

DA-VAE: Plug-in Latent Compression for Diffusion via Detail Alignment

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Figure 1. We propose **Detail-Aligned VAE (DA-VAE)**, a VAE model that increases the compression rate of a pretrained VAE, while requiring only light-weight finetuning of the original diffusion backbone while preserving image quality. Image results are from a finetuned SD3.5 Medium. DA-VAE accelerates the original SD3.5 Medium model by 6.04 times for 2048×2048 image generation.

Abstract

Reducing the token count is crucial for efficient training and inference of latent diffusion models, especially at high resolution. A common approach is to build high-compression image tokenizers that store more information by allocating more channels per token. However, when trained solely with

reconstruction objectives, high-dimensional latent spaces often fail to maintain meaningful structure, which complicates diffusion training. Existing methods introduce additional objectives, such as semantic alignment or selective dropout, to enforce structure, but typically require costly retraining of the diffusion model. In contrast, pretrained diffusion models already exhibit a structured, lower-dimensional latent space, suggesting a simpler strategy: expand the latent di-

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dimensionality while preserving this structure. To this end, we propose **Detail-Aligned VAE (DA-VAE)**, which increases the compression ratio of a pretrained VAE with only lightweight adaptation of the diffusion backbone. DA-VAE imposes an explicit latent layout: the first C channels are inherited from the pretrained VAE at a base resolution, while additional D channels encode high-resolution details. We introduce a simple yet effective detail-alignment mechanism that explicitly regularizes the expanded latent space to preserve the structural properties of the original space defined by the first C channels. Finally, we present a warm-start fine-tuning strategy that enables 1024×1024 image generation with Stable Diffusion 3.5 using only 32×32 tokens, $4\times$ fewer than the original model, within a compute budget of 5 H100-days. It further enables 2048×2048 generation with SD3.5, achieving a $6\times$ speedup while preserving image quality. We also validate the method and its design choices quantitatively on ImageNet.

1. Introduction

Recent text-to-image Diffusion Transformers (DiTs) have achieved state-of-the-art image generation quality. Various works therefore aim to improve efficiency for those models from different perspectives, such as quantization [28], few-step distillation [51], and efficient attention mechanisms [45]. Orthogonal to these aspects, another direction to improve efficiency is through token count reduction. Since self-attention’s computational cost is quadratic over number of tokens, a $4\times$ reduction of tokens would result in $16\times$ reduction for its computational cost.

Existing high-compression-ratio tokenizers [8, 11] are often trained from scratch, aiming to squeeze more pixels into a token with more channels. Since these works introduce a new latent space, the downstream diffusion model needs to be trained from scratch as well, which requires a tremendous training cost and a large training set. Adding more to the problem, it is known that high-dimensional features prohibit effective diffusion model training, where one needs to introduce structures to the new latent space, either through semantic alignment or through training time drop-out. Those challenges combined make this paradigm difficult to iterate—one needs to first train a tokenizer, balance between reconstruction and alignment/auxiliary tasks [48], then train a generative model from scratch to verify whether the newly introduced latent space is effective for generation.

We propose a different yet simple paradigm to increase the compression ratio of the VAE without complete retraining from scratch. That is, we start with a pretrained diffusion model, and aim to increase tokenizer efficiency by explicitly introducing a scale-space structure over the channel dimension of each token. Specifically, with a tokenizer that encodes an image at resolution $H \times W$ with T tokens, we aim to increase the dimension of each token, such that those

T tokens can represent an image at a higher resolution of $sH \times sW$. To achieve this without complete retraining, we keep the first C channels of each token the same as the latent of the image at base resolution. We then introduce D extra channels to each token, aiming to encode detail information only available at high resolution. With this design, we can then fine-tune the diffusion network trained on original $H \times W$ tokens, as our DA-VAE inherits those tokens.

Still, naively fine-tuning a diffusion denoising network on this new latent space may still fail, since the extra detail channels lack meaningful structure [8, 11], therefore hindering downstream diffusion training. To overcome this, we impose an explicit alignment constraint over the detail channels D , such that they should have similar structures to the pretrained latent channels C . This alignment proves to be crucial for downstream diffusion training.

