
EDT: An Efficient Diffusion Transformer Framework Inspired by Human-like Sketching

Xinwang Chen^{*1}, Ning Liu^{*1}, Yichen Zhu¹, Feifei Feng¹, Jian Tang^{†2}

¹ Midea Group, ² Beijing Innovation Center of Humanoid Robotics
chen_xinwang@xs.ustb.edu.cn, ningliu1220@gmail.com
{zhuyc25, feifei.feng}@midea.com, jian.tang@x-humanoid.com

Abstract

Transformer-based Diffusion Probabilistic Models (DPMs) have shown more potential than CNN-based DPMs, yet their extensive computational requirements hinder widespread practical applications. To reduce the computation budget of transformer-based DPMs, this work proposes the **Efficient Diffusion Transformer (EDT)** framework. The framework includes a lightweight-design diffusion model architecture, and a training-free Attention Modulation Matrix and its alternation arrangement in EDT inspired by human-like sketching. Additionally, we propose a token relation-enhanced masking training strategy tailored explicitly for EDT to augment its token relation learning capability. Our extensive experiments demonstrate the efficacy of EDT. The EDT framework reduces training and inference costs and surpasses existing transformer-based diffusion models in image synthesis performance, thereby achieving a significant overall enhancement. With lower FID, EDT-S, EDT-B, and EDT-XL attained speed-ups of 3.93x, 2.84x, and 1.92x respectively in the training phase, and 2.29x, 2.29x, and 2.22x respectively in inference, compared to the corresponding sizes of MDTv2. Our code is available at here.

1 Introduction

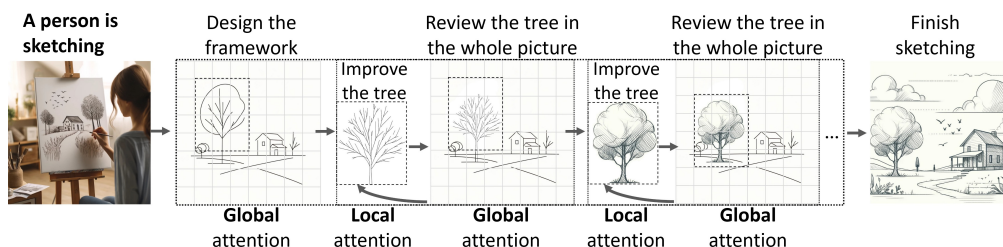


Figure 1: Illustration of the alternation process of local and global attention during sketching.

Numerous studies [1, 2, 3, 4, 5] and practical applications [6, 7, 8] have validated the effectiveness of Diffusion Probabilistic Models (DPMs), establishing them as a mainstream method in image generation. In past years, predominant works [1, 2, 3, 4, 9, 10, 11] have advanced diffusion models by incorporating a convolutional UNet-like [12] architecture as their backbone. On the other hand, transformers [13] have achieved significant milestones in both natural language processing [14,

^{*}Joint first authorship. Either author can be cited first.

[†]Corresponding author.

15] and computer vision [16, 17, 18, 19], prompting recent attempts to integrate these powerful transformer-based architectures into diffusion models with considerable success. For instance, U-ViT [20], an early work in diffusion leveraging ViT-based transformers, surpassed the contemporary CNN-based U-Net DPMs in class-conditional image generation on ImageNet, demonstrating their potential. Similarly, diffusion transformer (DiT) [21], which employs transformers as its backbone instead of the traditional U-Net backbone in latent diffusion models (LDM) [11], has shown excellent scalability. Further, masked diffusion transformer (MDT) [22] observes that DPMs often struggle to learn the relations among object parts in an image. To solve this, MDT introduces a masking training scheme to enhance the DPMs' ability to relation learning among object semantic parts in an image. MDT established a SOTA of class-condition image synthesis on the ImageNet.

While transformer-based DPMs offer scalability and a higher performance ceiling than their CNN counterparts, they also require more computational resources. For instance, in each inference step, DiT-XL-2 consumes 118 GFLOPs and U-ViT-H requires 133 GFLOPs. This computational demand escalates with increasing time steps or token length, limiting their practical application. Despite their computational inefficiency, few studies have explored enhancing the efficiency of transformer-based DPMs. Therefore, the trade-off between computation and performance underscores the importance of designing a lightweight model architecture that maintains excellent performance.

To improve the computational efficiency of transformers in DPMs, we introduced a comprehensive optimization framework named **Efficient Diffusion Transformer (EDT)**. Specifically, we developed a lightweight diffusion transformer architecture based on a comprehensive computation analysis. Moreover, we devised the Attention Modulation Matrix (AMM) and its alternation arrangement in EDT inspired by human-like sketching. AMM, functioning as a plug-in, can be seamlessly integrated into diffusion transformers to enhance image synthesis performance significantly without requiring additional training. Additionally, we introduced a novel token relation-enhanced masking training strategy tailored for EDT to enhance its relation learning capability.

Lightweight-design diffusion transformer Based on the empirical analysis of the number of tokens, token dimensions, and the FLOPs, we propose two principles to design the lightweight diffusion transformer, and redesign and incorporate the down-sampling, up-sampling, and long skip connection modules into diffusion transformers. The utilization of down-sampling module can reduce FLOPs, but harms performance, since the token merging operation in down-sampling and long skip connections modules leads to the loss of token information. To mitigate this loss, we enhance the key features by introducing token information enhancement and positional encoding supplement.

Attention Modulation Matrix The mind stores visual structures as a top-down hierarchy passing from general shape to the relationships between parts down to the detailed features of individual parts [23, 24]. Based on this storage structure in the mind, humans tend to follow a coarse-to-fine drawing strategy [25]. The logical structure of sketching of humans tends to first form a general framework (using global attention), then gradually refine local details (using local attention) driven by the global perspective (using global attention) shown in Figure 1. Inspired by the sketching process, we integrate the alternation process of local and global attention to EDT, and propose Attention Modulation Matrix (AMM) to modulate from the default global attention in self-attention mechanisms to local attention. AMM, functioning as a plug-in, which can be seamlessly integrated into diffusion transformers, enhancing image synthesis performance without necessitating additional training.

Token relation-enhanced masking training strategy The token compression in down-sampling modules may cause token information loss. Learning the relations among tokens can help token down-sampling modules compress tokens effectively. And it has been confirmed that masking training can enhance the DPMs' ability to learn relations among object parts in images [22]. We propose a novel masking training strategy to enhance the relation learning among tokens. Specifically, the full tokens are fed into EDT and the tokens masking is executed in down-sampling modules. This forces models to learn token relations before some of the tokens are masked. We compare our masking training method to the counterpart in MDT, both implemented on EDT. Our masking training method achieves better generation.

We summarize the contributions of our work: 1. We develop an Efficient Diffusion Transformer (EDT) framework and design a lightweight diffusion transformer architecture based on a comprehensive computation analysis. 2. Inspired by human sketching, we design EDT with an alternation process between global attention and location attention. Moreover, to the best of our knowledge, we introduce Attention Modulation Matrix for the first time, which improves the detail of generated images of

pre-trained diffusion transformers without any extra training cost. 3. We propose a novel token masking training strategy to enhance the token relation learning ability of EDT. 4. EDT has reached a new SOTA and achieves faster training and inference speed compared to existing representative works DiT and MDTv2. We conduct a series of exploratory experiments and ablation studies to analyze and summarize the key factors affecting the performance of EDT.

2 Method

2.1 Preliminaries

We briefly review several fundamental concepts necessary to understand classifier-free guidance class-condition diffusion models [11]. The primary objective of diffusion models is to learn a diffusion process that constructs a probability distribution for a specific dataset, subsequently enabling the sampling of new images. Given a classifier-free guidance class-condition diffusion model $\epsilon_\theta(x_t, c)$, the model can generate images of specific class c from Gaussian noise over multiple denoising time steps. The model operates through two main processes: the forward and reverse processes. The forward process simulates training data x_t to be denoised at time step t , by adding Gaussian noise $\epsilon_t \sim \mathcal{N}(0, \mathbf{I})$ to the original data x_0 . This process is mathematically described by $q(x_t|x_0) = \mathcal{N}(x_t; \sqrt{\alpha_t}x_0, (1 - \alpha_t)\mathbf{I})$, where α_t denotes a hyperparameter. The reverse process samples noise-reduced data x_{t-1} based on noise data x_t and class-condition c . The reverse process is represented as $p_\theta(x_{t-1} | x_t, c) = \mathcal{N}(x_{t-1} | \mu_\theta(x_t, c), \Sigma_\theta(x_t, c))$, where μ_θ and Σ_θ are the statistics of p_θ . By optimizing the variational lower-bound of the log-likelihood [26] $p_\theta(x_0)$ and reparameterizing μ_θ as a noise prediction network ϵ_θ , the model can be trained using simple mean-squared error between the predicted noise $\epsilon_\theta(x_t, c)$ and the ground truth ϵ_t sampled Gaussian noise: $\mathcal{L}_\theta(x_t, c, \epsilon_t) = \|\epsilon_\theta(x_t, c) - \epsilon_t\|_2^2$. Additionally, $\epsilon_\theta(x_t, c)$ is a standard class-condition model; when $c = \emptyset$, it functions as an unconditional model. To allow the controllability of class-condition guidance, the prediction of models is further derived as $\hat{\epsilon}_\theta(x_t, c) = \epsilon_\theta(x_t, \emptyset) + \omega \cdot (\epsilon_\theta(x_t, c) - \epsilon_\theta(x_t, \emptyset))$, where $\omega \geq 1$ is class-condition guidance intensity.

In this work, we employ a classifier-free guidance class-condition diffusion transformer architecture operating on latent space. The pre-trained variational autoencoder (VAE) model [26] from LDM [11] remains frozen and is used to encode/decode the image/latent tokens.

2.2 Lightweight-design diffusion transformer

Transformer-based diffusion probabilistic models (DPMs) have demonstrated greater scalability and superior performance compared to CNN-based DPMs [20, 21, 22]. However, these models also entail significant computational overhead during both the training and inference phases. In response, we design a lightweight diffusion transformer architecture in this section. We undertake a computational complexity analysis of the transform-based diffusion model. Based on the empirical analysis of the number of tokens, token dimensions, FLOPs, and the number of parameters, we establish two design principles: (1) reducing the number of tokens to decrease the FLOPs in the self-attention module through the down-sampling module; (2) ensuring that the FLOPs of each EDT stage post a down-sampling module are significantly reduced compared to the stages prior to the down-sampling module, to effectively lower the overall FLOPs.

