

REPA-E: Unlocking VAE for End-to-End Tuning with Latent Diffusion Transformers

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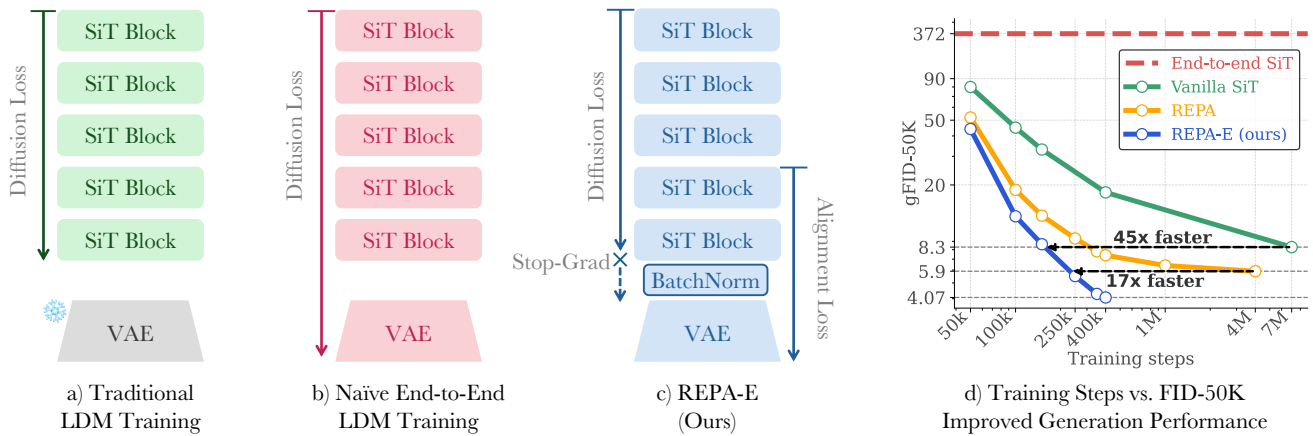


Figure 1. **Can we unlock VAE for end-to-end tuning with latent-diffusion models?** — Traditional deep learning wisdom dictates that end-to-end training is often preferable when possible. However, latent diffusion models usually only update the generator network while keeping the variational auto-encoder (VAE) fixed (a). This is because directly using the diffusion loss to update the VAE (b) causes the latent space to collapse. We show that while direct diffusion-loss is ineffective, end-to-end training can be unlocked through the representation-alignment (REPA) loss — allowing both encoder and diffusion model to be jointly tuned during the training process (c). Notably, this allows for significantly accelerated training; speeding up training by over 17 $\times$ and 45 $\times$ over REPA and vanilla training recipes, respectively (d).

Abstract

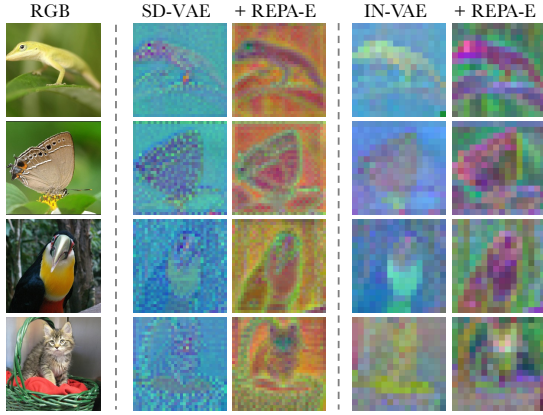
In this paper we tackle a fundamental question: “Can we train latent diffusion models together with the variational auto-encoder (VAE) tokenizer in an end-to-end manner?” Traditional deep-learning wisdom dictates that end-to-end training is often preferable when possible. However, for latent diffusion transformers, it is observed that end-to-end training both VAE and diffusion-model using standard diffusion-loss is ineffective, even causing a degradation in final performance. We show that while diffusion loss is ineffective, end-to-end training can be unlocked through the representation-alignment (REPA) loss — allowing both VAE and diffusion model to be jointly tuned during the training process. Despite its simplicity, the proposed training recipe (REPA-E) shows remarkable performance; speeding up diffusion model training by over 17 $\times$ and 45 $\times$ over REPA and

vanilla training recipes, respectively. Interestingly, we observe that end-to-end tuning with REPA-E also improves the VAE itself; leading to improved latent space structure and downstream generation performance. In terms of final performance, our approach sets a new state-of-the-art; achieving FID of 1.26 and 1.83 with and without classifier-free guidance on ImageNet 256 $\times$ 256. Code is available at <https://end2end-diffusion.github.io>.

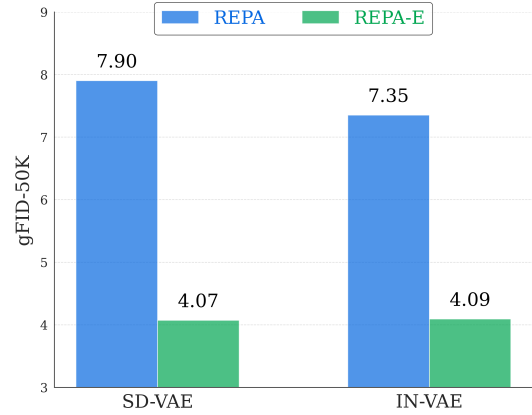
1. Introduction

End-to-end training has propelled the field forward for the past decade. It is understood that incorporating more components into end-to-end training can lead to increased performance, as evidenced by the evolution of the RCNN family [14, 15, 38]. With that said, training schemes of latent diffusion models (LDMs) [39] remain two-stage: first, the variational auto-encoder (VAE) [22] is trained with the re-

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(a) PCA Analysis on VAE Latent Space Structure



(b) Performance Improvements with REPA-E (400K Steps)