Based on this observation, our pipeline is designed as follows. Since we re-use the original latent in the first C dimension, we use a warm-start strategy to further speed up fine-tuning. Specifically, we zero initialize the patch embedder for the extra D channels, while using the original patch embedder for the first C channels from the pretrained weights. We further introduce an optimization schedule that penalizes the extra D channels less during the early training steps. We show that, through ablation studies, this recipe yields better generation results given a fixed training budget. We further validate our method by fine-tuning SD3.5M [40] from 512×512 to 1024×1024 image generation while keeping the token number fixed. This results in an overall $\approx 4\times$ speedup compared to naive 1024×1024 image generation, where adaptation only takes 5 H100-days. We further demonstrate 2048×2048 image generation for SD3.5M with a $6\times$ speedup, while the original model cannot reliably generate coherent structures.

In summary, our contributions are:

- A method that improves tokenizer efficiency on the pretrained DiT without costly retraining.
- An explicitly structured latent that supports downstream fine-tuning through detail alignment.
- A fine-tuning recipe that efficiently adapts a pretrained DiT to the structured latent, enabling $2\times$ higher resolution under the same token budget.
- We validate our method’s effectiveness quantitatively on ImageNet and qualitatively by fine-tuning SD3.5, where the adaptation for SD3.5M only takes 5 H100-days.

2. Related Work

Diffusion model acceleration. Diffusion models [23] achieve strong image quality [14, 36, 55] and have been widely adopted in diverse applications [3, 4, 12, 17], but are computationally expensive due to many function evaluations over large latent grids. Existing acceleration mainly follows three directions. First, improved ODE/SDE solvers and

consistency-style objectives reduce the number of sampling steps [29, 56, 57, 60, 62, 64]. Second, one- or few-step generators distill the full trajectory into a small number of evaluations [16, 18, 31, 37, 49, 50]. Third, per-step efficiency is improved via pruning and token/feature selection, quantization, and optimized attention or execution (e.g., compiler stacks, parallelization, caching) [1, 15, 30, 39, 41, 42, 45, 46, 59]. However, these methods preserve the tokenization scheme and thus still scale quadratically with the number of latent tokens. We instead target *token efficiency*: we design a structured latent representation that enables DiTs to operate with substantially fewer tokens while keeping the backbone and sampler largely unchanged, and our tokenizer can be combined with the above techniques for further speedup.

Image tokenizers for generation. Latent diffusion models replace pixel-space denoising with denoising in a lower-resolution latent space learned by a 2D continuous tokenizer, typically an $8\times$ VAE [35]. This design is widely adopted by subsequent systems, which mainly scale model size and data while keeping a similar tokenizer [2, 9, 10, 13, 14, 26, 32, 34, 65], so the number of latent tokens still grows quadratically with image resolution. To reduce this token burden, recent work proposes more aggressively compressed tokenizers: DC-AEs and follow-ups [8, 11] build deeper encoder-decoder hierarchies that operate at higher spatial downsampling factors, and several 1D tokenizers [6, 7, 24, 47, 52] further lower the number of tokens fed into the diffusion backbone. However, these token-reduction schemes typically require training a new generative model directly on the new latent space [45, 46].

A complementary direction focuses less on compression and more on learning *semantically aligned* latent spaces that improve the trade-off between reconstruction and generation [5, 38, 48, 54, 61]. Prior work shows that shaping the latent geometry to better match semantic structure can yield more robust generation. However, these methods mainly focus on improving the global semantic structure of the latent space, and pay less attention to preserving structured fine-grained details that are critical for high-resolution image synthesis.

Our method is orthogonal to both deep-compression and semantic-alignment tokenizers. We instead target a *token-efficient* latent space that remains compatible with an existing pretrained DiT: rather than discarding the original tokenizer, we introduce a structured base-detail composition and explicitly align the new latent representation to the original VAE space, allowing us to reduce tokens while keeping the DiT backbone and training objective largely unchanged.

Efficient autoencoder adaptation. A related line of work studies how to upgrade or replace the autoencoder while reusing as much of the generative backbone as possible. Previous work such as [9, 33] adopts a stronger tokenizer and adapts the DiT on top of it for high-resolution generation, but the retraining pipeline is still computationally expensive.

Concurrent work DC-Gen [11, 20] adapts a pretrained DiT to a new, more compressed latent space. However, this target space differs from the original VAE latent space, and the mismatch between them is non-trivial to compensate. In contrast, our method keeps the original VAE latent space as a reference: we introduce a structured latent space and train a compressor that reduces the number of tokens in an aligned latent space, so that the pretrained DiT can be reused with minimal modification.

