss convergence. However, directly increasing the expert number for performance enhancement may introduce more loss spikes. We leave how to reduce loss spike, such as spike regularization loss [98], in future work.

Scaling model size. We also explore scaling properties of DiT-MoE by examining the effect of model depth, *i.e.*, number of blocks, hidden dimension, and head number. Specifically, we train four variants of DiT-MoE model, spanning configurations from Small to XL, as detailed in Table 1, and denoted as (S, B, L, XL) for simple. As shown in Figure 3 (c), the performance improves as the depth increase from 12 to 28. Similarly, increasing the width from 384 to 1152 yields performance gains. Overall, across all configurations, impressive improvements in the FID metric are observed throughout all training stages by augmenting the depth and width of the model architecture.

3.3 Expert Specialization Analysis

Although large-scale MoEs have led to strong performance [77, 15], it remains essential to explore the internal mechanisms of these complex models within the context of DiT. We posit that a thorough routing analysis can provide valuable insights for designing new algorithms. Specifically, we first sample 50 images for each image class with 250 DDPM steps, resulting in a total of 50K data points. We then calculate the frequency of expert selection from three perspectives: image class, spatial position, and denoising time step. The visualization heat maps are presented in Figures 5, 6, and 7, respectively. From our observations, several key insights emerge: (i) Generally, there is no

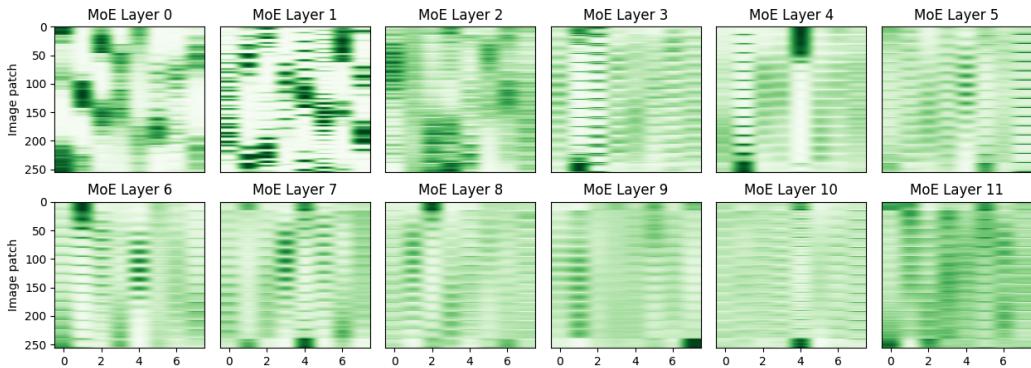


Figure 6: Frequency for selected experts per image patch position. We show the 12 MoE layers of DiT-MoE-S/2-8E2A. The x -axis corresponds to the 8 experts in a MoE layer. The y -axis are the 256 patches in ImageNet images with $\frac{32}{2} \times \frac{32}{2} = 256$ sequence length of patch size 2, at 256×256 resolution with VAE compression 8. For each pair (expert e , image patch id i), we show the average routing frequency for all the patches with patch-id i that were assigned to that particular expert e .

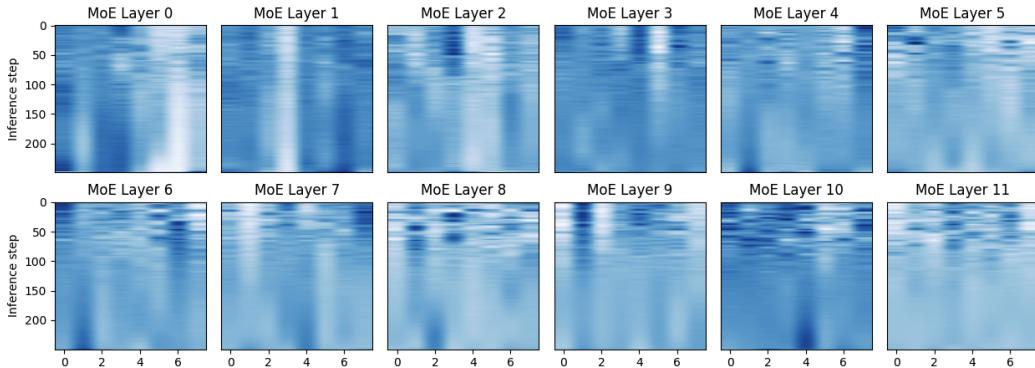


Figure 7: Frequency for selected experts per denoising time step. We show the 12 MoE layers of DiT-MoE-S/2-8E2A. The x -axis corresponds to the 8 experts in a layer. The y -axis are the 250 DDPM steps for sampling the synthesis image. For each pair (expert e , inference step i), we show the average routing frequency for all time step i that were assigned to that particular expert e .