Figure 2. **End-to-End Training Automatically Improves VAE Latent-Space Structure.** (a) Following [24], we visualize latent space structure from different VAEs before and after end-to-end training using principal component analysis (PCA) that projects them to three channels colored by RGB. We consider SD-VAE [39], and IN-VAE¹, a $16\times$ downsampling, 32-channel VAE trained on ImageNet [6]. For SD-VAE we find that latent representations have high-frequency noise. Applying end-to-end tuning helps learning a more smooth and less noisy latent representation. Interestingly to the contrast, the latent space for IN-VAE is over-smoothed (e.g., row-2). Applying end-to-end tuning automatically helps learn a more detailed latent space structure to best support final generation performance. (b) Jointly tuning both VAE and latent diffusion model (LDM) significantly improves final generation performance (gFID) across different VAE architectures.

construction loss; then, the diffusion model is trained with the diffusion loss while keeping the VAE fixed (see Fig. 1a).

The above two-stage division of the LDM training process, though popular, leads to a challenging optimization task: “How to best optimize the representation from first stage (VAE) for optimal performance while training the second stage (diffusion model)?” While recent works study the interplay between the performance of the two stages [24, 43], they are often limited to empirical analysis, which may vary depending on the architecture and training setting for both the VAE and the diffusion model. For instance, in a concurrent work [43] show that the latent space of popular autoencoders e.g., SD-VAE [39] suffer from high-frequency noise / components. However, as seen in Fig. 2 & 5, while the same holds for some VAEs (e.g. SD-VAE), it might not be true for other VAE architectures — which instead might suffer from an over-smoothed latent space (Fig. 2, 5).

In this paper, we therefore ask a fundamental question: “Can we jointly tune both VAE and LDM in an end-to-end manner to best optimize final generation performance?” Technically, it is straightforward to do end-to-end LDM training by simply back-propagating the diffusion loss to the VAE tokenizer. However, experiments (§3) reveal that this naive approach for end-to-end training is ineffective. The diffusion loss encourages learning a simpler latent space structure which is easier for denoising objective (refer §3.1), but leads to reduced generation performance (Fig. 1d).

To address this, we propose REPA-E; an end-to-end training recipe using representation alignment loss [52]. We show that while the diffusion loss is ineffective, end-to-end tuning can be unlocked through the recently proposed representation-alignment (REPA) loss - allowing both VAE

and diffusion model to be jointly tuned during training process. Through extensive evaluations, we demonstrate that end-to-end tuning with REPA-E offers several advantages; **End-to-End Training Leads to Accelerated Generation Performance**; speeding up diffusion training by over $17\times$ and $45\times$ over REPA and vanilla training recipes (Fig. 1d). Furthermore, it also helps significantly improve the final generation performance. For instance as seen in Fig. 1d, we find that when using the popular SiT-XL [30] architecture, REPA-E reaches an FID of 4.07 within 400K steps, significantly boosting final performance over even REPA which only reaches a final FID for 5.9 after 4M steps [52].

End-to-End Training improves VAE latent-space structure. As seen in Fig. 2 and §4.4, we find that jointly tuning the VAE and latent diffusion model during training, automatically improves the latent space structure across different VAE architectures. For instance, for SD-VAE [39], it is observed that the original latent space suffers from high-frequency noise (Fig. 2). Applying end-to-end tuning helps learn a more smooth latent space representation. In contrast, the latent space for IN-VAE¹ is over-smoothed. Applying REPA-E automatically helps learn more detailed latent space structure to best support generation performance. **End-to-End Tuning Improves VAE Performance.** Finally, we find that once tuned using REPA-E, the end-to-end tuned VAE can be used as a drop-in replacement for their original counterparts (e.g. SD-VAE) showing improved generation performance across diverse training settings and model architectures (refer §4.4).

To summarize, key contributions of this paper are: 1) We propose REPA-E; an end-to-end training recipe for jointly

¹trained on imagenet at *f16d32* using official training code from [39].

tuning both VAE and LDM using representation alignment loss (§3). 2) We find that despite its simplicity, REPA-E leads to accelerated generation performance; speeding up diffusion training by over $17\times$ and $45\times$ over REPA and vanilla training recipes, respectively (§4.2). 3) We show that end-to-end training is able to adaptively improve the latent space structure across diverse VAE architectures. 4) We demonstrate that once tuned using REPA-E, the end-to-end tuned VAE can be used as a drop-in replacement for their original counterparts (*e.g.*, SD-VAE), exhibiting significantly better downstream generation performance (§4.4).

2. Related Work

Tokenizers or autoencoders (AE) [3] use either the variational objective [22] for continuous tokenization or a vector quantization objective [9, 47] for discrete tokenization [8–10, 16, 21, 22, 36, 39, 47, 51, 53]. However, current tokenizers are primarily trained for minimizing the reconstruction error, which maybe not provide the optimal latent space for generation [24]. We show that improved latent space structure is achieved by end-to-end training of LDMs.

Latent diffusion models leverage pre-trained image tokenizers to compress images into a lower-dimensional latent space to simplify the generative task [5, 10, 10, 11, 26, 32, 36, 39, 42, 46]. Despite their effectiveness, existing tokenizers and diffusion models are trained separately [10, 36, 39]. In this paper, we explore jointly optimizing tokenizers and diffusion models to achieve faster convergence and improved generation performance (Sec. 4).

Representation alignment for generative learning has recently shown huge promise for improving the training speed and performance of diffusion models [35, 48, 52]. We find that instead of applying the REPA loss separately over LDM [52] or VAE [48], significantly better performance and training speed can be achieved through E2E training.

End-to-End Diffusion. LSGM [46] explores joint training with score-based generative models, which uses a variational lower bound objective with an entropy term for preventing latent space collapse while backpropagating the diffusion loss. We empirically find that while this helps prevent latent space collapse, REPA-E shows significantly faster convergence during E2E training (refer App. B).