Building on the aforementioned design principles, we have redesigned and incorporated the down-sampling, up-sampling, and long skip connection modules into the transformer-based diffusion model, successfully achieving a reduction in FLOPs and increased inference speed. For instance, in comparison to DiT-S [21], our smaller version model EDT-S achieves an inference speed of 5.5 steps per second, versus 2.7 steps per second for DiT-S, effectively doubling the speed. Figure 2 illustrates the architecture of our lightweight-designed diffusion transformer. The model includes three EDT stages in the down-sampling phase, viewed as an encoding process where tokens are progressively compressed, and two EDT stages in the up-sampling phase, viewed as a decoding process where tokens are gradually reconstructed. These five EDT stages are interconnected through down-sampling, up-sampling, and long skip connection modules. Note that each EDT stage comprises several consecutive transformer blocks. For more details on the computational complexity analysis and model design, please refer to Appendix A.2. It is important to note that *the down-sampling and up-sampling phases can be viewed as encoding and decoding processes, respectively, aligning with*

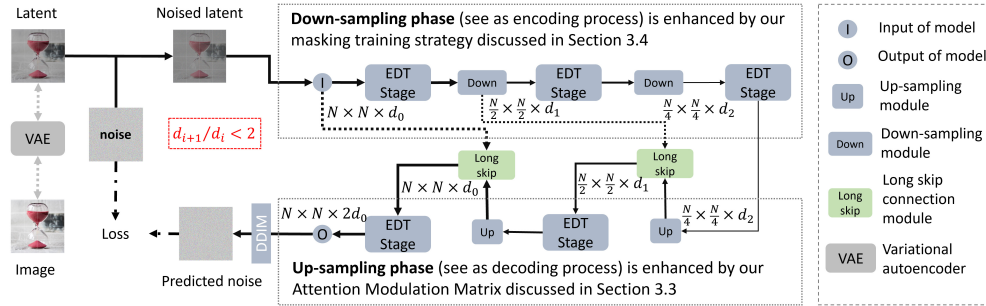


Figure 2: The architecture of lightweight-design diffusion transformer.

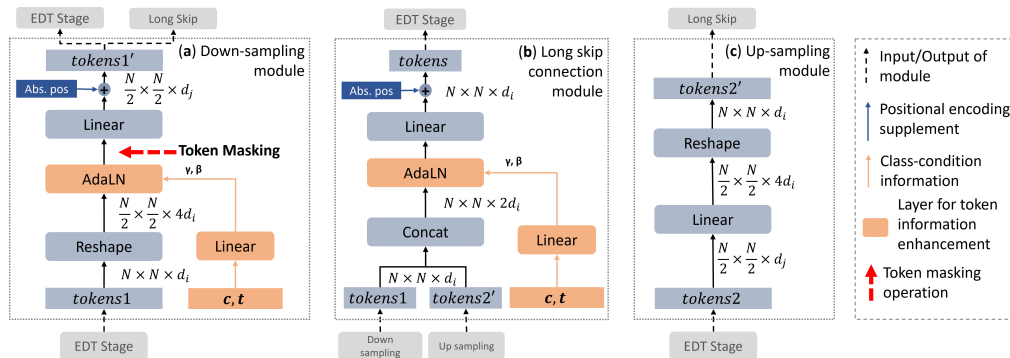


Figure 3: The design of down-sampling, long skip connection and up-sampling modules.

the conceptualization of drawing pictures in human sketching. These phases are crucial and will be further discussed in the following Section 2.3 and Section 2.4.

While we have successfully reduced the FLOPs of the model, the token merging operation in the down-sampling and long skip connection modules inevitably leads to a loss of token information, including the positional encoding and contextual data essential for class-condition generation of images. To mitigate this loss of token information, we propose two improvements, as illustrated in Figure 3: **token information enhancement** and **positional encoding supplement**.

Token information enhancement We enhance the contextual information required for class-condition generation by employing Adaptive Layer Normalization (AdaLN) before the token merging process. AdaLN adjusts the output by learning scaling factors γ and bias coefficients β , which can scale, negate, or shut off the features [27]. By utilizing AdaLN, we modulate the tokens based on class conditions and time steps before merging, thereby preserving more contextual information and minimizing the loss of token information. As depicted in Figure 3, class-condition information is integrated by the γ and β of AdaLN in both the down-sampling and long skip connection modules.

Positional encoding supplement We restore the absolute positional encoding of tokens following the token merging process. As illustrated in Figure 3, after merging the tokens, we add the absolute positional encoding to the merged tokens at the end of both the down-sampling and long skip connection modules.

2.3 Making EDT “sketch” like a human

The lightweight design of EDT might compromise the quality of image synthesis. To enhance the detail fidelity in generated images, we have refined the decoding process (up-sampling phase) of EDT by imitating the process of human sketching. We begin by examining how attention shifts during the act of sketching by humans. Human cognition stores visual structures as a top-down hierarchy passing from general shape to the relationships between parts down to the detailed features of individual parts [23, 24]. This hierarchical structuring of visual information in the brain makes humans tend to follow a coarse-to-fine strategy in sketching [25]. As shown in Figure 1, the process of human

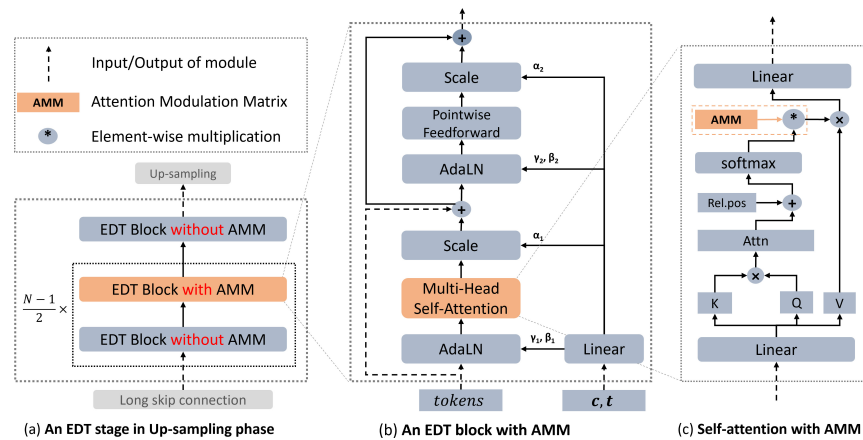


Figure 4: The position of Attention Modulation Matrix (local attention) in an EDT stage in the up-sampling phase.

sketching tends to first form a general framework (using global attention), then gradually refine local details [24, 28] (using local attention) hinted by the global perspective (using global attention). Even when concentrating on a local detail, humans do not become completely detached from the overall framework. Therefore, humans periodically shift attention back to a global view to scrutinize the local detail and further fine-tune it [29, 30]. This process reflects the alternation of global and local attention in the human brain when sketching.

Inspired by the sketching process, we aim to integrate the alternation process of local attention and global attention to EDT. In the current series of diffusion transformers [20, 22, 21], only default global attention mechanisms are employed, which may lead to poor generation of local details. Therefore, we introduce the Attention Modulation Matrix (AMM) to enhance focus on local details. Moreover, to mimic the alternation process in the EDT, we alternately incorporate the AMM into the lightweight-design transformer diffusion architecture.

2.3.1 Integrating local attention into the up-sampling phase of EDT

To imitate the alternation between global and local attention like the act of humans drawing, we integrate local attention into the up-sampling phase of EDT by introducing Attention Modulation Matrix (AMM). In this section, we concentrate on imitating the alternation process of attention. A detailed discussion of AMM is deferred to Section 2.3.2. We align the decoding process of EDT with the humans drawing pictures. Consequently, we incorporate local attention (AMM) into the decoding process (up-sampling phase) of EDT. Figure 4 illustrates the placement of AMM (local attention) in an EDT stage. As depicted in Figure 4(a), we alternately configure EDT blocks with and without the AMM, thereby mimicking the alternation between global and local attention observed in drawing activities. The EDT block with AMM is shown in Figure 4(b). As shown in Figure 4(c), the AMM is integrated into the self-attention module. The AMM and the global attention score matrix are combined via a Hadamard product to modulate global attention into local attention.

2.3.2 Attention modulation matrix

We develop the Attention Modulation Matrix (AMM) to modulate the default global attention in self-attention mechanisms into local attention, which imitates the local attention of humans during the act of drawing. Humans typically concentrate on either the actively engaged parts or the most salient aspects of a visual scene [31]. When drawing a specific local region of an image, areas closer to the region of interest tend to exhibit stronger contextual relations and thus warrant increased attention. Conversely, areas further from the region of interest generally show weaker contextual relations and can be allocated less attention. Thus, we articulate the principle: *for a local region, the strength of attention on contextual relations within a specific region is inversely related to the distance between the local region and the specific region*. In the self-attention mechanism, we regard the attention score between tokens as an indicator of the strength of attention on contextual relations between regions. Similarly, we aim to modulate the strength of attention based on the distance among tokens

on the image. Based on this concept, we have developed the Attention Modulation Matrix (AMM), functioning as a plug-in, which can be seamlessly integrated into diffusion transformers, significantly enhancing image synthesis performance without necessitating additional training.

Formally, given a sequence of $N \times N$ tokens and its corresponding attention score matrix $\mathbf{A} \in \mathbf{R}^{N^2 \times N^2}$, we take two arbitrary tokens as an example to illustrate the formulation. The two arbitrary tokens are denoted as $Token_i, Token_r$ and their attention score a_{ir} , where $a_{ir} \in \mathbf{A}$. The coordinates of $Token_i$ and $Token_r$ correspond to the (x_i, y_i) and (x_r, y_r) in the original $N \times N$ tokens grid, where $i = Nx_i + y_i$ and $r = Nx_r + y_r$. The distance between these two tokens can be calculated by Euclidean distance $d_{ir} = \sqrt{(x_i - x_r)^2 + (y_i - y_r)^2}$, and we can derive the token distance matrix $\mathbf{D} \in \mathbf{R}^{N^2 \times N^2}$. We aim to modulate the global attention into local attention by multiplying the attention score matrix to the AMM, which is generated based on the token distance matrix $\mathbf{D}$. The modulation matrix generation function F is designed with adherence to two principles: (1) the generation function should be monotonically decreasing within the interval $[0, d_{max}]$, ensuring that the modulation matrix elements are inversely correlated with distance, where $d_{max} = (N - 1)\sqrt{2}$ is the furthest distance, which is the distance between two diagonal opposite tokens; (2) the output range of this function should be limited to avoid significantly altering the original distribution of the attention score matrix. Based on the two principles, we utilize the monotonically decreasing interval in cosine function, $\cos(f d_{ir})$, $d_{ir} \in [0, d_{max}]$, where the monotonically decreasing interval can be flexibly adjusted by adjusting its period T or frequency f . According to the d_{max} , we set $T = 4d_{max}$ and $f = \frac{2\pi}{T}$. Further, we employ $\cos(f d_{ir})$ as the exponent of the Euler's number e , thereby smoothing the values of the modulation matrix elements. We obtain the final modulation matrix generation function $F(d_{ir}) = k e^{\cos(f d_{ir})}$, which can flexibly scale the function value to $[k, ke]$ by scaling factor k . We empirically set $k = 0.5$ and the output range within $[\frac{1}{2}, \frac{e}{2}]$, which allows the modulation matrix elements to appropriately adjust the attention scores. In addition, we define an effective radius R for local attention to exclude the interactions of tokens that occur over tokens with far distances. For each token pair, we only modulate the attention scores with distance $d_{ir} \leq R$, where R is the effective radius for local attention. We set $R = \sqrt{(N - 1)^2 + 4}$ based on experiments regarding the hyper-parameters of the AMM, detailed in Appendix A.3.3. And those $d_{ir} > R$, their attention scores are set to zero, indicating that tokens far from the region of interest exert less influence. Thus, we have the Attention Modulation Matrix $\mathbf{M} \in \mathbf{R}^{N^2 \times N^2}$, where $m_{ir} \in \mathbf{M}$ is defined as:

$$m_{ir} = \begin{cases} F(d_{ir}), & d_{ir} \leq R \\ 0, & d_{ir} > R \end{cases} \quad (1)$$

The modulated attention score element is $a'_{ir} = a_{ir} * m_{ir}$, where $a'_{ir} \in \mathbf{A}'$, and $\mathbf{A}'$ is the modulated attention score matrix. Further details about the entire process and an illustration of AMM can be found in Appendix A.3.1.