obvious redundancy in the learned experts routing and each expert at a different MoE layer is routed sometimes. (ii) Expert selection shows a preference for spatial position and denoising step, but is less sensitive to class-conditional information, consistent with previous assumption [36]; (iii) As shown in Figure 5, no clear patterns or variations are evident in the expert routing mechanism for different class-conditional scenarios. (iv) As the MoE layers become deeper, expert selection transitions from specific positional preferences to a more dispersed and balanced distribution. For instance, in Figure 6, the heat map of MoE layer 0 the heat map for MoE layer 0 indicates a strong correlation between image patches and spatial clustering, whereas the heat map for MoE layer 9 shows a more uniform expert selection distribution. (v) As in Figure 7, during the early inference steps (*e.g.*, steps less than 50), expert choices are more concentrated, while in later steps (*e.g.*, steps greater than 100), the distribution becomes more uniform. In summary, these findings on expert routing can effectively inform future structural designs and enhance network interpretability.

3.4 Compare with State-of-the-arts

We present the evaluation results of conditional image generation for various metrics compared with dense competitors in Tables 2 and 3. On the class-conditional ImageNet 256×256 dataset, our DiT-MoE-XL achieves an FID score of 1.72, surpassing all previous models with different architectures.

Table 2: **Benchmarking class-conditional image generation on ImageNet 256×256 dataset.** We can see that DiT-MoE-XL/2 achieves state-of-the-art FID metrics towards best competitors with less inference cost.

Class-Conditional ImageNet 256×256					
Model	FID↓	sFID↓	IS↑	Precision↑	Recall↑
<i>GAN</i>					
BigGAN-deep [7]	6.95	7.36	171.4	0.87	0.28
StyleGAN-XL [83]	2.30	4.02	265.12	0.78	0.53
<i>Diff. based on U-Net</i>					
ADM [19]	10.94	6.02	100.98	0.69	0.63
ADM-U	7.49	5.13	127.49	0.72	0.63
ADM-G	4.59	5.25	186.70	0.82	0.52
ADM-G, ADM-U	3.94	6.14	215.84	0.83	0.53
CDM [44]	4.88	-	158.71	-	-
LDM-8 [78]	15.51	-	79.03	0.65	0.63
LDM-8-G	7.76	-	209.52	0.84	0.35
LDM-4	10.56	-	103.49	0.71	0.62
LDM-4-G	3.60	-	247.67	0.87	0.48
VDM++ [51]	2.12	-	267.70	-	-
<i>Diff. based on Transformer</i>					
U-ViT-H2 [2]	2.29	5.68	263.88	0.82	0.57
DiT-XL/2 [68]	2.27	4.60	278.24	0.83	0.57
SiT-XL/2 [59]	2.06	4.50	270.27	0.82	0.59
Large-DiT-3B [34]	2.10	4.52	304.36	0.82	0.60
Large-DiT-7B [34]	2.28	4.35	316.20	0.83	0.58
LlamaGen-3B [90]	2.32	-	280.10	0.32	0.56
DiT-MoE-XL/2-8E2A	1.72	4.47	315.73	0.83	0.64

Notably, DiT-MoE-XL, which activates only 1.5 billion parameters, significantly outperforms the Transformer-based competitors Large-DiT-3B, Large-DiT-7B, and LlamaGen-3B. This demonstrates the potential of MoE in diffusion models. On the class-conditional ImageNet 512×512 dataset, we observe similar advancements in nearly all evaluation metrics as expected.

3.5 Scaling up DiT-MoE with Synthesis Data

Building on the previous expert routing analysis, finally, we test how well DiT-MoE can scale to a very large number of parameters, while continuing to improve performance. For this, we expand the size of the model into giant version, detailed hyper-parameter setting listed in Table 1, and use an extensive training dataset augmented with synthesis data. We train a 40-block DiT-MoE model, incorporating 32 total experts with 2 active experts, resulting in a model with 16.5B parameters while keeping a prominent inference efficient. We successfully train DiT-MoE-G/2-16E2A, which is, as far as we are aware, the largest diffusion transformer model for class-condition image generation to date. It achieves an impressive state-of-the-art FID50K score of 1.80 at a 512×512 resolution at the ImageNet benchmark. Figure 1 showcases a selection of generated samples at different resolutions, demonstrating the high-quality image generation capacities of both DiT-MoE models.