3. REPA-E: Unlocking VAE for Joint Training

Overview. Given a variational autoencoder (VAE) and latent diffusion transformer (*e.g.*, SiT [30]), we wish to jointly tune the VAE latent representation and diffusion model features in an end-to-end manner to best optimize the final generation performance. To this end, we first make three key insights in §3.1: 1) Naive end-to-end tuning - directly back-propagating the diffusion loss to the VAE is ineffective. The diffusion loss encourages learning a more simpler latent space structure (Fig. 3a) which is easier for min-

imizing the denoising objective [39], but degrades the final generation performance. We next analyze the recently proposed representation-alignment loss [52] showing that; 2) Higher representation-alignment score [52] correlates with improved generation performance (Fig. 3b). This offers an alternate path for improving final generation performance using representation-alignment score as a proxy. 3) The maximum achievable alignment score with vanilla-REPA is bottlenecked by the VAE latent space features. We further show that backpropagating the REPA loss to the VAE during training can help address this limitation, significantly improving final representation-alignment score (Fig. 3c).

Given the above insights, we finally propose REPA-E (§3.2); an end-to-end tuning recipe for both VAE and LDM features. Our key idea is simple: instead of directly using diffusion loss for end-to-end tuning, we can use the representation alignment score as a proxy for the final generation performance. This motivates our final approach, where instead of the diffusion loss, we propose to perform end-to-end training using the representation-alignment loss. The end-to-end training with REPA loss helps better improve the final representation-alignment score (Fig. 3b), which in turn leads to improved final generation performance (§3.1).

3.1. Motivating End-to-End Training with REPA

Naive End-to-End Tuning is Ineffective. We first analyze the naive approach for end-to-end tuning; directly backpropagating the diffusion loss to the VAE tokenizer. As shown in Fig. 3a, we observe that directly backpropagating the diffusion loss encourages learning a more simpler latent space structure with lower variance along the spatial dimensions (Tab. 9). The simpler latent-space structure poses an easier problem for the denoising objective [39], but leads to reduced generation performance (Fig. 1). Consider an intermediate latent $z_t = \alpha_t z_{\text{VAE}} + \sigma_t \epsilon_{\text{orig}}$ for any timestep t . The denoising objective [34] mainly aims to predict ϵ_{pred} ; estimating the originally added noise ϵ_{orig} from VAE features z_{VAE} and timestep t . As the variance along the spatial dimensions for VAE latent z_{VAE} goes down, the denoising objective effectively reduces to predicting a bias term for recovering back the originally added noise ϵ_{orig} . Thus, back-propagation the diffusion loss effectively hacks the latent space structure to create an easier denoising problem, but leads to a reduced generation performance (Fig. 1).

Higher Representation Alignment Correlates with Better Generation Performance. Similar to the findings of [52], we also measure representation alignment using CKNN scores [19] across different model sizes and training iterations. As seen in Fig. 3b, we observe that higher representation alignment during the training process leads to improved generation performance. This suggests an alternate path for improving generation performance by using the representation alignment objective instead of the diffusion loss for end-to-end training (refer §3.2).

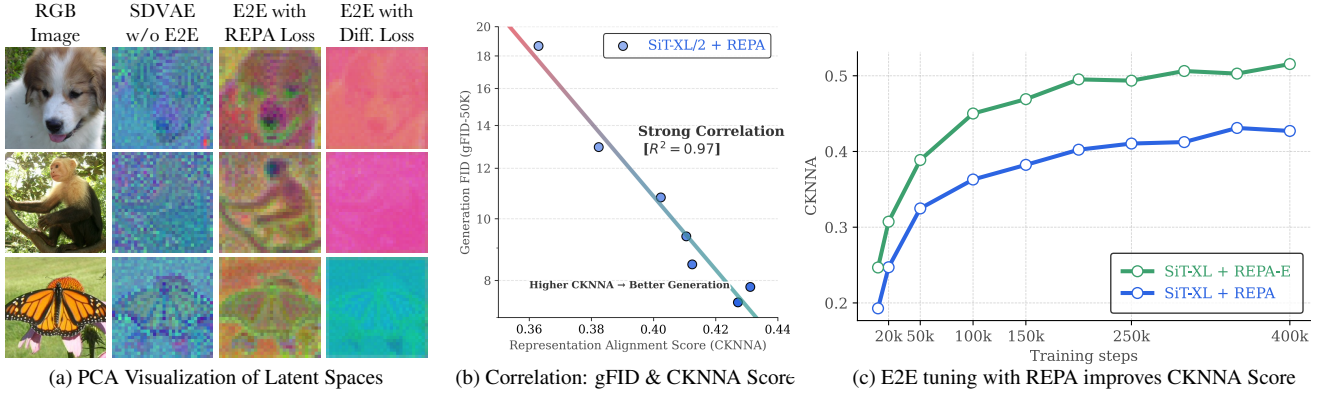


Figure 3. **Motivating End-to-End Tuning using Representation Alignment (REPA) Loss.** We make three key insights: **1)** Naive end-to-end (E2E) tuning using diffusion loss is ineffective. The diffusion encourages learning a more simpler latent space structure (a) which is easier for denoising objective (refer §3.1) but degrades final generation performance (Fig. 1). We next analyze the recently proposed representation alignment (REPA) loss [52] showing: **2)** Higher representation alignment (CKNNA) leads to better generation performance. This suggests an alternate path for improving performance by using representation-alignment (CKNNA) as proxy for generation performance. **3)** The maximum achievable CKNNA score with vanilla-REPA is bottlenecked by the VAE features (c) saturating around ~ 0.42 . Back-propagating the REPA-loss to the VAE helps address this limitation and improve the final CKNNA score. Given the above insights: we propose REPA-E (§3.2) for end-to-end LDM training. The key idea is simple: instead of using the diffusion loss, we perform end-to-end training using the REPA loss. The end-to-end training with REPA loss helps improve the final representation-alignment (CKNNA), which in turn leads to improved generation performance (§4).