2.4 Token relation-enhanced masking training strategy

The ability to learn relations among object parts in images is crucial for image generation, as highlighted in MDT [22]. However, the down-sampling process in EDT inevitably leads to the loss of token information. Establishing relations among tokens can alleviate performance degradation caused by the loss of token information. To enhance the relation-learning ability in EDT, we introduce a relation-enhanced masking training strategy. Before detailing the proposed masking training strategy, we first explore the integration of MDT into EDT. Figure 5 (a) shows the masking training strategy of MDT. In MDT, the training loss L contains two parts as shown in Eqn. 2.

$$L = L_{full} + L_{masked} = \mathcal{L}_\theta(x_t, c, \epsilon_t) + \mathcal{L}_\theta(mask * x_t, c, \epsilon_t) \quad (2)$$

L_{full} is the loss when the input consists of the full token input, the L_{masked} is the loss when the input consists of the remained tokens after masking, and $mask$ is a matrix to mask tokens randomly.

However, our analysis reveals that the masking training method used in MDT excessively focuses on masked region reconstruction at the expense of diffusion training, potentially leading to a degradation in image generation performance. Additionally, our evaluation of MDT is observed a conflict between the training objectives of L_{full} and L_{masked} . Specifically, as L_{full} decreases, L_{masked} increases, and vice versa, demonstrating the conflicting nature of these training objectives. To mitigate this conflict and allow the model to focus on the diffusion generation task, as shown in Figure 5 (b), we

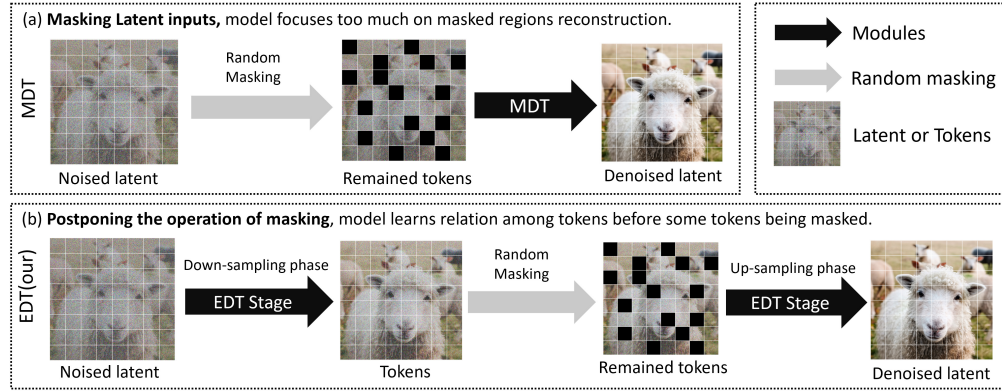


Figure 5: Token relation-enhanced masking training strategy. MDT is fed the remained tokens after token masking into models. EDT is fed full tokens into shallow EDT blocks, and the operation of token masking is performed in down-sampling modules.

design the token relation-enhanced masking training strategy, which feeds full tokens into shallow blocks and postpones the token masking operation to occur within the down-sampling modules. This strategy is designed to facilitate learning relationships among tokens and reduce the loss of token information without the issues arising from conflicting training objectives. When training, the masked tokens are unseen to the EDT blocks following the operation of masking, which forces the EDT blocks before the operation of masking to learn the relations among tokens. As the relations among tokens are learned, the key information in each token is dispersed and stored across various tokens. This avoids reliance on certain tokens and reduces the loss of token information from compression in down-sampling. Figure 3(a) shows, with a red arrow in the down-sampling module, the specific point at which token masking is performed. After passing through the down-sampling modules, the EDT stages in up-sampling phase generate images solely relying on the remained tokens. The loss function of EDT with token relation-enhanced masking training strategy is shown in Eqn. 3, where the token masking operation is executed in the down-sampling modules.

$$L = L_{full} + L_{masked} = \mathcal{L}_{\theta}(x_t, c, \epsilon_t) + \mathcal{L}_{\theta}(x_t, c, mask, \epsilon_t) \quad (3)$$

We discover that EDT is particularly well-suited for masking training due to its up-sampling modules, which inherently are used for the reconstruction of tokens. Unlike MDT, which requires an additional interpolator module for reconstructing masked tokens, EDT eliminates the need for such a module, thereby reducing unnecessary training overhead associated with an interpolator compared to MDT. For a more detailed analysis, please refer to Appendix A.4.1.

3 Experiment

3.1 Implementation Details

Models: We develop three different sizes of EDT including small (EDT-S), base (EDT-B) and extra large (EDT-XL), each using a patch size of two. Details regarding token dimensions, head numbers, and parameter counts are provided in Table 5 of Appendix A.2.2. **Training and evaluation:** The training dataset is ImageNet [32] with 256×256 and 512×512 resolution. For a fair comparison, we follow the training settings of MDTv2 [33]. EDT uses the Adan [34] optimizer with a global batch size of 256 and without weight decay. The learning rate linearly decreases from 1e-3 to 5e-5 over 400k iterations. **Masking training strategy:** We set the mask ratio 0.4 ~ 0.5 in the first down-sampling module, and 0.1 ~ 0.2 in the second. The investigation of mask ratio refers to Appendix A.4.2. **GPUs:** Training is conducted on eight L40 48GB GPUs, while the speed test for inference is performed on a single L40 48GB GPU. **Evaluation metrics:** Common metrics such as Fre'chet Inception Distance (FID) [35], sFID [36], Inception Score (IS) [37], Precision, and Recall [38] are used to assess the model performance. The training speed is evaluated by iterations per second, and inference speed is assessed by steps per second using a batch size of 256 in FP32. For fair comparison, we follow [21, 33] and employ the TensorFlow evaluation suite from ADM [4], reporting FID-50K results with 250 DDIM [10] sampling steps. These metrics are reported by default without the classifier-free guidance.

Table 1: The comparison with existing SOTA methods on class-conditional image generation without classifier-free guidance on ImageNet 256×256. We report the training speed (T-speed), inference speed (I-speed), and memory consumption (Mem.) of inference. The EDT* denotes the EDT without our proposed token relation-enhanced masking training strategy.

Model	Cost↓ (Iter×BS)	Params. (M)	T-speed (iter/s)	GFLOPs↓	I-Speed (step/s)	Mem. (MB)	FID↓
DiT-S[21]	400K×256	32.90	12.50	6.06	2.70	4296	68.40
SD-DiT-S[39]	400K×256	32.90	-	-	-	-	48.39
EDT-S*(our)	400K×256	38.30	13.20	2.66	5.50	4268	38.73
MDTv2-S[33]	400K×256	33.10	2.25	6.07	2.40	4902	39.50
EDT-S (our)	400K×256	38.30	8.86	2.66	5.50	4268	34.27
DiT-B[21]	400K×256	130.30	4.30	23.01	1.11	8978	43.47
SD-DiT-B[39]	400K×256	130.30	-	-	-	-	28.62
EDT-B*(our)	400K×256	152.00	5.80	10.20	2.20	8584	23.19
MDTv2-B[33]	400K×256	130.80	1.42	23.02	0.96	9212	19.55
MDTv2-B[33]	1600K×256	130.80	1.42	23.02	0.96	9212	13.60
EDT-B(our)	400K×256	152.00	4.03	10.20	2.20	8584	19.18
EDT-B(our)	1000K×256	152.00	4.03	10.20	2.20	8584	13.58
ADM[4]	1980k×256	554.00	-	1120.00	-	-	10.94
LDM-4[11]	178k×1200	400.00	-	104.00	-	-	10.56
DiT-XL[21]	400K×256	674.80	0.93	118.64	0.25	17538	19.47
SD-DiT-XL[39]	1300K×256	740.60	-	-	-	-	9.01
EDT-XL*(our)	400K×256	698.40	1.49	51.83	0.51	14486	10.48
MDTv2-XL[33]	400K×256	675.80	0.51	118.69	0.23	23436	7.70
EDT-XL(our)	400K×256	698.40	0.98	51.83	0.51	14486	7.52

Table 2: The comparison with existing transformer-based models on class-conditional image generation without classifier-free guidance on ImageNet 512×512.

Model	T-speed (iter/s)	GFLOPs↓	FID↓	IS↑	sFID↓
DiT-S	2.26	31.42	85.21	23.68	13.53
MDTv2-S	0.53	31.46	51.16	29.94	8.57
EDT-S(our)	1.63	13.25	51.84	29.92	7.86

3.2 Comparison with SOTA transformer-based diffusion methods

To validate the enhancements in speed and generation performance of EDT, we conducted comparisons with both classical methods [4, 11, 21] and recent advancements [33, 39, 40].

Experiment on ImageNet 256×256 The result of image generation without classifier-free guidance is shown in Table 1. Our comparisons across three different sizes demonstrate that EDT consistently achieves the best FID scores: EDT-S scored an FID of 34.2, EDT-B scored 19.1, and EDT-XL scored 7.5. Notably, EDT also showed significant reductions in GFLOPs compared to the second-best MDTv2 across all sizes (2.66 GFLOPs vs. 6.07 GFLOPs, 10.2 GFLOPs vs. 23.02 GFLOPs, 51.83 GFLOPs vs. 118.69 GFLOPs). Moreover, EDT exhibited the lowest memory consumption during inference across all three sizes, underscoring the efficiency of our lightweight design. We further investigated the training speed of EDT. Given that both EDT and MDTv2 incorporate additional training strategies, we specifically compared the training speeds of these two models. Additionally, we assessed the training speed of EDT without the masking training strategy (denoted as EDT*) against other methods. In both scenarios, EDT trained faster than the baseline models. For example, EDT-XL* achieved a training speed of 1.49 iter/s, compared to 0.93 iter/s for DiT-XL. In comparison to MDTv2-XL, which trained at 0.51 iter/s, EDT-XL was nearly twice as fast at 0.98 iter/s. We further perform the experiment on **the image generation with classifier-free guidance**. The result is shown in Table 13 of Appendix A.5.1. Under the same training cost, EDT-S-G achieves the lowest FID score compared to MDTv2-S-G (9.89 vs. 15.62). Overall, these findings confirm that EDT significantly enhances both the speed and performance of image synthesis. Additionally, the training cost of EDT is efficient. We include a training cost analysis of EDT in Appendix A.2.3.