4 Related Works

Conditional computation. To increase the number of model parameters without a corresponding rise in computational costs, conditional computation [4, 12, 16] selectively activates only relevant parts of the model based on the input, similar to decision trees [57]. This dynamic adaptation of neural networks has been applicable to various deep learning tasks [5, 3, 18, 80, 37]. For instance, [93] propose dynamically combining a set of base convolution kernels based on input image features to enhance model capacity. Additionally, techniques in [92, 29, 26, 27] adjust the forward Transformer layers at the token level to expedite inference. For efficient deployment, [8, 95] dynamically alter the neural network architecture according to specified efficiency constraints, thereby optimizing the balance between efficiency and accuracy. In a similar vein, we employ the mixture-of-experts strategy, which utilizes a gating network to dynamically route inputs to various experts.

Table 3: **Benchmarking class-conditional image generation on ImageNet 512×512 dataset.**
DiT-MoE demonstrates a promising performance compared with dense networks for diffusion.

Class-Conditional ImageNet 512×512					
Model	FID↓	sFID↓	IS↑	Precision↑	Recall↑
<i>GAN</i>					
BigGAN-deep [7]	8.43	8.13	177.90	0.88	0.29
StyleGAN-XL [83]	2.41	4.06	267.75	0.77	0.52
<i>Diff. based on U-Net</i>					
ADM [19]	23.24	10.19	58.06	0.73	0.60
ADM-U	9.96	5.62	121.78	0.75	0.64
ADM-G	7.72	6.57	172.71	0.87	0.42
ADM-G, ADM-U	3.85	5.86	221.72	0.84	0.53
VDM++ [51]	2.65	-	278.10	-	-
<i>Diff. based on Transformer</i>					
U-ViT-H/4 [2]	4.05	6.44	263.79	0.84	0.48
DiT-XL/2 [68]	3.04	5.02	240.82	0.84	0.54
Large-DiT-3B [34]	2.52	5.01	303.70	0.82	0.57
DiT-MoE-XL/2-8E2A	2.30	4.82	298.35	0.85	0.57

Mixture of experts. MoEs [48, 49, 11, 96] typically integrate the outputs of sub-models, or experts, through an input-dependent router, and have been successfully applied in diverse scenarios [47, 35, 91, 97]. In the field of NLP, [85] introduced top-k gating in LSTMs, incorporating auxiliary losses to maintain expert balance [38]. [55] extended to transformers, demonstrating substantial improvements in neural machine translation [86]. Recent advancements in large-scale language models [85, 55, 25] have enabled input tokens to select either all experts [22] or a sparse mixture, facilitating the scaling of language models to trillions of parameters [15]. [35] sped up pre-training with over one trillion parameters and one expert per input, outperforming dense baseline [73] with transfer and distillation benefits. [56] alternatively employed balanced routing via a linear assignment problem. In the domain of CV, [99, 67] combine CNN with MoE for robust image classification. [77, 81, 76] scale vision transformers with adaptive per-image computing, thereby reducing the computational burden by half compared to dense competitors.

MoEs for diffusion models. While previous studies predominantly utilize a single model to tackle denoising tasks across various timesteps [68, 32, 69, 31, 28, 46], several investigations have explored the deployment of multiple expert models, each specializing in a distinct range of timesteps [13]. PPAP [36] achieves this by training multiple classifiers on segmented timesteps, each employed for classifier guidance. Similarly, e-Diffi [1] and ERNIE-ViLG [33] utilize a consistent set of denoisers across these experts, whereas MEME [54] advocates for distinct architectures tailored to each timestep segment. These methodologies enhance generative quality while maintaining comparable inference costs, albeit at the expense of increased memory requirements. They operate on the premise that the characteristics of denoising tasks vary significantly across timesteps. We extend it by analyzing the expert routing mechanism and demonstrating that both temporal and spatial elements without class-conditional information influence different MoE layers. The most similar to work is [64], which also explores experts routing, however, they focus on a form of multi-task learning for time step and not actually sparse, *i.e.*, base version vs. dense version comes to 144M vs. 131M. In contrast, we delve into the time-space routing mechanism and modeling of >10B model size.

5 Conclusion

In this paper, we employ sparse conditional computation to train some of the largest diffusion transformer models, achieving efficient inference and substantial improvements in image generation tasks. Alongside DiT-MoE, we incorporate simple designs to facilitate the effective utilization of model sparsity in relation to inputs. We further provide a detailed analysis of the expert routing mechanism, demonstrating the characters of space-time preference for different MoE layers. This methodology aligns with recent analyses indicating that model sparsity is a highly promising strategy for reducing CO₂ emissions associated with model training. Our work represents an initial exploration of large-scale conditional computation for diffusion models. Future extensions could involve training

stable and faster, heterogeneous expert architectures and better knowledge distillation. We anticipate that the importance of sparse model scaling will continue to grow in multimodal generation.

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