

All are Worth Words: A ViT Backbone for Diffusion Models

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Abstract

Vision transformers (ViT) have shown promise in various vision tasks while the U-Net based on a convolutional neural network (CNN) remains dominant in diffusion models. We design a simple and general ViT-based architecture (named U-ViT) for image generation with diffusion models. U-ViT is characterized by treating all inputs including the time, condition and noisy image patches as tokens and employing long skip connections between shallow and deep layers. We evaluate U-ViT in unconditional and class-conditional image generation, as well as text-to-image generation tasks, where U-ViT is comparable if not superior to a CNN-based U-Net of a similar size. In particular, a latent diffusion model with a small U-ViT achieves a record-breaking FID of 5.48 in text-to-image generation on MS-COCO, among methods without accessing large external datasets during the training of generative models.

Besides, our results suggest that, for diffusion-based image modeling, the long skip connection is crucial while the down-sampling and up-sampling operators in CNN-based U-Net are not always necessary. We believe that U-ViT can provide insights for future research on backbones in diffusion models and benefit generative modeling on large scale cross-modality datasets.

1. Introduction

Diffusion models [24, 56, 61] are powerful deep generative models that emerge recently for high quality image generation [12, 25, 49]. They grow rapidly and find applications in text-to-image generation [47, 49, 51], image-to-image generation [10, 42, 74], video generation [23, 27], speech synthesis [6, 33], and 3D synthesis [46].

Along with the development of algorithms [2, 3, 14, 24,

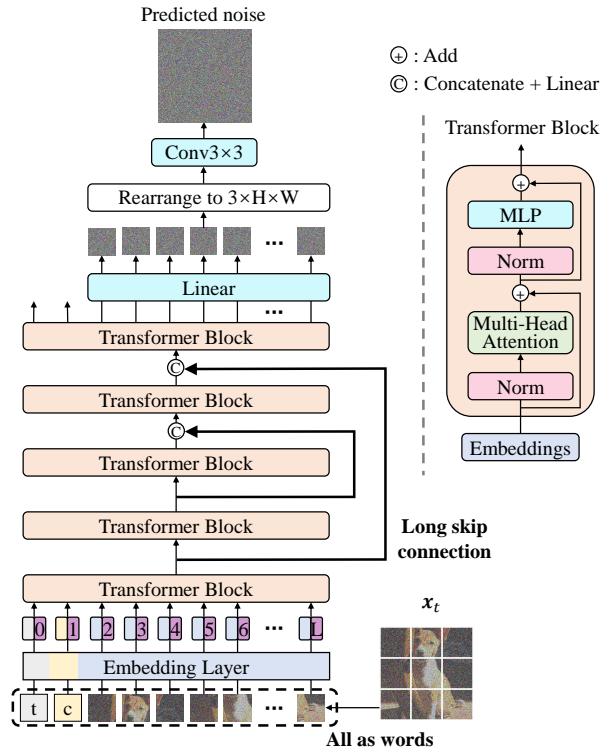


Figure 1. The **U-ViT** architecture for diffusion models, which is characterized by treating **all** inputs including the time, condition and noisy image patches **as tokens** and employing **long skip connections** between shallow and deep layers.

32, 40, 41, 45, 57, 58, 61, 65], the revolution of backbones plays a central role in the success of diffusion models. A representative example is U-Net based on a convolutional neural network (CNN) employed in prior work [24, 59]. The CNN-based U-Net is characterized by a group of down-sampling blocks, a group of up-sampling blocks, and long

skip connections between the two groups, which dominates diffusion models for image generation tasks [12, 47, 49, 51]. On the other hand, vision transformers (ViT) [15] have shown promise in various vision tasks, where ViT is comparable or even superior to CNN based approaches [9, 20, 35, 62, 75]. Therefore, a very natural question arises: *whether the reliance of the CNN-based U-Net is necessary in diffusion models?*

In this paper, we design a simple and general ViT-based architecture called U-ViT (Figure 1). Following the design methodology of transformers, U-ViT treats all inputs including the time, condition and noisy image patches as tokens. Crucially, U-ViT employs long skip connections between shallow and deep layers inspired by the U-Net. Intuitively, low-level features are important to the pixel-level prediction objective in diffusion models and such connections can ease the training of the corresponding pixel-level prediction network. Additionally, U-ViT adds an extra 3×3 convolutional block before output for better visual quality. See a systematical ablation study for all elements in Figure 2.