Experiment on ImageNet 512×512 As shown in Table 2, we train DiT-S, MDTv2-S and EDT-S on ImageNet 512×512 for 60 epochs. Under the same training cost, both MDTv2-S and EDT-S achieve better FID scores than DiT-S (51.16 vs. 85.21, 51.84 vs. 85.21). In terms of training speed and inference overhead, EDT-S is 3.07 and 2.37 times faster than MDTv2-S respectively. This indicates that EDT achieves competitive image generation performance with lower resource overhead.

Table 3: Results on various models with (w) AMM and without (w/o) AMM. These models are trained for 400k iterations by default. We evaluate models using FID scores.

Model	W/o AMM	W AMM	Model	W/o AMM	W AMM
EDT-S*	50.90	38.73	EDT-S	46.90	34.27
EDT-B*	33.19	23.19	EDT-B	26.30	19.18
EDT-XL*	14.92	10.48	EDT-XL	12.80	7.52
DiT-S	67.16	63.11	MDTv2-S	39.02	31.89
DiT-XL	18.48	14.73	DiT-XL-7000k	9.62	3.75

3.3 Ablation Study

3.3.1 Attention Modulation Matrix

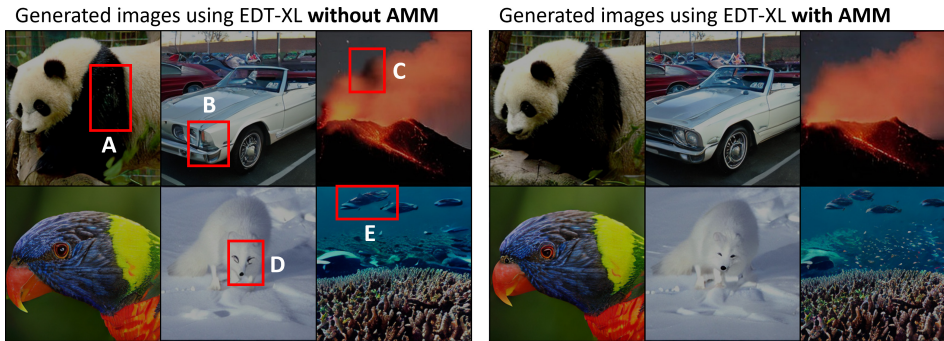


Figure 6: EDT-XL with AMM achieves more realistic visual effects. **Area A:** There are some blue stains on the panda’s arm. **Area B:** An unreasonable gray area. **Area C:** Black smoke in the red fog. **Area D:** Unrealistic eyes of the fox. **Area E:** Fish with an odd shape. The parrot image generated by EDT-XL without AMM is realistic. And the parrot image generated by EDT-XL with AMM remains equally realistic. The add of AMM does not negatively affect the original quality.

Quantitative analysis We demonstrate the effectiveness and broad applicability of AMM across various models by comparing the FID scores between models with AMM and without AMM in Table 3. Extensive results show that the pre-trained models with AMM consistently outperform models without AMM, thereby verifying the generality and effectiveness of AMM. For instance, MDTv2-S with AMM achieves a better FID score than MDTv2-S without AMM (31.89 vs. 39.02). Using AMM enhances the FID of DiT-XL from 18.48 to 14.73. EDT-XL also has a lower FID score of 7.52 compared to EDT-XL without AMM of an FID score of 12.8.

Qualitative analysis We demonstrate the effectiveness of AMM by comparing the synthesis images from EDT-XL and DiT-XL with and without the AMM. As shown in Figure 6, the red boxes highlight the unrealistic regions in the images generated by EDT-XL without AMM. In the corresponding regions of the images generated by EDT-XL with AMM, the results appear more realistic. Moreover, the parrot image generated by EDT-XL without AMM is realistic and the parrot image generated by EDT-XL with AMM still remains equally realistic. This visual analysis demonstrates the effectiveness of the AMM plugin. Please refer to A.3, and A.5.2 for more analysis about AMM. While AMM is effective, there is potential for improvement. Please refer to A.6 for details regarding its limitations.

3.3.2 Lightweight-design diffusion transformer

We investigate the effectiveness of the key components in our proposed diffusion transformer architecture. We denote the token information enhancement as TIE and the positional encoding supplement

Table 4: The ablation study of the key components of the lightweight-design and masking training strategy of EDT. The experiment is conducted on the small-size EDT model (W/o AMM).

Model	TIE	PES	masking training strategy of MDT	masking training strategy of EDT	FID↓	IS↑
Baseline	✗	✗	✗	✗	53.90	29.29
A	✗	✓	✗	✗	52.76	29.38
B	✓	✗	✗	✗	52.13	30.60
C	✓	✓	✗	✗	50.90	31.02
D	✓	✓	✓	✗	49.60	33.11
E	✓	✓	✗	✓	46.90	35.40

as PES in Table 4. Model A incorporates TIE without PES, with an FID score of 52.8. Model B integrates PES without TIE, with an FID score of 52.1. Model C represents EDT-S*, and utilizes both components, with an FID score of 50.9. Upon comparing Models A and C, we observed that the usage of token information enhancement leads to an improved FID score, decreasing from 52.8 to 50.9. Similarly, the comparison between Models B and C demonstrates that the addition of a positional encoding supplement also results in a better FID score, reducing from 52.1 to 50.9. The experimental results confirm the effectiveness of both components in enhancing model performance.

3.3.3 Token relation-enhanced masking training strategy

We investigate the effectiveness of the token relation-enhanced masking training strategy and compare it with the training strategy used in MDT in Table 4. Model C does not employ any masking training strategy, with an FID score of 50.9 and an IS score of 31.0. Model D, a small-size EDT trained using the masking strategy of MDT, with an FID score of 49.6 and an IS score of 33.1. Model D shows only a slight improvement compared to Model C. Model E is a small-size EDT trained with the masking strategy of EDT, with an FID score of 46.9 and an IS score of 35.4. Model E achieved the best performance in terms of both FID and IS. This result suggests that the masking training strategy of EDT successfully improves performance by enhancing the learning ability of token relations.

4 Conclusions

In this work, we propose the Efficient Diffusion Transformer (EDT) framework, which includes a lightweight-design of diffusion transformer, a training-free Attention Modulation Matrix (AMM) inspired by human-like sketching, and the token relation-enhanced masking training strategy. Our lightweight-design reduces the number of tokens through down-sampling to lower computational costs. We redesigned down-sampling module and masking training strategy to address token information loss caused by the reduction of tokens. During inference, we introduce local attention through AMM, further enhancing image generation performance. Extensive experiments demonstrate that the EDT surpasses existing SOTA methods in both inference speed and image synthesis performance.

5 Related Work

Diffusion Probabilistic Models: Denoising diffusion probabilistic models (DDPM) [1], have marked a significant advancement in generative models. DDPM improves image generation by progressively reducing noise. ADM [4] innovates further by introducing a classifier-guided approach to refine the balance between image diversity and fidelity. Subsequent developments include a classifier-free method [9], which increases the flexibility of diffusion models by eliminating classifier constraints. DiT [21] replacing U-Net with transformer in LDM [11], achieving superior scalability. However, transformers-based models are computationally intensive. **Efficient Diffusion:** Various methods have been developed to enhance the efficiency of diffusion models. DDIM [10] redefines the diffusion process as non-Markovian, speeding up-sampling by removing dependencies on sequential time steps in DDPM [1]. LDM [11] reduces computational demands by transforming high-resolution images into a latent space for diffusion, thus balancing complexity with image detail. Current research in lightweight diffusion transformers is limited but offers potential for further efficiency improvements in diffusion model technologies. For more related work, please refer to Appendix A.1.

References

- [1] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.
- [2] Yang Song and Stefano Ermon. Generative modeling by estimating gradients of the data distribution. *Advances in neural information processing systems*, 32, 2019.
- [3] Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. *arXiv preprint arXiv:2011.13456*, 2020.
- [4] Prafulla Dhariwal and Alexander Nichol. Diffusion models beat gans on image synthesis. *Advances in neural information processing systems*, 34:8780–8794, 2021.
- [5] Minjie Zhu, Yichen Zhu, Jinming Li, Junjie Wen, Zhiyuan Xu, Ning Liu, Ran Cheng, Chaomin Shen, Yaxin Peng, Feifei Feng, et al. Scaling diffusion policy in transformer to 1 billion parameters for robotic manipulation. *arXiv preprint arXiv:2409.14411*, 2024.
- [6] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. *arXiv preprint arXiv:2112.10741*, 2021.
- [7] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in neural information processing systems*, 35:36479–36494, 2022.
- [8] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 1(2):3, 2022.
- [9] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598*, 2022.
- [10] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. *arXiv preprint arXiv:2010.02502*, 2020.
- [11] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022.
- [12] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention—MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18*, pages 234–241. Springer, 2015.
- [13] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.
- [14] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
- [15] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- [16] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *European conference on computer vision*, pages 213–229. Springer, 2020.
- [17] Sixiao Zheng, Jiachen Lu, Hengshuang Zhao, Xiatian Zhu, Zekun Luo, Yabiao Wang, Yanwei Fu, Jianfeng Feng, Tao Xiang, Philip HS Torr, et al. Rethinking semantic segmentation from a sequence-to-sequence perspective with transformers. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6881–6890, 2021.
- [18] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021.

- [19] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4015–4026, 2023.
- [20] Fan Bao, Shen Nie, Kaiwen Xue, Yue Cao, Chongxuan Li, Hang Su, and Jun Zhu. All are worth words: A vit backbone for diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22669–22679, 2023.
- [21] William Peebles and Saining Xie. Scalable diffusion models with transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4195–4205, 2023.
- [22] Shanghua Gao, Pan Zhou, Ming-Ming Cheng, and Shuicheng Yan. Masked diffusion transformer is a strong image synthesizer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 23164–23173, 2023.
- [23] D Man and A Vision. A computational investigation into the human representation and processing of visual information. *WH San Francisco: Freeman and Company, San Francisco*, 1:1, 1982.
- [24] Jonathan Fish and Stephen Scrivener. Amplifying the mind’s eye: sketching and visual cognition. *Leonardo*, 23(1):117–126, 1990.
- [25] Mathias Eitz, James Hays, and Marc Alexa. How do humans sketch objects? *ACM Transactions on graphics (TOG)*, 31(4):1–10, 2012.
- [26] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.
- [27] Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville. Film: Visual reasoning with a general conditioning layer. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2018.
- [28] Aaron Hertzmann. Toward modeling creative processes for algorithmic painting. *arXiv preprint arXiv:2205.01605*, 2022.
- [29] Marion Botella, Franck Zenasni, and Todd Lubart. What are the stages of the creative process? what visual art students are saying. *Frontiers in psychology*, 9:389647, 2018.
- [30] Kees Dorst and Nigel Cross. Creativity in the design process: co-evolution of problem–solution. *Design studies*, 22(5):425–437, 2001.
- [31] Geoffrey M Boynton. Attention and visual perception. *Current opinion in neurobiology*, 15(4):465–469, 2005.
- [32] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.
- [33] Shanghua Gao, Pan Zhou, Ming-Ming Cheng, and Shuicheng Yan. Mdtv2: Masked diffusion transformer is a strong image synthesizer. *arXiv preprint arXiv:2303.14389*, 2023.
- [34] Xingyu Xie, Pan Zhou, Huan Li, Zhouchen Lin, and Shuicheng Yan. Adan: Adaptive nesterov momentum algorithm for faster optimizing deep models. *arXiv preprint arXiv:2208.06677*, 2022.
- [35] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems*, 30, 2017.
- [36] Charlie Nash, Jacob Menick, Sander Dieleman, and Peter W Battaglia. Generating images with sparse representations. *arXiv preprint arXiv:2103.03841*, 2021.
- [37] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans. *Advances in neural information processing systems*, 29, 2016.
- [38] Tuomas Kynkäänniemi, Tero Karras, Samuli Laine, Jaakko Lehtinen, and Timo Aila. Improved precision and recall metric for assessing generative models. *Advances in neural information processing systems*, 32, 2019.
- [39] Rui Zhu, Yingwei Pan, Yehao Li, Ting Yao, Zhenglong Sun, Tao Mei, and Chang Wen Chen. Sd-dit: Unleashing the power of self-supervised discrimination in diffusion transformer. *arXiv preprint arXiv:2403.17004*, 2024.