3. Method

State-of-the-art text-to-image diffusion models [26, 34, 35] typically compress latent spaces to reduce computational cost. To describe the compression ability of a tokenizer, three metrics are often used: feature down-sampling rate f , number of channels per token C , and the patch size p of the downstream diffusion model. For an image of size $H \times W$, the latent dimension of all tokens is $(H \times W \times C)/(f^2 \times p^2)$. To increase token efficiency, previous works [45] have shown that increasing the downsampling ratio f is both efficient and friendly to downstream generation model training than increasing the patch size p . Moreover, simply increasing the downsampling ratio f limits the reconstruction abilities of the tokenizer, and previous tokenizers [8, 11] therefore increase the channel number C to compensate for that.

However, increasing C naively brings many challenges to the downstream diffusion training. As discussed in [11, 48], training a diffusion model on wide-channel tokens is unstable, and semantic alignment or auxiliary tasks are often needed to increase convergence of diffusion. This process usually requires retraining both tokenizer and the diffusion model from scratch, which is prohibitively expensive, introducing significant training cost and data collection cost.

We therefore propose DA-VAE together with a fine-tuning recipe that can both reduce the token size (larger downsampling ratio f) and generate friendly tokens for diffusion training. Core to our method is an explicitly structured latent space with an alignment strategy, and a warm-start diffusion fine-tuning recipe that adapts to the structured latent within a reasonable compute budget.

3.1. Structured Latent and Alignment

We describe the designs and training of DA-VAE, which increases a pretrained VAE’s spatial compression rate f and number of channels C with a structured latent space.

Structured latent space. We start with a pretrained VAE encoder E that encodes an image $\mathbf{I}$ of resolution $H \times W$ into latent space z , whose dimensions are $C \times \frac{H}{f} \times \frac{W}{f}$. To improve its efficiency, we encode a higher resolution image $\mathbf{I}_{hr}$ of size $sH \times sW$ into latent z_{hr} of size $C' \times \frac{H}{f} \times \frac{W}{f}$, where $C' > C$. In our experiment, we set $s = 2$.

Our structured latent is designed such that $C' = C + D$, where the first C channels are exactly the latent of $\mathbf{I}$.

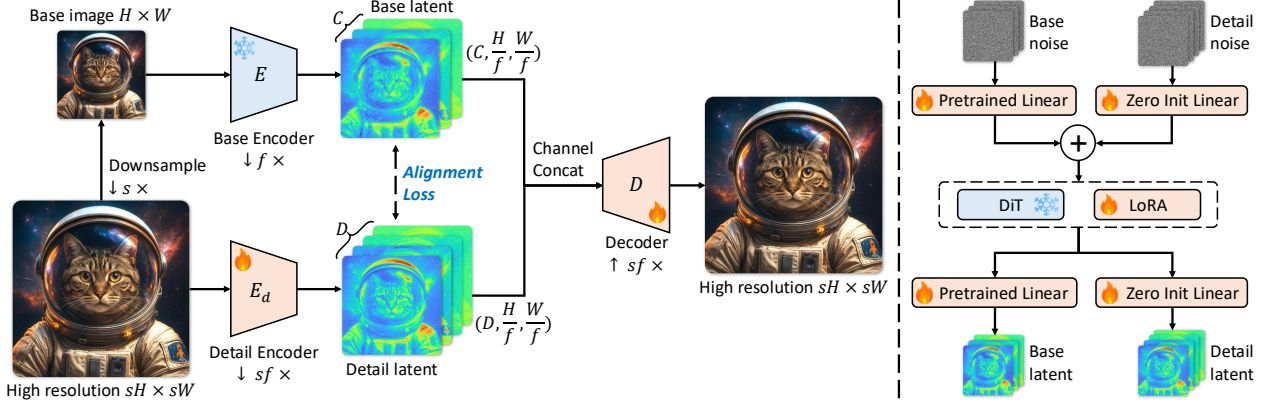


Figure 2. **Overview of our method.** Left: **Illustration of our Detail-Aligned VAE (DA-VAE)**, which encodes a high-resolution image using the same number of visual tokens as the base image. Right: **Zero initialization** of the linear layer for detail latent. At the beginning of training, the model keep pretrained diffusion model capability of generating images at the base resolution.

We augment the latent with an additional D -channel detail branch, encoded from a separate encoder E_d using I_{hr} .