Representation Alignment is Bottlenecked by the VAE Features. Fig. 3c shows that while the naive application of REPA loss [52] leads to improved representation-alignment (CKNNA) score, the maximum achievable alignment score is still bottlenecked the VAE features saturating around a value of 0.4 (maximum value of 1). Furthermore, we find that backpropagating the representation-alignment loss to the VAE helps address this limitation; allowing end-to-end optimization of the VAE features to best support representation-alignment objective [52].

3.2. End-to-End Training with REPA

Given the above insights, we next propose REPA-E (§3.2); an end-to-end tuning recipe for jointly training both VAE and LDM features. Instead of directly using diffusion loss, we propose to perform end-to-end training using the representation-alignment loss. The end-to-end training with REPA loss helps better improve the final representation-alignment score (Fig. 3c), which in turn leads to improved final generation performance (refer §4.2). We next discuss key details for implementation of REPA-E for training.

Batch-Norm Layer for VAE Latent Normalization.

To enable end-to-end training, we first introduce a batch-norm layer between the VAE and latent diffusion model (Fig. 1). Typical LDM training involves normalizing the VAE features using precomputed latent statistics (e.g., $\text{std} = 1/0.1825$ for SD-VAE [39]). This helps normalize the VAE latent outputs to zero mean and unit variance for more efficient training for the diffusion model. However, with end-to-end training the statistics need to be recomputed whenever the VAE model is updated - which is expensive. To address this, we propose the use of a batch-

norm layer [20] which uses the exponential moving average (EMA) mean and variance as a surrogate for dataset-level statistics. The batch-norm layer thus acts as a differentiable normalization operator without the need for recomputing dataset level statistics after each optimization step.

End-to-End Representation-Alignment Loss. We next enable end-to-end training, by using the REPA loss [52] for updating the parameters for both VAE and LDM during training. Formally, let $\mathcal{V}_\phi$ represent the VAE, $\mathcal{D}_\theta$ be the diffusion model, f be the fixed pretrained perceptual model (e.g., DINO-v2 [33]) for REPA [52] and $\mathbf{x}$ be a clean image. Also similar to REPA, consider $h_\omega(\mathbf{h}_t)$ be the projection of diffusion transformer output $\mathbf{h}_t$ through a trainable projection layer h_ω . We then perform end-to-end training by applying the REPA loss over both LDM and VAE as,

$$\mathcal{L}_{\text{REPA}}(\theta, \phi, \omega) = -\mathbb{E}_{\mathbf{x}, \epsilon, t} \left[\frac{1}{N} \sum_{n=1}^N \text{sim}(\mathbf{y}^{[n]}, h_\omega(\mathbf{h}_t^{[n]})) \right],$$

where $\mathbf{y} = f(\mathbf{x})$ is the output of the pretrained perceptual model (e.g., DINO-v2 [33]), N is number of patches, $\text{sim}(\cdot, \cdot)$ computes the patch-wise cosine similarities between pretrained representation $\mathbf{y}$ from perceptual model (e.g., DINO-v2) and diffusion transformer hidden state $\mathbf{h}_t$.

Diffusion Loss with Stop-Gradient. As discussed in Fig. 3a and §3.1, backpropagating the diffusion loss to the VAE causes a degradation of latent-space structure. To avoid this, we introduce a simple `stopgrad` operation which limits the application of diffusion loss $\mathcal{L}_{\text{DIFF}}$ to only the parameters θ of the latent diffusion model $\mathcal{D}_\theta$.

VAE Regularization Losses. Finally, we introduce regularization losses $\mathcal{L}_{\text{REG}}$ for VAE $\mathcal{V}_\phi$, to ensure that the end-to-end training process does not impact the reconstruction

performance (rFID) of the original VAE. In particular, following [1], we use three losses, 1) Reconstruction Losses ($\mathcal{L}_{\text{MSE}}, \mathcal{L}_{\text{LPIPS}}$), 2) GAN Loss ($\mathcal{L}_{\text{GAN}}$), 3) KL divergence loss ($\mathcal{L}_{\text{KL}}$) as regularization loss $\mathcal{L}_{\text{REG}}$ for the VAE $\mathcal{V}_\phi$.

Overall Training. The overall training is then performed in an end-to-end manner using the following loss,

$$\mathcal{L}(\theta, \phi, \omega) = \mathcal{L}_{\text{DIFF}}(\theta) + \lambda \mathcal{L}_{\text{REPA}}(\theta, \phi, \omega) + \eta \mathcal{L}_{\text{REG}}(\phi),$$

where θ, ϕ, ω refer to the parameters for the LDM, VAE and trainable REPA projection layer [52], respectively. Further implementation details are provided in §4.1 and Appendix.