- [40] Katherine Crowson, Stefan Andreas Baumann, Alex Birch, Tanishq Mathew Abraham, Daniel Z Kaplan, and Enrico Shippole. Scalable high-resolution pixel-space image synthesis with hourglass diffusion transformers. *arXiv preprint arXiv:2401.11605*, 2024.
- [41] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.
- [42] Tim Salimans and Jonathan Ho. Progressive distillation for fast sampling of diffusion models. *arXiv preprint arXiv:2202.00512*, 2022.
- [43] Chenlin Meng, Robin Rombach, Ruiqi Gao, Diederik Kingma, Stefano Ermon, Jonathan Ho, and Tim Salimans. On distillation of guided diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14297–14306, 2023.
- [44] Hongkai Zheng, Weili Nie, Arash Vahdat, and Anima Anandkumar. Fast training of diffusion models with masked transformers. *arXiv preprint arXiv:2306.09305*, 2023.
- [45] Eslam Mohamed Bakr, Liangbing Zhao, Vincent Tao Hu, Matthieu Cord, Patrick Perez, and Mohamed Elhoseiny. Toddlerdiffusion: Flash interpretable controllable diffusion model. *arXiv preprint arXiv:2311.14542*, 2023.
- [46] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10012–10022, 2021.
- [47] Syed Waqas Zamir, Aditya Arora, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan, and Ming-Hsuan Yang. Restormer: Efficient transformer for high-resolution image restoration. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5728–5739, 2022.
- [48] Hu Cao, Yueyue Wang, Joy Chen, Dongsheng Jiang, Xiaopeng Zhang, Qi Tian, and Manning Wang. Swin-unet: Unet-like pure transformer for medical image segmentation. In *European conference on computer vision*, pages 205–218. Springer, 2022.

A Appendix

The appendix is structured as follows. In Appendix A.2, we provide a computational complexity analysis of DiT and the lightweight architecture design of EDT. In Appendix A.3, we show the computational process of the AMM and explore the usage methods of AMM, hyper-parameters. In Appendix A.4, we analyze the loss changes of different masking training strategies and explore the selection of mask ratio. In Appendix A.5, we report additional experimental results and visualization of generated images by EDT-XL-2000k. Appendix A.6 discusses the limitations.

A.1 Related Work

Diffusion Probabilistic Models In the field of generative models, diffusion models have achieved significant success. The Denoising diffusion probabilistic model (DDPM) [1] is the most classic denoising diffusion model, which generates new images by gradually removing noise from the noising data. NCSN [2] guides the data from low to high probability density areas by predicting the gradient of the data distribution. SDE [3] considers the noise addition and removal process as continuous and uses stochastic differential equations to guide the data generation process, theoretically unifying DDPM and NCSN and providing a new perspective for generative models. ADM [4] introduces a classifier-guided mode, using classifier gradients to guide the diffusion model's generation process, balancing the diversity and fidelity of generated images. Building on ADM, [9] proposes a classifier-free guidance method, removing the constraints of the classifier and significantly enhancing the flexibility of conditional diffusion generation. Compared to earlier works based on the U-Net backbone, models based on the Transformers backbone achieved better results. U-ViT [20] adds U-Net's skip connections to ViT [41] for diffusion generation in the pixel space, showcasing the broad prospects for diffusion transformers. DiT [21] replaces the U-Net backbone with ViT based on LDM [11], surpassing previous U-Net-based performances and showing good scalability. However, due to the intensive computational nature of transformers, integrating them effectively into diffusion models still presents significant challenges.

Efficient Diffusion Several methods have been proposed previously to improve the inference efficiency of diffusion models. DDIM [10] defines the diffusion process as a non-Markov process, thus eliminating the dependency on adjacent time steps in the reverse process of DDPM[1], achieving faster sampling speeds. LDM [11] compresses images from high-resolution pixel space to latent space and performs diffusion generation in latent space, achieving a balance between computational complexity and image detail. [42] introduces a method of gradual distillation for unconditional and classifier-guided diffusion models, which optimizes higher iteration counts into lower ones. Building on the work of [42], [43] proposes a two-stage distillation method for classifier-free guided diffusion models. Studies [22, 44] improves the training speed of DiT [21] by masking inputs. HDiT [40] introduces an hourglass-structured diffusion transformer for generating high-resolution images, which requires 70% fewer inference FLOPs in pixel space compared to DiT [21], but since HDiT operates in pixel space with high input and output resolution, it still demands substantial computational resources. ToddlerDiffusion [45] proposes a novel approach that extends the diffusion framework into modality space, decomposing the complex task of RGB image generation into simpler, interpretable stages. Currently, research on lightweight diffusion transformers is relatively sparse, but it is orthogonal to the methods in [10, 42, 43]. Building on existing research, lightweight diffusion transformers will further enhance the efficiency of diffusion models, which is one of the core contributions of this paper.

A.2 Computational analysis and lightweight design

We preset two lightweight design rules: (1) to reduce the FLOPs in the self-attention module, we decrease the number of tokens by token down-sampling; (2) to guarantee the total FLOPs significant reduction, the FLOPs of the EDT blocks after down-sampling should be significantly reduced compared to the EDT blocks before down-sampling. Utilizing the down-sampling module is key to achieving these two design rules.

We first analyze the applicable scenarios of conventional down-sampling modules in Appendix A.2.1. In Appendix A.2.2, we improve the down-sampling module to adapt to our scenario of latent diffusion models. Then, in Appendix A.2.3, the training costs of EDT, DiT, and MDT are reported.

Table 5: The model details of EDT across three different sizes.

Model	Params.	Number of blocks	Blocks in each stage	Dimensions in each stage	Heads in each stage
EDT-S/2	32.2M+6.1M	12	[2,2,2,3,3]	[312,416, 520,416,312]	[6,8, 10,8,6]
EDT-B/2	128M+24.1M	12	[2,2,2,3,3]	[624,832, 1040,832,624]	[12,16, 20,16,12]
EDT-XL/2	644M+54.4M	28	[6,4,4,7,7]	[936,1248, 1560,1248,936]	[18,24, 30,24,18]

A.2.1 Applicable scenarios of the conventional down-sampling module

Firstly, we review the conventional down-sampling module. We have a token sequence of shape $N \times N$, where n is the number of tokens ($n = N^2$). The dimension of token is denoted by d . The number of heads in multi-head attention is h , and D denotes the dimension of a head. **Conventional down-sampling module [46, 47, 48] reduces the number of tokens by a factor of k^2 and increase the token dimensions by a factor of k at the same time, where k is down-sampling factor ($k \geq 2$).** Large down-sampling factor k will cause too many tokens to be merged, harming performance. Therefore, k is generally equal to 2. That means, in a $N \times N$ token sequence, we reduce the number of tokens n by down-sampling adjacent 2 tokens into one. Then we obtain a $\frac{N}{2} \times \frac{N}{2}$ token sequence with fewer tokens and the token dimensions increase to $2d$ from d . Table 6 shows FLOPs analysis of a DiT block. The total FLOPs F is $2n^2d + 12nd^2 + 6d^2$ and the number of parameters P is $18d^2$ in a DiT block.

Now we analyze how much can down-sampling module reduce FLOPs, and its applicable scenarios. To facilitate derivation and calculation, we set $j = \frac{n}{d}$, where j is the proportional coefficient between the number of tokens and the dimension of token. We explore the relationship between proportional coefficient j and FLOPs drop ratio ρ after using conventional down-sampling.

In Figure 7, before down-sampling, the total FLOPs of a DiT block F is $2j^2d^3 + 12jd^3 + 6d^2$, where $n = N^2$ and $j = \frac{n}{d}$. After feeding tokens into conventional down-sampling, the number of tokens n' is $\frac{n}{4}$ and token dimensions d' is $2d$. Then feeding these tokens into a DiT block, the total FLOPs of the DiT block becomes $F' = 2n'^2d' + 12n'd'^2 + 6d'^2 = \frac{n^2d}{4} + 12nd^2 + 24d^2 = \frac{j^2d^3}{4} + 12jd^3 + 24d^2$ and the number of parameters in the DiT block is $P' = 72d^2$.

Comparing DiT blocks after and before the down-sampling module, the FLOPs drop is $\nabla F = F - F' = \frac{7j^2d^3}{4} - 18d^2$. We calculate the relationship between the FLOPs drop ratio $\rho = \frac{\nabla F}{F}$ and the proportional coefficient j :

$$\begin{aligned}
\rho &= \frac{\nabla F}{F} \\
&= \frac{\frac{7j^2d^3}{4} - 18d^2}{2j^2d^3 + 12jd^3 + 6d^2} \\
&= \frac{7j^2d - 72}{8j^2d + 48jd + 24} \\
&< \frac{7j^2d}{8j^2d + 48jd} \\
&= \frac{7j}{8j + 48} \\
&= \frac{7}{8 + \frac{48}{j}}
\end{aligned} \tag{4}$$

The Eqn.4 shows that $\frac{7j}{8j+48}$ is the upper limit of the FLOPs drop ratio ρ and proportional to j . **Significant reductions in FLOPs can be achieved through down-sampling, only when the number of tokens n is larger than the token dimensions d , namely $j > 1$.** For instance, when

Table 6: FLOPs in a DiT block

Module	Operator	Input Shape	Params	Output Shape	FLOPs
AdaLN	fc	$1 \times d$	$d \times 6d$	$1 \times 6d$	$6d^2$
Attention	Att-kqv	$1 \times n \times d$	$d \times 3d$	$1 \times n \times 3d$	$3nd^2$
	K@Q	K: $1 \times h \times n \times D$ Q: $1 \times h \times D \times n$	-	$1 \times h \times n \times n$ ($d = hD$)	dn^2
	Att@V	Att: $1 \times h \times n \times n$ V: $1 \times h \times n \times D$	-	$1 \times h \times n \times D$ ($d = hD$)	dn^2
	fc	$1 \times n \times d$	$d \times d$	$1 \times n \times d$	nd^2
FFN	fc1	$1 \times n \times d$	$d \times 4d$	$1 \times n \times 4d$	$4nd^2$
	fc2	$1 \times n \times 4d$	$4d \times d$	$1 \times n \times d$	$4nd^2$
Total		$1 \times n \times d$	$18d^2$	$1 \times n \times d$	$2n^2d + 12nd^2 + 6d^2$

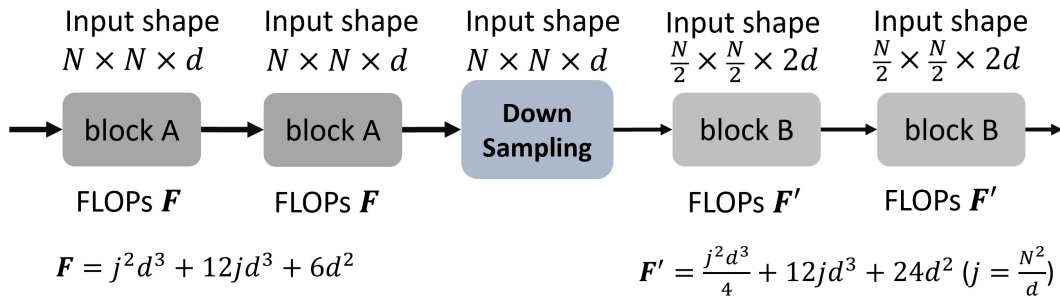


Figure 7: Input shape and FLOPs of DiT block before and after the conventional down-sampling module.