Specifically, our structured latent z_{hr} is composed of two parts concatenated over the channel dimension:

$$\mathbf{z}_{hr} = [\mathbf{z}, \mathbf{z}_d] \in \mathbb{R}^{(C+D) \times \frac{H}{f} \times \frac{W}{f}}, \quad (1)$$

where

$$\begin{aligned} \mathbf{z} &= E(I) \in \mathbb{R}^{C \times \frac{H}{f} \times \frac{W}{f}}, \\ \mathbf{z}_d &= E_d(I_{hr}) \in \mathbb{R}^{D \times \frac{H}{f} \times \frac{W}{f}}. \end{aligned} \quad (2)$$

To decode the structured latent into image, we use a single decoder D such that $D(z_{hr})$ reconstructs I_{hr} . Throughout our experiments, we keep E fixed to its pretrained weights, and only optimize parameters of E_d and D . Fig. 2 shows this design.

Latent alignment. Naively adding more channels to the existing latent makes diffusion training difficult. When the VAE encoder is trained only with a reconstruction loss, the extra detail channels $\mathbf{z}_d$ tend to absorb noisy residuals rather than forming a meaningful semantic structure. As shown in the right column of Fig. 3, features derived from $\mathbf{z}_d$ are poorly organized and weakly correlated with either the original latent $\mathbf{z}$ or the underlying labels, which makes them hard for the downstream diffusion model to exploit.

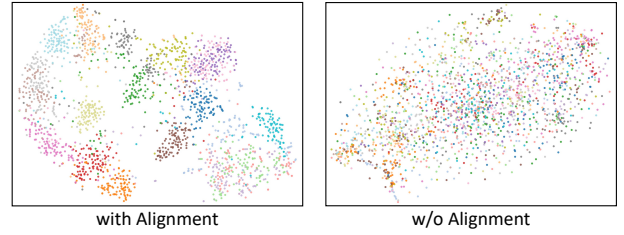
To regularize these channels, inspired by recent semantic-alignment works, we introduce a latent alignment loss that encourages $\mathbf{z}_d$ to be consistent with the pretrained latent $\mathbf{z}$. Specifically, we minimize

$$\mathcal{L}_{\text{align}} = \|\text{Proj}(\mathbf{z}_d) - \mathbf{z}\|^2, \quad (3)$$

where $\text{Proj}(\cdot) : \mathbb{R}^{D \times H \times W} \rightarrow \mathbb{R}^{C \times H \times W}$ is a parameter-free channel-wise group reduction, defined as:

$$\text{Proj}(\mathbf{z}_r)[i, h, w] = \frac{1}{r} \sum_{j=1}^r \mathbf{z}_d[ir + j, h, w], \quad (4)$$

(a) t-SNE of Detail Latent on ImageNet Based on VA-VAE



(b) First PCA component of Detail Latent Based on SD3-VAE

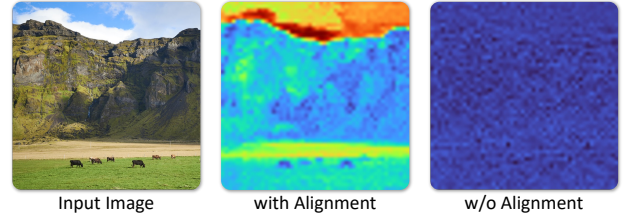


Figure 3. **Effect of the proposed latent alignment loss** on the learned detail feature $\mathbf{z}_d$. In each pair, the right column shows training with only reconstruction loss (no alignment), and the left column shows training with our alignment loss. (a) DA-VAE on VA-VAE: the detail features (points colored by class) become more class-separable and well clustered under alignment, suggesting that $\mathbf{z}_d$ inherits the semantic structure of the original latent. (b) DA-VAE on SD3-VAE: alignment encourages the detail branch to capture fine-grained textures while preserving the global image layout, instead of collapsing into noisy residuals.

where $r = D/C$, and i, h, w are indices over channel, height and width. Note that for special cases where $r = 1$, this reduces to a simple L_2 norm between $\mathbf{z}_d$ and $\mathbf{z}$.

With the alignment loss, the additional latent $\mathbf{z}_d$ learns a structure that closely mirrors $\mathbf{z}$ rather than drifting to arbitrary residuals, as illustrated in the left column of Fig. 3. This makes the enriched latent representation much more amenable to downstream diffusion training.