4. Experiments

We next validate the performance of REPA-E and the effect of proposed components through extensive evaluation. In particular, we investigate three key research questions:

1. Can REPA-E significantly improve generation performance and training speed? (Sec. 4.2, Tab. 1, Fig. 1, 4)
2. Does REPA-E generalize across variations in training settings including model-scale, architecture, encoder model for REPA *etc.*? (Sec. 4.3, Tab. 2, 3, 4, 5, 6, 7)
3. Analyze the impact of end-to-end tuning (REPA-E) on VAE latent-space structure and downstream generation performance. (please refer Sec. 4.4, Fig. 5, Tab. 8, 13)

4.1. Setup

Implementation Details. We follow the same setup as in SiT [30] and REPA [52] unless otherwise specified. All training is conducted on the ImageNet [6] training split. We adopt the same data preprocessing protocol as in ADM [7], where original images are center-cropped and resized to 256×256 resolution. We experiment with publicly available VAEs, including SD-VAE (*f8d4*) [39], VA-VAE (*f16d32*) [39], and our own *f16d32* VAE trained on ImageNet, referred to as IN-VAE. Depending on the VAE downsampling rate, we adopt SiT-XL/1 and SiT-XL/2 for $4\times$ and $16\times$ downsampling rates, respectively, where 1 and 2 denote the patch sizes in the transformer embedding layer. We disable affine transformations in the BN [20] layer between the VAE and SiT, relying solely on the running mean and standard deviation. The VAE regularization loss combines multiple objectives and is defined as: $\mathcal{L}_{\text{REG}} = \mathcal{L}_{\text{KL}} + \mathcal{L}_{\text{MSE}} + \mathcal{L}_{\text{LPIPS}} + \mathcal{L}_{\text{GAN}}$. For alignment loss, we use DINOv2 [33] as external visual features and apply alignment to the eighth layer of the SiT model. Empirically, we set the alignment loss coefficient to $\lambda_{\text{REPA}_g} = 0.5$ for updating SiT and $\lambda_{\text{REPA}_v} = 1.5$ for VAE. For optimization, we use AdamW [23, 29] with a constant learning rate of 1×10^{-4} , and a global batch size of 256. During training, we apply gradient clipping and exponential moving average (EMA) to the generative model for stable optimization. All experiments are conducted on 8 NVIDIA H100 GPUs.

Evaluation. For image generation evaluation, we strictly follow the ADM setup [7]. We report generation quality using Fréchet inception distance (gFID) [17], structural FID (sFID) [31], inception score (IS) [41], precision (Prec.) and recall (Rec.) [25], measured on 50K generated images. For sampling, we follow the approach in SiT [30] and REPA [52], using the SDE Euler-Maruyama sampler with 250 steps. In terms of VAE benchmark, we measure the reconstruction FID (rFID) on 50K images from the ImageNet [6] validation set at a resolution of 256×256 .

4.2. Impact on Training Performance and Speed

We first analyze the impact of end-to-end tuning using REPA-E (Sec. 3.2) for improving generation performance and speed when training latent-diffusion transformers.

Quantitative Evaluation. We compare REPA-E against various latent diffusion model (LDM) baselines in Tab. 1. We evaluate models of similar sizes ($\sim 675\text{M}$ parameters) on ImageNet 256×256 generation task. All results are reported without classifier-free guidance [18] using popular SiT-XL [30] model for training. We make two observations; 1) End-to-End tuning leads to faster training: consistently improving generation FID (gFID) from $19.40 \rightarrow 12.83$ (20 epochs), $11.10 \rightarrow 7.17$ (40 epochs), and $7.90 \rightarrow 4.07$ (80 epochs), even when comparing with REPA [52]. 2) End-to-End training leads to better final performance: REPA-E at 80 epochs surpasses FasterDiT [49] (gFID=7.91) trained for 400 epochs and even MaskDiT [54], DiT [34], and SiT [30] which are trained over 1400 epochs. For instance, REPA-E reaches an FID of 4.07 within 400K steps, significantly boosting final performance over even REPA which only reaches a final FID for 5.9 after 4M steps [52].

Qualitative Evaluation. We provide qualitative comparisons between REPA [52] and REPA-E in Fig. 4. We generate images from the same noise and label using checkpoints at 50K, 100K, and 400K training iterations, respectively. As seen in Fig. 4, we observe that REPA-E demonstrates superior image generation quality compared to the REPA baseline, while also generating more structurally meaningful images during early stages of training process.

4.3. Generalization and Scalability of REPA-E

We next analyze the generalization of the proposed approach to variation in training settings including model-size, tokenizer architecture, representation encoder, alignment depth [52] *etc.* Unless otherwise specified, all analysis and ablations use SiT-L [30] as the generative model, SD-VAE as the VAE, and DINOv2-B [33] as the pretrained vision model for REPA loss [52]. Default REPA alignment-depth of 8 is used. We train each variant for 100K iterations and report results without classifier-free guidance [18]. All baseline numbers are reported using vanilla REPA and compared with end-to-end training using REPA-E.