$j = 6$ (or $n = 6d$), the FLOPs drop ratio ρ is about 50%; and when $j = 1$ (or $n = d$), the FLOPs drop ratio ρ is about 12.5%.

However, in our application scenarios of latent diffusion transformer, where $\frac{n}{d} = j < 1$, the FLOPs drop ratio ρ is smaller than 12.5%. Only using conventional down-sampling in our scenarios of latent diffusion transformers can hardly reduce the computational complexity of the DiT blocks. So it does not meet the design rule (2): the FLOPs of the blocks after down-sampling should be significantly reduced compared to the blocks before down-sampling, to guarantee the total FLOPs reduction.

A.2.2 Redesign the down-sampling module

Now, we redesign the down-sampling to make the architecture meet rule (2).

According to Appendix A.2.1, before the down-sampling module, the total FLOPs of a DiT block is $F = 2n^2d + 12nd^2 + 6d^2 = 2j^2d^3 + 12jd^3 + 6d^2$. And after the down-sampling module, the total FLOPs of a DiT block after down-sampling is $F' = \frac{n^2d}{4} + 12nd^2 + 24d^2$. Among the three items of F and F' , the second term $12nd^2$ predominates due to $d > n$. However, this term isn't affected by the down-sampling process. This results from the conventional down-sampling module, which reduces the number of tokens by a factor of k^2 and increases the token dimensions by a factor of k at the same time, namely $12nd^2 = 12 \times \frac{n}{k^2} \times (kd)^2$.

To reduce the second item $12nd^2$, we should redesign the process of down-sampling module: we reduce the number of tokens by down-sampling factor $k = 2$ and increase the token dimensions by a factor of r at the same time, where r is token dimension expansion coefficient and $1 < r < k$. This design makes the second item reduce, namely $12 \times \frac{n}{k^2} \times (rd)^2 < 12nd^2$, and the total FLOPs $F' = \frac{rn^2d}{8} + 3nr^2d^2 + 6r^2d^2 = \frac{rj^2d^3}{8} + 3jr^2d^3 + 6r^2d^2$ in the blocks after our down-sampling

module. The FLOPs drop ratio ρ is:

$$\begin{aligned}
\rho &= \frac{\nabla F}{F} = \frac{F - F'}{F} = 1 - \frac{F'}{F} \\
&= 1 - \frac{\frac{rn^2d}{8} + 3nr^2d^2 + 6r^2d^2}{2n^2d + 12nd^2 + 6d^2} \\
&= 1 - \frac{rn^2 + 24ndr^2 + 48dr^2}{16n^2 + 96nd + 48d} \\
&= 1 - \frac{rj + 24r^2 + \frac{48r^2}{n}}{16j + 96 + \frac{48}{n}} \\
&\approx 1 - \frac{rj + 24r^2}{16j + 96} \\
&= r \left(\frac{1}{r} - \frac{j + 24r}{16j + 96} \right) \\
&> r \left(\frac{1}{r} - \frac{j + 48}{16j + 96} \right) \\
&= r \left(\frac{1}{r} - \frac{1}{16 - \frac{672}{j+48}} \right) \\
&\geq r \left(\frac{1}{r} - \frac{1}{16 - \frac{672}{1+48}} \right) \\
&= 1 - 0.43r
\end{aligned} \tag{5}$$

In Eqn.5, $\rho = 1 - \frac{rj+24r^2}{16j+96}$ shows that the FLOPs drop ratio ρ is inversely proportional to the token dimension expansion coefficient r and $1 - 0.43r$ is the lower bound of ρ . We can adjust the FLOPs of the DiT block after down-sampling by adjusting the token dimension expansion coefficient r . When r is within the range $[1, k]$ and $k = 2$, the FLOPs drop ratio ρ falls within the interval $[0.57, 0.14]$. To make the number of parameters in EDT network approximate to that in other works (DiT and MDT), we set $r \approx 1.25$. Namely, after a down-sampling, we reduce the number of tokens by a factor of 4 and increase the token dimensions by a factor of 1.25 at the same time. This leads to about 47% FLOPs drop ratio of the block after down-sampling compared to that before down-sampling, which meets the requirement of rule (2).

Table 5 shows three different sizes of EDT. The number of blocks is consistent with that in the DiT network of the corresponding size. The number of parameters in the EDT network is also approximate to that in DiT. Our parameters consist of two parts, one is the EDT blocks parameter, and the other is the sampling module and long-skip connection module. In the table, the number of parameters is written as the sum of these two parts.

Figure 2 illustrates the architecture of our lightweight-designed diffusion transformer. The model includes three EDT stages in the down-sampling phase, viewed as an encoding process where tokens are progressively compressed, and two EDT Stages in the up-sampling phase, viewed as a decoding process where tokens are gradually reconstructed. These five EDT stages are interconnected through down-sampling, up-sampling, and long skip connection modules. The ‘blocks in each stage’ in Table 5 displays how many blocks there are in the corresponding EDT stage.

A.2.3 Training costs

On ImageNet, we estimated the training cost of EDT, MDTv2, and DiT on a 48GB-L40 GPU in Table 7, using a batch size of 256 and FP32 precision. EDT achieves the best performance with a low training cost. GPU days refer to the days required for training the models on a single L40 GPU.

A.3 Exploring Attention Modulation Matrix

During the sketching process, humans alternately use global attention and local attention. Therefore, we design Attention Modulation Matrix (AMM), to introduce local attention into the self-attention

Table 7: Training cost of EDT, MDTv2, and DiT on ImageNet

Model	Resolution	Epochs	Cost (Images)	GPU days	GFLOPs↓	FID
EDT-S*	256×256	80	102M	2.75	2.66	38.73
DiT-S	256×256	80	102M	2.96	6.06	68.40
MDTv2-S	256×256	80	102M	16.47	6.07	39.50
EDT-B	256×256	80	102M	9.19	10.20	19.18
DiT-B	256×256	80	102M	8.62	23.01	43.47
MDTv2-B	256×256	80	102M	26.17	23.02	19.55
EDT-XL	256×256	80	102M	37.79	51.83	7.52
DiT-XL	256×256	80	102M	39.82	118.64	19.47
MDTv2-XL	256×256	80	102M	72.62	118.69	7.70
EDT-S	512×512	60	77M	19.02	13.25	51.84
DiT-S	512×512	60	77M	12.26	31.42	85.21
MDTv2-S	512×512	60	77M	51.96	31.46	51.16

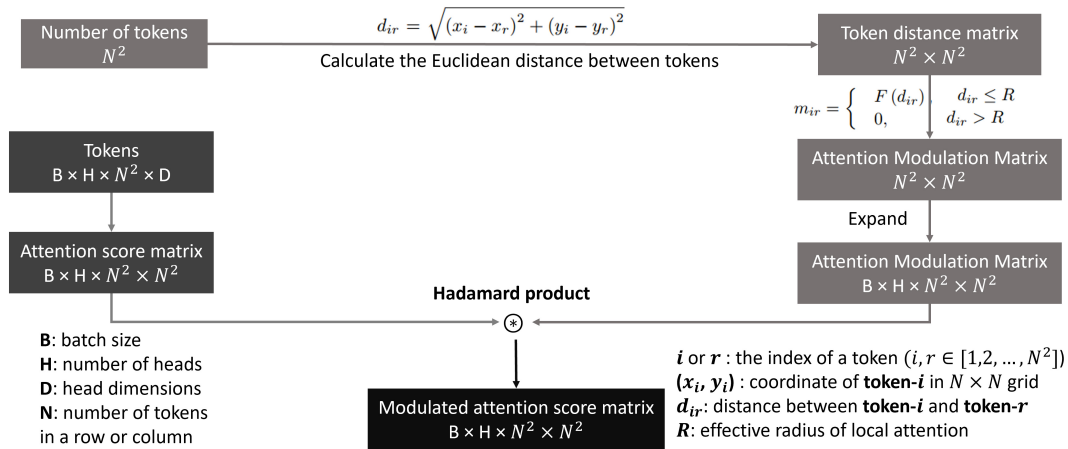


Figure 8: The process of modulating the attention score matrix and the changes in tensor shape.

module which uses global attention by default. Appendix A.3.1 shows the process of modulating the attention score matrix and the changes in tensor shape. In Appendix A.3.2, we explore the usage and arrangement of AMM in models. In Appendix A.3.3, we explore the settings of the hyper-parameters of AMM. The computational cost of AMM is discussed in Appendix A.3.4.

A.3.1 The process of modulating the attention

The process of modulating the attention score matrix and the changes in tensor shape are shown in Figure 8. Image can be split into N^2 patches and each token is the feature of a patch. Each token (patch) corresponds to a rectangular area of the image and has a corresponding 2-D coordinate (x, y) in the image grid. We calculate an Euclidean distance value d for each pair of tokens, resulting in a distance matrix $\mathbf{D}$, which is an $N^2 \times N^2$ tensor. Based on the distance matrix, we generate modulation values m via the modulation matrix generation function $F(d)$, which assigns lower modulation values to tokens that are farther apart. These modulation values form an Attention Modulation Matrix (AMM), another $N^2 \times N^2$ tensor. **Importantly, we integrate the AMM into the pre-trained EDT without any additional training.** The attention modulation matrix is calculated when the model is instantiated. During inference, the modulated attention score matrix is obtained by performing a Hadamard product between the attention modulation matrix and the attention score matrix.

Table 8: Comparison of adding AMM into EDT-S* during training versus inference on ImageNet 256×256 .