Objective for VAE. In addition to alignment, we adopt the standard reconstruction losses for VAE training, *i.e.*, perceptual loss, $L1$ loss, adversarial loss and KL regularization:

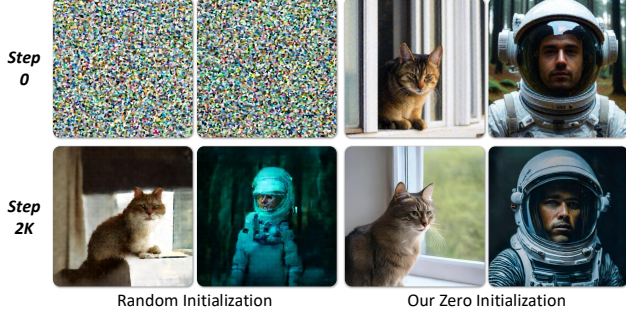


Figure 4. **Comparison of zero initialization and random initialization.** Benefiting from our zero initialization, the model starts from a well-behaved point and converges faster during training.

$$\mathcal{L}_{\text{rec}} = \lambda_L \text{LPIPS} + \lambda_1 L_1 + \lambda_{\text{adv}} \mathcal{L}_{\text{adv}} + \lambda_{KL} L_{KL}. \quad (5)$$

The full training loss is therefore given by:

$$\mathcal{L} = \mathcal{L}_{\text{rec}} + \lambda_{\text{align}} \mathcal{L}_{\text{align}}. \quad (6)$$

We empirically show that alignment introduces slight degradation in terms of reconstruction, yet greatly boosts generation, as shown by our experiments in Tab. 2.

3.2. Warm Start for Diffusion Fine-tuning

To adapt the pretrained DiT to the new latent space, we introduce a zero-init strategy and a gradual loss scheduling such that fine-tuning the diffusion model can be warm-started effectively from pretrained weights.

A zero-init strategy. As shown in right part of Fig. 2, the Diffusion Transformer uses a patch embedder P to map image latents into the DiT high-dimensional space, i.e.,

$$P(\cdot) : \mathbb{R}^{C \times \frac{H}{f} \times \frac{W}{f}} \rightarrow \mathbb{R}^{L \times \frac{H}{f_p} \times \frac{W}{f_p}}. \quad (7)$$

At the end of the network, an output layer O maps the DiT features back to the image latent space,

$$O(\cdot) : \mathbb{R}^{L \times \frac{H}{f_p} \times \frac{W}{f_p}} \rightarrow \mathbb{R}^{C \times \frac{H}{f} \times \frac{W}{f}}. \quad (8)$$

To accommodate our new latent space with more channels, we introduce an additional patch embedder P' and output layer O' :

$$\begin{aligned} P'(\cdot) &: \mathbb{R}^{D \times \frac{H}{f} \times \frac{W}{f}} \rightarrow \mathbb{R}^{L \times \frac{H}{f_p} \times \frac{W}{f_p}}, \\ O'(\cdot) &: \mathbb{R}^{L \times \frac{H}{f_p} \times \frac{W}{f_p}} \rightarrow \mathbb{R}^{D \times \frac{H}{f} \times \frac{W}{f}}. \end{aligned} \quad (9)$$

Under this design, the input to the DiT space is

$$P(z) + P'(z_{\text{hr}}), \quad (10)$$

and the DiT output L is decoded to the latent spaces via

$$\hat{u} = O(L), \quad \hat{u}_{\text{hr}} = O'(L), \quad (11)$$

where $\hat{u}$ and $\hat{u}_{\text{hr}}$ are the predictions for the original and high-resolution latents, respectively.

To preserve the pretrained behavior, we keep the original latent z path intact and zero-initialize P' and O' so that their outputs are zero at initialization. In this way, the overall model is exactly equivalent to the pretrained DiT at the beginning of fine-tuning, so the learned priors are fully preserved and training starts from a valid diffusion model. As illustrated in Fig. 4, this zero initialization leads to a much more stable optimization and significantly faster convergence compared to standard random initialization.