We evaluate U-ViT in three popular tasks: unconditional image generation, class-conditional image generation and text-to-image generation. In all settings, U-ViT is comparable if not superior to a CNN-based U-Net of a similar size. In particular, a latent diffusion model with a small U-ViT achieves a record-breaking FID of 5.48 in text-to-image generation on the MS-COCO dataset, among methods without accessing large external datasets during the training of generative models.

Besides, our results suggest that the long skip connection is crucial while the down-sampling and up-sampling operators in CNN-based U-Net are not always necessary for image diffusion models. We believe that U-ViT can provide insights for future research on backbones in diffusion models and benefit generative modeling on large scale cross-modality datasets.

2. Background

Diffusion models [24, 56, 61] gradually inject noise to data, and then reverse this process to generate data from noise. The noise-injection process, also called the forward process, is formalized as a Markov chain:

$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1}),$$

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t|\sqrt{\alpha_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}).$$

Here \mathbf{x}_0 represents the data, α_t and β_t represent the noise schedule such that $\alpha_t + \beta_t = 1, \forall t$. To reverse this process, a Gaussian model $p(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}|\mu_t(\mathbf{x}_t), \sigma_t^2\mathbf{I})$ is adopted to approximate the ground truth reverse transition

$q(\mathbf{x}_{t-1}|\mathbf{x}_t)$, and the optimal mean [3] is

$$\mu_t^*(\mathbf{x}_t) = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\alpha_t}} \mathbb{E}[\epsilon|\mathbf{x}_t] \right).$$

Here $\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$, and ϵ is the standard Gaussian noises injected to \mathbf{x}_t . Thus, the learning is equivalent to a noise prediction task. Formally, a noise prediction network $\epsilon_\theta(\mathbf{x}_t, t)$ is adopted to learn $\mathbb{E}[\epsilon|\mathbf{x}_t]$ by predicting the noise ϵ injected to \mathbf{x}_t :

$$\min_{\theta} \mathbb{E}_{t, \mathbf{x}_0, \epsilon} \|\epsilon - \epsilon_\theta(\mathbf{x}_t, t)\|_2^2,$$

where t is uniform between 1 and T . To learn conditional diffusion models, e.g., class-conditional [12] or text-to-image [47] models, the condition information is further fed into the noise prediction objective:

$$\min_{\theta} \mathbb{E}_{t, \mathbf{x}_0, c, \epsilon} \|\epsilon - \epsilon_\theta(\mathbf{x}_t, t, c)\|_2^2, \quad (1)$$

where c is the condition or its continuous embedding. In prior work on image modeling, the success of diffusion models heavily rely on CNN-based U-Net [50, 59], which is a convolutional backbone characterized by a group of down-sampling blocks, a group of up-sampling blocks and long skip connections between the two groups, and c is fed into U-Net by mechanisms such as adaptive group normalization [12] and cross attention [49].

Vision Transformer (ViT) [15] is a pure transformer architecture that treats an image as a sequence of tokens (words). ViT rearranges an image into a sequence of flattened patches. Then, ViT adds learnable 1D position embeddings to linear embeddings of these patches before feeding them into a transformer encoder [66]. ViT has shown promise in various vision tasks but it is not clear whether it is suitable for diffusion-based image modeling yet.

3. Method

U-ViT is a simple and general backbone for diffusion models in image generation (Figure 1). In particular, U-ViT parameterizes the noise prediction network¹ $\epsilon_\theta(\mathbf{x}_t, t, c)$ in Eq. (1). It takes the time t , the condition c and the noisy image \mathbf{x}_t as inputs and predicts the noise injected into \mathbf{x}_t . Following the design methodology of ViT, the image is split into patches, and U-ViT treats all inputs including the time, condition and image patches as tokens (words).