Model	adding AMM when training	adding AMM when inference	FID↓	IS↑
A	✗	✗	50.9	31.0
B	✓	✓	52.1	30.3
C	✗	✓	38.7	36.4

Table 9: Performance of EDT-S* with varying insertion points of AMM on ImageNet 256×256 .

Model	AMM in encoder	AMM in decoder	Alternately inserting	FID↓	IS↑
A	✗	✗	✗	50.9	31.0
B	✓	✓	✓	60.4	24.9
C	✗	✓	✗	44.4	35.1
D	✗	✓	✓	38.7	36.4

A.3.2 When and where to use AMM in EDT

This section empirically discusses and demonstrates how to use AMM through experiments.

Just adding AMM into the pre-trained model when inference Table 8 shows when to use AMM in EDT. Model A is a pre-trained EDT-S* without AMM, getting an FID score of 50.8. Model B, which is added AMM from initialization and then trained, achieves an FID score of 52.1. Model C gains an FID score of 38.7, which is the model that added AMM to model A. The results show that using AMM during training will lead to poorer performance, and just adding AMM to the pre-trained model can greatly improve performance.

Alternately inserting AMM into the decoder of EDT We view the process of drawing pictures as a decoding process. So we think the decoder of EDT should be aligned with the act of humans drawing pictures. This inspires us where to place AMM in EDT. Namely, the alternation of attention range between global and local in drawing acts of humans should be imitated in the decoder of EDT. The AMM should be alternately or discontinuously inserted into the blocks of decoder.

To demonstrate the inspiration, in Figure 9, we try to compare Model A: pre-trained EDT-S* without AMM; Model B: alternately inserting AMM into encoder and decoder of pre-trained EDT-S*; Model C: consecutively inserting AMM into decoder of pre-trained EDT-S*; and Model D: alternately inserting AMM into the decoder of pre-trained EDT-S*. As shown in Table 9, Model D which is alternately inserted AMM into decoder of pre-trained EDT-S*, gets the lowest FID score.

When integrating AMM into a pre-trained model, the best arrangement of AMM in blocks varies across different models. Identifying the optimal placement and configuration of AMM requires testing and adjusting to realize its full potential.

A.3.3 The determination of hyper-parameter

Table 10 shows the determination of hyper-parameter about the effective radius of local attention $R \in [0, d_{max}]$, where $d_{max} = \sqrt{2}(N - 1)$ is the farthest distance in a $N \times N$ token grid. In the table, when $R = \sqrt{(N - 1)^2 + 4}$, EDT-S* achieves the lowest FID and highest Prec. So we set $R = \sqrt{(N - 1)^2 + 4}$ in all sizes of model.

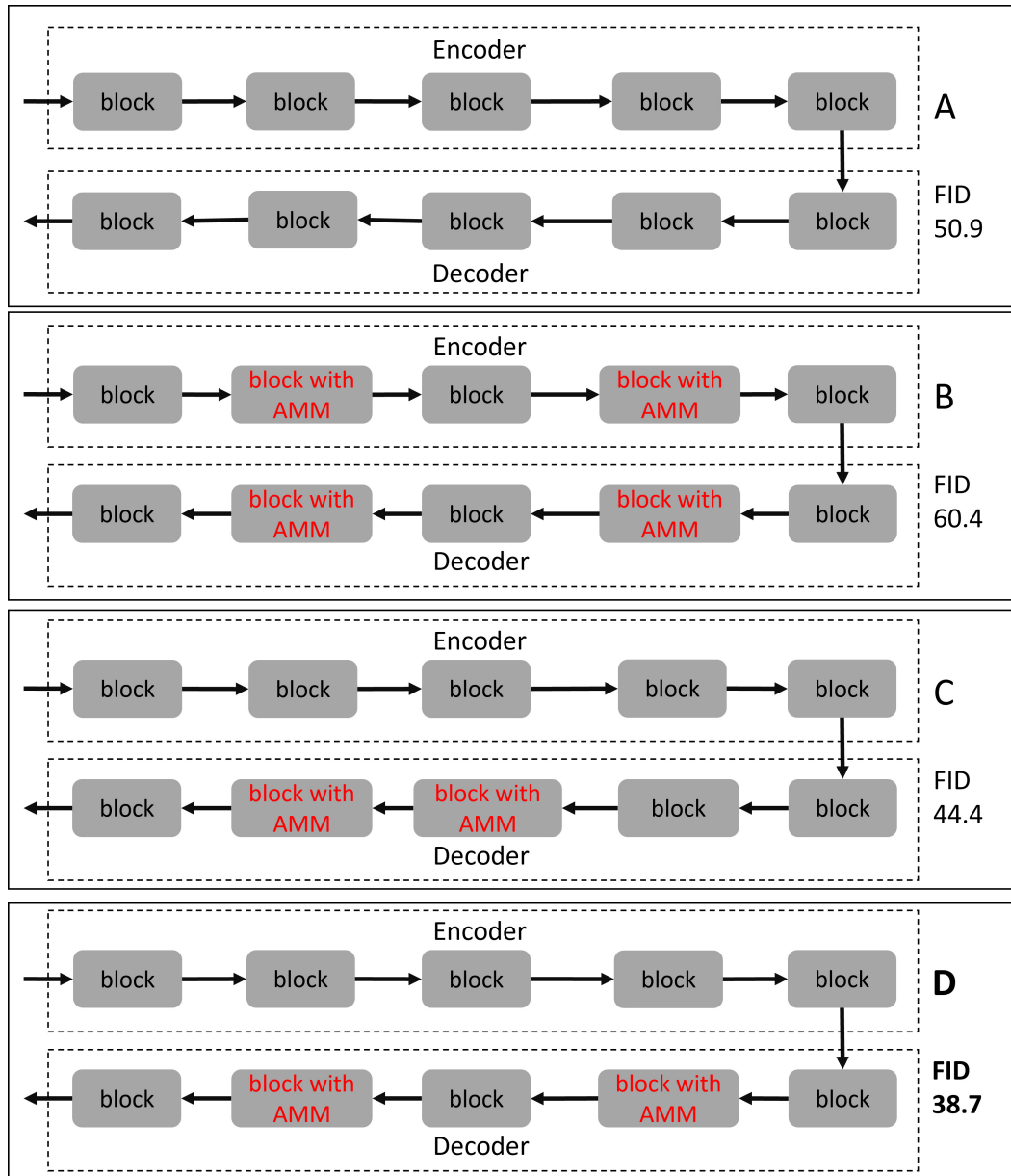


Figure 9: Different arrangement forms of AMM in EDT and their corresponding FID scores.

Table 10: Exploring the value of the effective radius of local attention in EDT-S* for 256×256 resolution.

R	FID50K↓	IS↑	sFID↓	Prec.↑	Recall↑
no AMM	50.9	31.0	13.3	0.427	0.604
$\sqrt{2}(N-1)$	38.9	36.6	9.3	0.472	0.626
$\sqrt{(N-1)^2+4}$	38.7	36.4	9.3	0.473	0.623
$\sqrt{(N-1)^2+1}$	39.0	36.5	9.3	0.474	0.621
N-1	39.1	36.2	9.2	0.472	0.628
$3N/4$	41.0	35.4	9.6	0.483	0.604
$N/2$	47.4	32.1	11.7	0.495	0.583
$N/4$	72.0	23.9	23.6	0.476	0.516

A.3.4 The computational cost of AMM

The addition of AMM introduces minimal computational costs. Firstly, AMM can be incorporated into a pre-trained model without requiring additional fine-tuning, resulting in no additional training costs. Secondly, the increased computational cost of AMM during inference is negligible. For instance, in the last block of EDT-XL, the attention score matrix and the Attention Modulation Matrix are both $18 \times 256 \times 256$ tensors. The computational cost of the Hadamard product between the attention score matrix and AMM is only 1.18M FLOPs for multiplication calculations, out of a total of 2819.3M FLOPs for the block. This amounts to merely 0.04% of the total FLOPs, making the computational cost of AMM negligible. In our experiments, we added 4 AMM modules to a pre-trained DiT-XL model, and the FID score decreased from 18 to 14.

A.4 Discussion about token relation-enhanced masking training strategy

A.4.1 Analysis of the loss of EDT and MDT

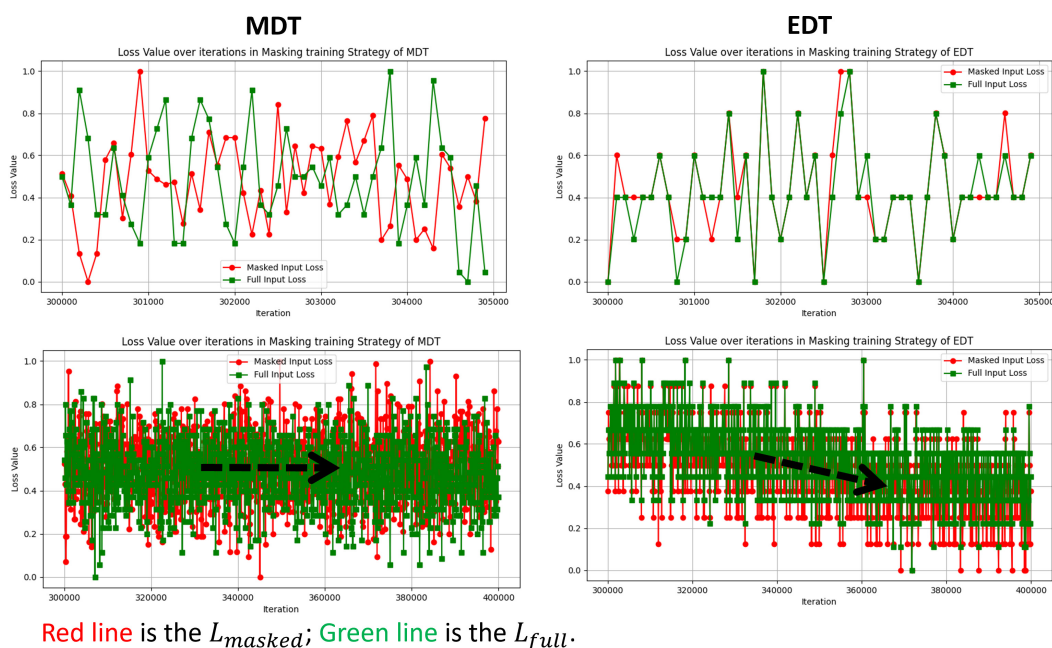


Figure 10: Comparing the loss changes of different masking training strategies.

In Figure 10, we separately applied the masking training strategies of MDT and EDT to train EDT-S and extracted L_{masked} and L_{full} values at the $300k \sim 305k$ and $300k \sim 400k$ training iterations. The left-top of the figure depicts the loss changes when using MDT's masking training strategy. As L_{full} decreases, L_{masked} increases, and vice versa, illustrating the conflict between these two losses. This conflict arises because L_{masked} in MDT causes the model to focus on masked token reconstruction while ignoring diffusion training. As shown in the bottom-left of the figure, both the L_{full} and L_{masked} hardly decreased during the $300k$ to $400k$ training iterations. The right side of the figure shows the loss changes when using EDT's masking training strategy. The L_{masked} and L_{full} exhibit synchronized changes, and the loss values continuously decrease during the $300k$ to $400k$ training iterations.