Gradual loss scheduling. Besides the zero-init strategy, we introduce a loss scheduling that allows the diffusion fine-tuning process to gradually adapt to the extra channels. Specifically, we introduce a cosine-annealed weighting strategy applied to the diffusion training loss. Let $\hat{u}_{\text{hr}} = [\hat{u}, \hat{u}_d]$ denote the DiT's prediction on the structured latent $[z_b \parallel z_r]$, and $u_{\text{hr}} = [u, u_d]$ are the target of v parameterization. We introduce a loss scheduling weight as:

$$w(n) = \begin{cases} \frac{1 - \cos(\pi n / N_{\text{warm}})}{2}, & n < N_{\text{warm}} \\ 1, & n \geq N_{\text{warm}} \end{cases} \quad (12)$$

where N_{warm} is a hyper-parameter for the number of warm-up steps, and n is the current training step. We apply this weight only to $\hat{u}_d$, that is:

$$\mathcal{L}_{\text{DiT}}(n) = \frac{1}{|B| + w(n)|R|} (\|\hat{u} - u\|_2^2 + w(n)\|\hat{u}_d - u_d\|_2^2) \quad (13)$$

At early iterations ($w(n) \approx 0$), gradients are dominated by the base latent channels, ensuring stable alignment with the pretrained backbone. As training proceeds, the diffusion model is gradually forced to model the extra detail channels z_d . This scheduling effectively regularizes the pretrained model to gradually adapt to the new latents.

End-to-end fine-tuning. With the above recipes, we fine-tune all blocks of a pretrained DiT, together with both patch embedders P , P' and output layers O and O' . For large model SD3.5 [40], we use LoRA on all attention and FFN layers, but still optimize all parameters of P , P' , O and O' .

4. Experiments

We evaluate our method on both ImageNet and general text-to-image generation. On ImageNet, we show both qualitative and quantitative results by fine-tuning a base model to generate 512×512 images. To show the importance of individual components of our method, we perform ablation studies with quantitative results. For general text-to-image experiments, we fine-tune over SD3.5 Medium with LoRA and report qualitative and quantitative results, starting from a base resolution of 512×512 to generate 1024×1024 images. We also show qualitative results by fine-tuning from 1024×1024 to generate 2048×2048 images.

ImageNet experiment details. We use the pretrained VA-VAE and LightningDiT-XL from [48] as our base model, which is trained to generate images at the resolution of $256 \times$

Method	Training Regime	Reconstruction		Token-nums (# of latent tokens)	Training Epochs	FID-50k ↓		Inception Score ↑
		AutoEncoders	rFID			w/o CFG	w/ CFG	
DiT-XL [†] [32]	Scratch	SD-VAE (f8c4p2)	0.48	32×32	2400	12.04	3.04	255.3
REPA [†] [53]	Scratch				200	-	2.08	274.6
DiT-XL [†] [32]	Scratch	DC-AE (f32c32p1)	0.66	16×16	2400	9.56	2.84	117.5
DC-Gen-DiT-XL [†] [21]	Fine-tune				80	8.21	2.22	122.5
LightningDiT-XL* [48]	Scratch	VA-VAE (f16c32p2)	0.50	16×16	80	21.79	3.98	229.7
LightningDiT-XL [48]	Fine-tune				80	11.31	3.12	254.5
Ours	Fine-tune	DA-VAE (f32c128p1)	0.47	16×16	25 80	6.04 4.84	2.07 1.68	277.6 314.3

Table 1. **ImageNet** 512×512 comparison in training regime, efficiency, and performance. **Training Regime:** *Scratch* trains the generator from random initialization for the target setting; *Fine-tune* starts from a pretrained generator (or a closely-related pretrained checkpoint) and adapts it to the target setting (e.g., resolution/tokenizer/architecture change). [†] indicates numbers are directly copied from the corresponding papers; * follows the original paper’s from-scratch setting.



Figure 5. Qualitative samples from our model trained at 512×512 resolution on ImageNet.

Autoencoder	Reconstruction				Generation
	rFID ↓	PSNR ↑	LPIPS ↓	SSIM ↑	FID-10k ↓
SD-VAE (f8c4p4)	0.48	29.22	0.13	0.79	58.17
DC-AE (f32c32p1)	0.66	27.78	0.16	0.74	35.97
VA-VAE (f16c32p2)	0.50	28.43	0.13	0.78	44.65
DA-VAE (f32c128p1)	0.47	28.53	0.12	0.78	31.51

Table 2. **Performance comparison of different autoencoders.** All generation models were trained from scratch.