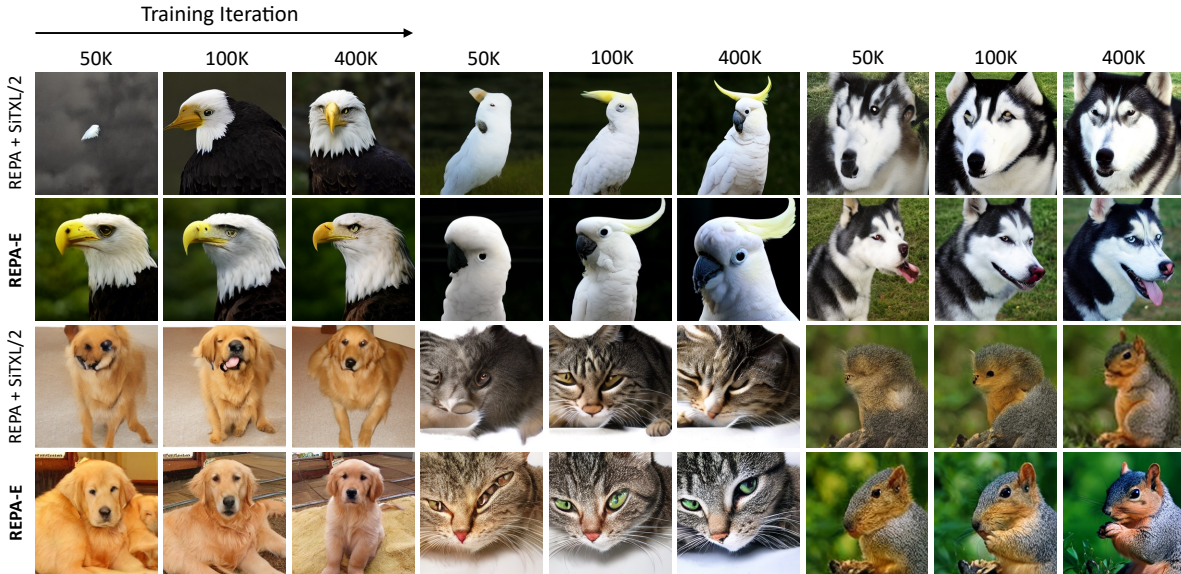


Figure 4. **End-to-End Tuning (REPA-E) Improves Visual Scaling.** We observe that REPA-E produces higher-quality images at 400K steps compared with the vanilla-REPA and generates more structurally meaningful images even in the early stages of training. Results for both methods are sampled using the same seed, noise and class label. We use a classifier-free guidance scale of 4.0 during sampling.

Method	Tokenizer	Epochs	gFID↓	sFID↓	IS↑
Without End-to-End Tuning					
MaskDiT [54]	SD-VAE	1600	5.69	10.34	177.9
DiT [34]		1400	9.62	6.85	121.5
SiT [30]		1400	8.61	6.32	131.7
FasterDiT [49]		400	7.91	5.45	131.3
REPA [52]	SD-VAE	20	19.40	6.06	67.4
		40	11.10	6.06	67.4
		80	7.90	5.06	122.6
		800	5.90	5.73	157.8
With End-to-End Tuning (Ours)					
REPA-E	SD-VAE*	20	12.83	5.04	88.8
		40	7.17	4.39	123.7
		80	4.07	<u>4.60</u>	<u>161.8</u>

Table 1. **REPA-E for Accelerated Generation Performance.** End-to-End training with REPA-E achieves significantly better performance (lower gFID) while using fewer epochs. Notably, REPA-E with only 80 epochs surpasses vanilla REPA using $10\times$ epochs. * indicates that VAE is updated during end-to-end training. All results are w/o classifier-free guidance on ImageNet 256 $\times$ 256. Additional system-level comparisons with classifier-free guidance and **state-of-the-art** results are provided in Tab. 13.

Impact of Model Size. Tab. 2 compares SiT-B, SiT-L, and SiT-XL to evaluate the effect of model size. We make two key observations. First, across all configurations, REPA-E consistently improves performance over the REPA baseline. Specifically, it reduces gFID from 49.5 $\rightarrow$ 34.8 for SiT-B, 24.1 $\rightarrow$ 16.3 for SiT-L, and 19.4 $\rightarrow$ 12.8 for SiT-XL, demonstrating the effectiveness. Second, surprisingly the percentage gains in gFID achieved with REPA-E (over REPA) improve with increasing model size. For instance, for SiT-B model REPA-E leads to a 29.6% improvement in gFID over REPA. Surprisingly even more gains

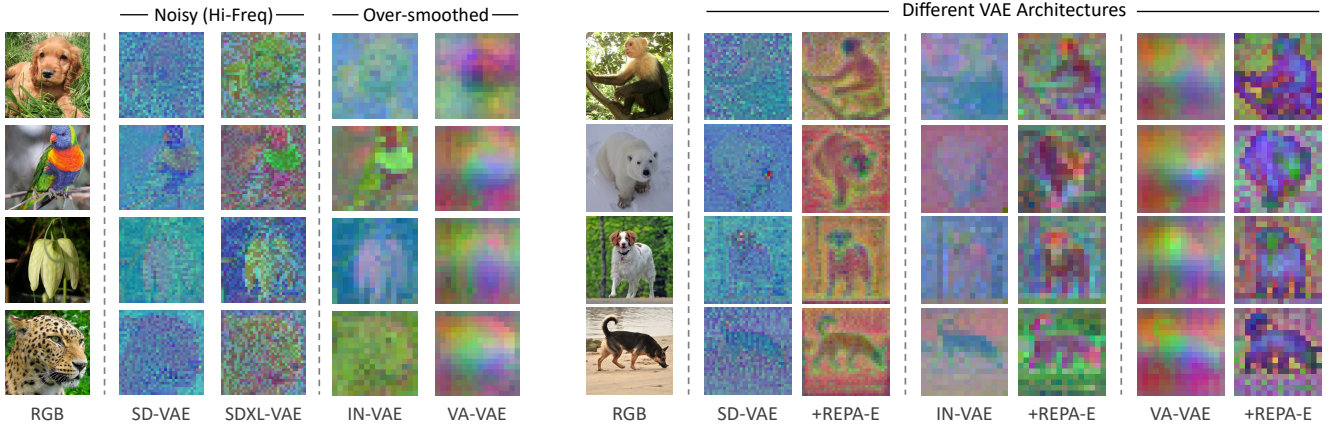
Diff. Model	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
SiT-B (130M)	49.5	7.00	27.5	0.46	0.59
+REPA-E (Ours)	34.8	6.31	39.1	0.57	0.59
SiT-L (458M)	24.1	6.25	55.7	0.62	0.60
+REPA-E (Ours)	16.3	5.69	75.0	0.68	0.60
SiT-XL (675M)	19.4	6.06	67.4	0.64	0.61
+REPA-E (Ours)	12.8	5.04	88.8	0.71	0.58

Table 2. **Variation in Model-Scale.** We find that REPA-E brings substantial performance improvements across all model-scales. All baselines are reported using vanilla-REPA [52] for training.

are achieved for bigger models improving gFID by 32.3% and 34.0% for SiT-L and SiT-XL models respectively. This trend highlights the scalability of REPA-E; larger models achieve better percentage gains over vanilla-REPA.