A.4.2 The determination of the mask ratio

We explore the mask ratio of our masking training strategy. There are two down-sampling modules in EDTs. So we have two positions to implement token masking. As shown in Table 11, we determine the masking ratio in the first down-sampling module by training EDT-S. The best masking ratio in the first down-sampling module is $0.4 \sim 0.5$.

Table 11: Mask Ratio in the first down-sampling module.

Mask Ratio	FID50K↓	IS↑	sFID↓	Prec.↑	Recall↑
0.1 ~ 0.2	51.3	31.1	13.7	0.434	0.612
0.2 ~ 0.3	48.6	33.5	13.2	0.441	0.631
0.3 ~ 0.4	47.3	34.9	13.2	0.442	0.622
0.4 ~ 0.5	46.4	34.1	11.7	0.449	0.621
0.5 ~ 0.6	48.8	33.4	13.5	0.431	0.623

Table 12: Mask Ratio in the second down-sampling module. (Based on the 0.4 ~ 0.5 mask ratio in the first down-sampling module)

Mask Ratio	FID50K↓	IS↑	sFID↓	Prec.↑	Recall↑
0.1 ~ 0.2	45.4	34.8	13.2	0.440	0.621
0.2 ~ 0.3	46.2	34.6	13.5	0.441	0.619
0.3 ~ 0.4	46.5	34.7	13.2	0.438	0.620
0.4 ~ 0.5	47.2	34.4	13.4	0.432	0.620

Table 13: The comparison with existing SOTA methods on class-conditional image generation with classifier-free guidance on ImageNet 256×256 (CFG=2 in EDT; according to DiT and MDTv2, their optimal CFG settings are 1.5 and 3.8, respectively).

Model	Cost↓ (Iter×BS)	GFLOPs↓	FID↓
DiT-S-G	400K×256	6.06	21.03
MDTv2-S-G	400K×256	6.07	15.62
EDT-S-G(our)	400K×256	2.66	9.89
ADM-G[4]	1980k×256	1120.00	4.59
LDM-4-G[11]	178k×1200	104.00	3.60
DiT-XL-G	400K×256	118.64	5.50
DiT-XL-G[21]	7000K×256	118.64	2.27
MDTv2-XL-G[33]	4600K×256	118.69	1.58
EDT-XL-G(our)	400K×256	51.83	4.65
EDT-XL-G(our)	1000K×256	51.83	4.30
EDT-XL-G(our)	2000K×256	51.83	3.54

At the base of 0.4 ~ 0.5 mask ratio in the first down-sampling module, we then determine the mask ratio in the second down-sampling module as shown in Table 12. According to the results, the best masking ratio in the second down-sampling module is 0.1 ~ 0.2, at the base of 0.4 ~ 0.5 mask ratio in the first down-sampling module.

A.5 Additional Results

A.5.1 Image generation with classifier-free guidance on ImageNet 256×256

The result of image generation with classifier-free guidance on ImageNet 256×256 is shown in Table 13. Under the same training cost, EDT-S-G achieves the lowest FID score compared to MDTv2-S-G (9.89 vs. 15.62). EDT-XL-G achieves a good balance in training cost, inference GFLOPs, and image generation performance.

A.5.2 Comprehensive evaluation of AMM

Using AMM under different iterations We report the FID of EDT* with and without AMM under different iterations in Table 14. The results show that all EDTs* with AMM obtain lower FID.

Table 14: FID of EDTs* under different iterations on Imagenet 256×256 .

Iterations	EDT-S*		EDT-B*		EDT-XL*	
	no AMM	AMM	no AMM	AMM	no AMM	AMM
50k	96.4	80.8	79.5	64.8	50.1	45.8
100k	64.5	58.5	46.0	40.4	23.7	21.3
150k	58.2	51.0	39.7	32.6	17.9	15.3
200k	55.8	47.0	37.3	29.0	15.6	12.6
250k	53.3	44.0	35.5	26.9	14.6	11.4
300k	52.4	42.0	34.2	25.1	14.1	10.7
350k	51.2	40.1	33.5	24.2	14.5	10.6
400k	50.9	38.7	33.2	23.2	14.9	10.5

Table 15: Results on various models across different sizes with (w) AMM and without (w/o) AMM on ImageNet.

Model	Resolution	FID↓	IS↑	sFID↓	Prec.↑	Recall ↑
EDT-S*(w/o)	256×256	50.9	31.0	13.3	0.427	0.604
EDT-S*	256×256	38.7	36.4	9.2	0.474	0.620
EDT-S(w/o)	256×256	46.9	35.4	13.5	0.442	0.624
EDT-S	256×256	34.3	42.6	13.1	0.501	0.612
EDT-S(w/o)	512×512	55.7	28.9	12.8	0.513	0.586
EDT-S	512×512	51.8	29.9	7.9	0.563	0.572
EDT-B*(w/o)	256×256	33.2	50.0	10.5	0.512	0.648
EDT-B*	256×256	23.2	62.3	8.9	0.573	0.624
EDT-B(w/o)	256×256	26.3	64.5	10.3	0.544	0.659
EDT-B	256×256	19.2	74.4	9.9	0.586	0.639
EDT-XL*(w/o)	256×256	14.9	96.5	8.0	0.617	0.667
EDT-XL*	256×256	10.5	117.8	9.9	0.663	0.637
EDT-XL(w/o)	256×256	12.8	111.7	8.2	0.627	0.685
EDT-XL	256×256	7.5	142.4	7.4	0.684	0.648
DiT-XL/2(w/o)	256×256	18.5	71.3	6.1	0.641	0.632
DiT-XL/2	256×256	14.7	83.9	10.5	0.720	0.511

More types of evaluation indicators on EDT with AMM The Table 15 shows more types of evaluation indicators comparing EDTs without AMM and with AMM. EDTs* means the EDT models that don't use masking training strategy. In the table, when using AMM, the FID, IS and Precision are all improved. Furthermore, AMM is versatile and can be adapted to various diffusion transformers. For instance, the performance of DiT-XL is improved by AMM (18.5 FID vs. 14.7 FID).

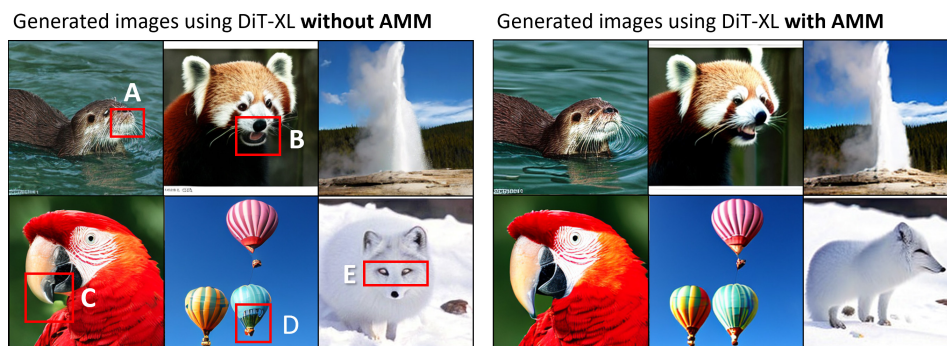


Figure 11: DiT-XL-400k with AMM achieves more realistic visual effects.

Qualitative analysis on DiT-XL with AMM We conduct qualitative analysis on DiT with and without AMM in Figure 11, which demonstrates AMM can also improve the local details of the synthesis images of DiT. The red boxes highlight the unrealistic areas in the images generated by DiT-XL without AMM. In the corresponding areas of the images generated by DiT-XL with AMM, the results appear more realistic. **Area A:** The otter lacks a mouth. **Area B:** The red panda's mouth is slightly distorted. **Area C:** The parrot's beak is not sharp enough. **Area D:** There are black stains on the right side of the hot air balloon. **Area E:** The fox's eyes are white. The steam image generated by DiT-XL without AMM is realistic. And the steam image generated by DiT-XL with AMM remains equally realistic. The addition of AMM does not negatively affect the original quality. The effectiveness of AMM on DiT-XL further demonstrates the universal applicability of AMM.



Figure 12: Visualization of images generated by the EDT-XL-2000K.

A.5.3 Visualization

More visualized examples of EDT-XL-2000k generated images are shown in Figure 12. The sampling step is 250.

A.6 Limitations

In this work, we propose the Efficient Diffusion Transformer (EDT) framework, which includes a lightweight-design of diffusion transformer, a training-free Attention Modulation Matrix (AMM), and its alternation arrangement in EDT inspired by human-like sketching and the token relation-enhanced masking training strategy. EDT effectively improves the training and inference speed of diffusion transformers. Notably, AMM is a new approach to improving diffusion models, with many aspects still worth exploring. When integrating AMM into a pre-trained model, the insertion and arrangement of AMM in blocks differ across various models. Thus, identifying the optimal placement and configuration of AMM requires testing to unlock its full potential. Moreover, the generation function of AMM still has room for improvement and deserves further exploration. For example, in addition to directly scaling attention scores by AMM, we can convert global attention into local attention during inference through methods like: (1) using attention window to exclude the interactions of tokens with far distance; (2) or scaling the attention based on token distance before the operation of softmax in attention modules. It is encouraged to further explore the idea of AMM, which incorporates local attention into transformers during inference, to improve other transformer-based models.

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and precede the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes], [No], or [NA].
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes]" is generally preferable to "[No]", it is perfectly acceptable to answer "[No]" provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No]" or "[NA]" is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

IMPORTANT, please:

- **Delete this instruction block, but keep the section heading “NeurIPS paper checklist”,**
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers.**

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope?

Answer: [Yes]

Justification: Please refer to the abstract and Sections 1. We introduce the problem our work solved and the contributions we made in both the abstract and final paragraph of the introduction.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: We discuss the limitations of this work in Appendix A.6.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: Please refer to Section 3.3, Appendix A.3 and Appendix A.4.1.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: Please refer to Section 3.1 for the training details. Please refer to Section 3.2, Section 3.3 and Appendix A.5 for experimental results. And we will release the code and checkpoints.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: All the data used is from public available dataset (ImageNet). Please refer to Section 3.1. And we will release code and checkpoints.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.

- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [\[Yes\]](#)

Justification: Please refer to Appendix A.3.3 and Appendix A.4.2 for hyperparameter selection. Please refer to Section 3.1 for the training and test details.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [\[NA\]](#)

Justification: The training procedure for the proposed and baseline models takes a considerable amount of time. It is infeasible to perform enough repeated experiments to calculate the statistical significance. Therefore, error bars are not reported.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [\[Yes\]](#)

Justification: Please refer to Section 3.1 and Appendix A.2.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: The research conducted in the paper conforms, in every respect, with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: In Appendix A.6, we discuss the positive impacts of our efficient transformer-based diffusion model design and Attention Modulation Matrix, and the limitations of Attention Modulation Matrix.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: The paper poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: The creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. New Assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: The paper does not release new assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.

- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.