256. VA-VAE uses a spatial compression factor $f = 16$ and $C = 32$ latent channels. Our structural latent adds additional $D = 96$ channels to the latent space, resulting in a total of 128 channels for each token. LightningDiT-XL is a DiT-XL/1 [32] diffusion model trained on the latent space of VA-VAE for 256×256 image generation, with a patch size $p = 1$. DA-VAE is trained for 100k steps with a batch size of 1024 and the DiT backbone is fully fine-tuned for 25 epochs with a batch size of 640 on 8 H100 GPUs, following our proposed recipe. We set $N_{warm} = 10k$ steps for our loss scheduling strategy as described in Sec. 3.2. Other details can be found in the supplementary material.

Text-to-image generation details. For text-to-image generation, we conduct quantitative and qualitative experiments based on Stable Diffusion 3.5 Medium (SD3.5M) [14], fine-tuning it to generate at a resolution of 1024×1024 with a base resolution of 512×512 . The SD3.5M uses a VAE with $f = 8$ compression ratio and $C = 16$ channels in the latent space. Our structural latent adds an additional $D = 16$ channels to the latent space, resulting in a total of 32 channels per token. SD3.5 uses a MMDDiT-X diffusion backbone with 2.5B parameters and patch size of $p = 2$. We train DA-VAE for 10k steps with a batch size of 32 on SAM dataset [25] and fine-tune the SD3.5M backbone for 20k steps with a batch size of 128 on a synthetic dataset generated from the base model using the prompts from DiffusionDB [44]. During fine-tuning, we use our proposed recipe and set $N_{warm} = 5k$ steps. Due to compute constraints, we apply LoRA with a rank of 256 for all blocks in the DiT backbone, except for the patch embedder and the output layer. For quantitative evaluation, we use the MJHQ-



Figure 6. Comparison between our method (1024×1024) and Stable Diffusion 3.5 (1024×1024 by 512×512 upsample).



Figure 7. Comparison between our method and Stable Diffusion 3.5 on a 2048×2048 resolution. Zoom in for a better view.

30K [27] dataset and report CLIP-Score [63] and GenEval [19] results; see supplementary material for other details.

4.1. ImageNet results

Autoencoder evaluation. We first evaluate the reconstruction and generation performance of DA-VAE compared to the base VA-VAE and other baselines. For reconstruction, we report rFID [22], PSNR, LPIPS [58] and SSIM [43] on the ImageNet validation set. For generation, we train a DiT-XL for 20k steps **from scratch** under the same token budget and report FID-10k on ImageNet 512×512 ; no classifier-free guidance is applied for fair comparisons. Our DA-VAE achieves a better trade-off between reconstruction and generation compared to other autoencoder baselines

(Tab. 2), and its structured latent enables faster diffusion training despite having high channel dimensionality.

Diffusion fine-tuning evaluation. We compare class-to-image generation against state-of-the-art methods at 512×512 resolution. Starting from VA-VAE with LightningDiT-XL ($p = 1$), we compare against fine-tuning LightningDiT-XL with $p = 2$ via the DC-Gen strategy [21], and against training LightningDiT-XL with $p = 2$ from scratch, annotated by an asterisk (*) in Tab. 1. We also compare with other autoencoders for 512×512 generation that use the same or more tokens; our strategy shows better generation performance. Qualitative results in Fig. 5 further demonstrate rich details and complex structures.

Method	AutoEncoders	Token-nums (# of latent tokens)	Params (B)	Throughput (img/s)	FID ↓	CLIP Score ↑	GenEval ↑
PixArt-Σ	—	64 × 64	0.6	0.40	6.15	28.26	0.54
Hunyuan-DiT	—	64 × 64	1.5	0.05	6.54	28.19	0.63
SANA-1.5	DC-AE(f32c32p1)	32 × 32	4.8	0.26	5.99	29.23	0.80
FLUX-dev	FLUX-VAE(f8c16p2)	64 × 64	12	0.04	10.15	27.47	0.67
SD3-medium	SD3-VAE (f8c16p2)	64 × 64	2.0	0.36	11.92	27.83	0.62
SD3.5-medium	SD3-VAE (f8c16p2)	64 × 64	2.5	0.25	10.31	29.74	0.63
SD3.5-medium [†]	SD3-VAE (f8c16p2)	32 × 32	2.5	1.03	12.04	30.17	0.63
Ours (SD3.5-M + DA-VAE)	DA-VAE (f16c32p2)	32 × 32	2.5	1.03	10.91	31.91	0.64

Table 3. **Comparison of our method with SOTA approaches in efficiency and performance.** FID and CLIP Score are reported on MJHQ-30K (1024 × 1024). Throughput is measured on a single A100 GPU (BF16, batch size 10). **Data sources:** the first five baselines (PixArt-Σ, Hunyuan-DiT, SANA-1.5, FLUX-dev, and SD3-medium) are copied from [46] under the same evaluation protocol.