Variation in Representation Encoder. We report results across different perception model encoders (CLIP-L, I-JEPA-H, DINOv2-B, and DINOv2-L) Tab. 3. We observe that REPA-E gives consistent performance improvements over REPA, across different choices of the perceptual encoder model. In particular, with DINOv2-B and DINOv2-L, REPA-E significantly reduces gFID from 24.1 $\rightarrow$ 16.3 and from 23.3 $\rightarrow$ 16.0, respectively.

Variation in VAE. Tab. 4 evaluates the impact of different VAEs on REPA-E performance. In particular, we report results using three different VAEs 1) SD-VAE [1], 2) VA-VAE [48] and 3) IN-VAE (a $16\times$ downsampling, 32-channel VAE trained on ImageNet [6] using official training code from [39]). Across all variations, REPA-E consistently improves performance over the REPA baseline. REPA-E reduces gFID from 24.1 $\rightarrow$ 16.3, from 22.7 $\rightarrow$ 12.7, and 12.8 $\rightarrow$ 11.1, for SD-VAE, IN-VAE and VA-VAE, respectively. The results demonstrate that REPA-E robustly im-



(a) PCA Visualization of Latent Space Structure [24]

(b) Impact of End-to-End Tuning for Automatically Improving Latent Space Structure

Figure 5. End-to-End Training Improves Latent Space Structure. (a) We observe that the latent space of pretrained VAEs can suffer either high noise components (*e.g.*, SDXL-VAE, SD-VAE [39]), or, be over-smoothed and lack details (*e.g.*, VA-VAE [48]). (b) The use of end-to-end tuning (§3.2) automatically helps improve the latent space structure in a model-agnostic manner across different VAE architectures. For instance, similar to findings of concurrent work [43], we observe that SD-VAE suffers from high noise components in the latent space. Applying end-to-end training automatically helps adjust the latent space to reduce noise. In contrast, other VAEs such as recently proposed VA-VAE [48] suffer from an over-smoothed latent space. The use of end-to-end tuning with REPA-E automatically helps learn a more detailed latent-space structure to best support generation performance.

Target Repr.	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
I-JEPA-H [2]	23.0	5.81	60.3	0.62	0.60
+REPA-E (Ours)	16.5	5.18	73.6	0.68	0.60
CLIP-L [37]	29.2	5.98	46.4	0.59	0.61
+REPA-E (Ours)	23.4	6.44	57.1	0.62	0.60
DINOv2-B [33]	24.1	6.25	55.7	0.62	0.60
+REPA-E (Ours)	16.3	5.69	75.0	0.68	0.60
DINOv2-L [33]	23.3	5.89	59.9	0.61	0.60
+REPA-E (Ours)	16.0	5.59	77.7	0.68	0.58

Table 3. **Variation in Representation Encoder.** REPA-E yields consistent performance improvements across different choices for the representation-encoder used for representation-alignment [52]. All baselines are reported using vanilla-REPA [52] for training.

Autoencoder	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
SD-VAE [39]	24.1	6.25	55.7	0.62	0.60
+REPA-E (Ours)	16.3	5.69	75.0	0.68	0.60
IN-VAE (<i>f16d32</i>)	22.7	5.47	56.0	0.62	0.62
+REPA-E (Ours)	12.7	5.57	84.0	0.69	0.62
VA-VAE [48]	12.8	6.47	83.8	0.71	0.58
+REPA-E (Ours)	11.1	5.31	88.8	0.72	0.61

Table 4. **Variation in VAE Architecture.** All baselines are reported using vanilla-REPA [52] for training.

proves generative quality across diverse variations in architecture, pretraining dataset and training setting of the VAE.

Variation in Alignment Depth. Tab. 5 investigates the effect of applying the alignment loss at different layers the diffusion model. We observe that REPA-E consistently enhances generation quality over the REPA baseline across variation in choice of alignment depth; with gFID improving from 23.0 $\rightarrow$ 16.4 (6th layer), 24.1 $\rightarrow$ 16.3 (8th layer), and 23.7 $\rightarrow$ 16.2 (10th layer).

Aln. Depth	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
6th layer	23.0	5.72	59.2	0.62	0.60
+REPA-E (Ours)	16.4	6.64	74.3	0.67	0.59
8th layer	24.1	6.25	55.7	0.62	0.60
+REPA-E (Ours)	16.3	5.69	75.0	0.68	0.60
10th layer	23.7	5.91	56.9	0.62	0.60
+REPA-E (Ours)	16.2	5.22	74.7	0.68	0.58

Table 5. **Variation in Alignment Depth.** End-to-End tuning (REPA-E) gives consistent performance improvements over original REPA [52] across varying alignment-depths.

Component	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
w/o stopgrad	444.1	460.3	1.49	0.00	0.00
w/o batch-norm	18.1	5.32	72.4	0.67	0.59
w/o $\mathcal{L}_{\text{GAN}}$	19.2	6.47	68.2	0.64	0.58
REPA-E (Ours)	16.3	5.69	75.0	0.68	0.60

Table 6. **Ablation Study on Role of Different Components.**

Ablation on Design Components. We also perform ablation studies analyzing the importance of each component discussed in Sec. 3.2. Results are shown in Tab. 6. We observe that each component plays a key role in the final performance for REPA-E. In particular, we observe that the `stop-grad` operation on the diffusion loss helps prevent degradation of the latent-space structure. Similarly, the use of batch norm is useful adaptively normalizing the latent-statistics and helps improve the gFID from 18.09 $\rightarrow$ 16.3. Similarly, the regularization losses play a key role in maintaining the reconstruction performance of the finetuned VAE, thereby improving the gFID from 19.07 $\rightarrow$ 16.3.

End-to-End Training from Scratch. We next analyze the impact of VAE initialization on end-to-end training. As shown in Tab. 7, we find that while initializing the

Method	gFID↓	sFID↓	IS↑	Prec.↑	Rec.↑
100K Iterations (20 Epochs)					
REPA [52]	19.40	6.06	67.4	0.64	0.61
REPA-E (scratch)	14.12	7.87	83.5	0.70	0.59
REPA-E (VAE init.)	12.83	5.04	88.8	0.71	0.58
200K Iterations (40 Epochs)					
REPA [52]	11.10	5.05	100.4	0.69	0.64
REPA-E (scratch)	7.54	6.17	120.4	0.74	0.61
REPA-E (VAE init.)	7.17	4.39	123.7	0.74	0.62
400K Iterations (80 Epochs)					
REPA [52]	7.90	5.06	122.6	0.70	0.65
REPA-E (scratch)	4.34	4.44	154.3	0.75	0.63
REPA-E (VAE init.)	4.07	4.60	161.8	0.76	0.62

Table 7. **End-to-End Training from Scratch.** We find that while initializing the VAE with pretrained weights (SD-VAE [39]) helps slightly improve performance, REPA-E can be used to train both VAE and LDM from scratch in an end-to-end manner; still achieving significantly superior performance over REPA which requires a separate stage for training VAE in addition to LDM training.

VAE from pretrained weights helps slightly improve performance, REPA-E can be used to train both VAE and LDM from scratch still achieving superior performance over REPA, which technically requires a separate stage for VAE training in addition to LDM training. For instance, while REPA achieves a FID of 5.90 after 4M iterations, REPA-E while training entirely from scratch (for both VAE and LDM) achieves much faster and better generation FID of 4.34 within just 400K iterations.

4.4. Impact of End-to-End Tuning on VAE

We next analyze the impact of end-to-end tuning on the VAE. In particular, we first show that end-to-end tuning improves the latent-space structure (Fig. 5). We next show that once tuned using REPA-E, the finetuned VAEs can be used as a drop-in replacement for their original counterparts offering significantly improved generation performance.

End-to-End Training improves Latent Space Structure. Results are shown in Fig. 5. Following [24], we visualize latent space structure using principal component analysis (PCA) that projects them to three channels colored by RGB. We consider three different VAEs: 1) SD-VAE [39], 2) IN-VAE (a $16\times$ downsampling, 32-channel VAE trained on ImageNet [6]). 3) VA-VAE from recent work from [48]. We observe that end-to-end tuning using REPA-E automatically improves the latent space structure of the original VAE. For instance, similar to findings of concurrent work [43], we observe that SD-VAE suffers from high noise components in the latent space. Applying end-to-end training automatically helps adjust the latent space to learn reduce noise. In contrast, other VAEs such as recently proposed VA-VAE [48] suffer from over-smoother latent space. Application of E2E tuning automatically helps learn a more detailed latent-space to best support generation performance.

End-to-End Training Improves VAE Performance.

VAE	Diffusion model	REPA	gFID-50K
SD-VAE [39]	DiT-XL [34]	✗	19.82
VA-VAE [48]	DiT-XL [34]	✗	6.74
E2E-VAE (Ours)	DiT-XL [34]	✗	6.75
SD-VAE [39]	SiT-XL [30]	✗	17.20
VA-VAE [48]	SiT-XL [30]	✗	5.93
E2E-VAE (Ours)	SiT-XL [30]	✗	5.26
SD-VAE [39]	DiT-XL [34]	✓	12.29
VA-VAE [48]	DiT-XL [34]	✓	4.71
E2E-VAE (Ours)	DiT-XL [34]	✓	4.20
SD-VAE [39]	SiT-XL [30]	✓	7.90
VA-VAE [48]	SiT-XL [30]	✓	4.88
E2E-VAE (Ours)	SiT-XL [30]	✓	3.46

Table 8. **Impact of End-to-End Tuning on VAE Performance.** We find that once tuned using REPA-E, the finetuned VAEs can be used as a drop-in replacement for their original counterparts offering significantly accelerated generation performance. We fix all the VAEs and only train the diffusion models (with and w/o REPA). E2E-VAE is obtained from REPA-E fine-tuning (VA-VAE + SiT-XL). All results are reported at 80 epochs (400K iterations).

We next evaluate the impact of end-to-end tuning on downstream generation performance of the VAE. To this end, we first use end-to-end tuning for finetuning the recently proposed VA-VAE [48]. We then use the resulting end-to-end finetuned-VAE (named E2E-VAE), and compare its downstream generation performance with current state-of-the-art VAEs; including SDVAE [39] and VA-VAE [48]. To do this, we conduct traditional latent diffusion model training (w/o REPA-E), where only the generator network is updated while keeping the VAE frozen. Tab. 8 shows the comparison of VAE downstream generation across diverse training settings. We observe that end-to-end tuned VAEs consistently outperform their original counterparts for downstream generation tasks across variations in LDM architecture and training settings. Interestingly, we observe that a VAE tuned using SiT-XL yields performance improvements even when using a different LDM architecture such as DiT-XL; thereby demonstrating the robustness of our approach.

5. Conclusion

“Can we unlock VAE’s for performing end-to-end training with latent diffusion transformers?” Directly backpropagating diffusion loss to the VAE is ineffective and even degrades final performance. We show that while diffusion loss is ineffective, end-to-end training can be unlocked using REPA loss. Our end-to-end training recipe (REPA-E), significantly improves latent-space structure, shows remarkable performance; speeding up diffusion model training by over $17\times$ and $45\times$ over REPA and vanilla training recipes. Overall, our approach achieves a new state-of-the-art results with generation FID of 1.26 and 1.83 with and without use of classifier-free guidance. We hope that our work can help foster further research for enabling end-to-end training with latent diffusion transformers.

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