Alignment	Reconstruction				Generation
loss weight λ_{align}	rFID ↓	PSNR ↑	LPIPS ↓	SSIM ↑	FID-10k ↓
0.0	0.59	29.23	0.11	0.80	16.37
0.1	0.55	28.70	0.12	0.79	9.58
0.5	0.47	28.53	0.12	0.78	9.27
1.0	0.63	27.90	0.14	0.76	9.23

Table 4. **Ablation on alignment-loss weight.** Increasing λ_{align} slightly degrades reconstruction (higher rFID / LPIPS, lower PSNR / SSIM) but improves generation quality (lower gFID), with the best trade-off at a moderate weight.

Method	Alignment	Zero Init	Weight Scheduler	FID-10k ↓
Ours (full)	✓	✓	✓	9.27
w/o alignment	✗	✓	✓	16.37
w/o zero init	✓	✗	✓	29.73
w/o weight scheduler	✓	✓	✗	9.80

Table 5. **Ablation on three components.** Our full model enables all three (✓); each ablation disables exactly one component (✗).

4.2. Text-to-image results

We evaluate text-to-image generation by applying our recipe to Stable Diffusion 3.5 Medium, using a base resolution of 512×512 to generate images at 1024×1024 . We compare against state-of-the-art methods for 1024×1024 image generation. As summarized in Tab. 3, SD3.5 Medium fine-tuned with our DA-VAE models achieves quantitative results comparable to its base model, while improving throughput by about 4× at 1K resolution. For qualitative comparison, Fig. 6 shows that our method produces images with more complex structures, richer details, and better prompt fidelity than the 512×512 SD3.5-M baseline. We further evaluate scaling to 2048×2048 . Naively running SD3.5-M at this resolution leads to clear quality degradation, with distorted large objects and occasional layout collapse. In contrast, our DA-VAE-augmented model generates high-quality 2048×2048 samples that better preserve both global structure and fine details, as shown in Fig. 7.

4.3. Ablation studies

We ablate the alignment loss weight and validate our design choices by removing core components one at a time. All ablation studies use VA-VAE and LightningDiT-XL on Im-

geNet 512×512 , with VAE models trained for 50 epochs and DiT models for 20 epochs without classifier-free guidance.

Impact of alignment loss weights. As shown in Tab. 4, we vary the alignment loss weight λ_{align} in Eq. (6) and report reconstruction and generation performance. Without alignment ($\lambda_{align} = 0$), the model attains strong reconstruction fidelity but yields poor generation quality due to an unstructured latent space. With a small weight ($\lambda_{align} = 0.1$), generation quality improves substantially while reconstruction remains largely preserved. With a large weight ($\lambda_{align} = 1.0$), generation quality further improves, but reconstruction degrades due to over-regularization. A moderate weight of 0.5 achieves the best trade-off; we use $\lambda_{align} = 0.5$ throughout.

Effectiveness of design choices. As shown in Tab. 5, we ablate the three main components: (a) alignment loss, (b) zero-initialization, and (c) loss scheduling. Among the three, alignment and zero-init are crucial for effective generation, and loss scheduling yields a further improvement.

5. Conclusion and Limitations

Our method provides a simple and efficient recipe to increase the effective compression ratio of a pretrained VAE while keeping the token count unchanged, enabled by detail alignment. This approach does not require expensive retraining. We showcase promising results for generic text-to-image tasks, where our method enables higher-resolution generation with the same number of visual tokens. However, our work has several limitations. First, we deliberately choose our current detail alignment loss due to its simplicity; there may be better alternatives. Second, given our compute budget, we have not yet evaluated full fine-tuning on SD3.5 or applied our method to more recent but costly backbones such as FLUX. Finally, as a proof-of-concept, our method currently uses synthetic data for fine-tuning. Therefore, our generated images are less photorealistic than SD3.5’s native generation at 1024×1024 . We leave these directions for future work.

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