Inspired by the success of the CNN-based U-Net in diffusion models [59], U-ViT also employs similar long skip connections between shallow and deep layers. Intuitively, the objective in Eq. (1) is a pixel-level prediction task and is sensitive to low-level features. The long skip connections

¹U-ViT can also parameterize other types of prediction, e.g., \mathbf{x}_0 -prediction [24].

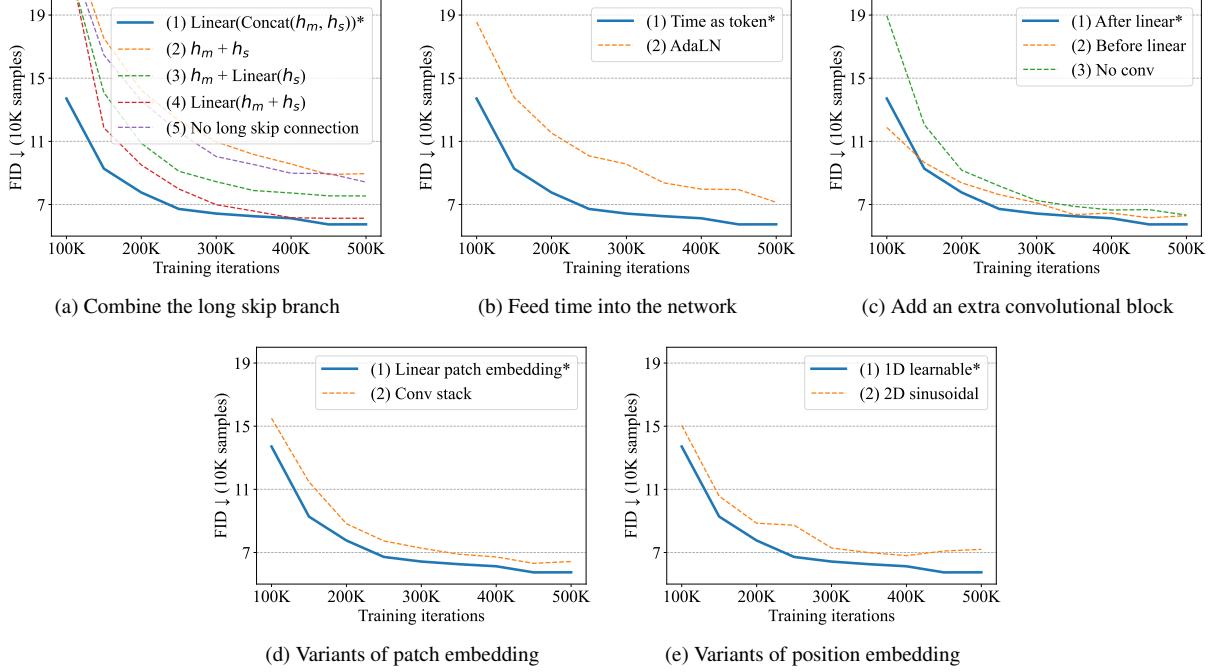


Figure 2. Ablate design choices. The one marked with * is the adopted choice of U-ViT illustrated in Figure 1. Since this ablation aims to determine implementation details, we evaluate FID on 10K generated samples (instead of 50K samples for efficiency).

provide shortcuts for the low-level features and therefore ease the training of the noise prediction network.

Additionally, U-ViT adds a 3×3 convolutional block before output. This is intended to prevent the potential artifacts in images produced by transformers [72]. The block improves the visual quality of the samples generated by U-ViT according to our experiments.

3.1. Implementation Details

Although U-ViT is conceptually simple, we carefully design its implementation. To this end, we perform a systematical empirical study on key elements in U-ViT. In particular, we ablate on CIFAR10 [34], evaluate the FID score [22] every 50K training iterations on 10K generated samples (instead of 50K samples for efficiency), and determine all implementation details that are shared across all experiments.

The way to combine the long skip branch. Let $\mathbf{h}_m, \mathbf{h}_s \in \mathbb{R}^{L \times D}$ be the embeddings from the main branch and the long skip branch respectively. We consider several ways to combine them before feeding them to the next transformer block: (1) concatenating them and then performing a linear projection as illustrated in Figure 1, i.e., $\text{Linear}(\text{Concat}(\mathbf{h}_m, \mathbf{h}_s))$; (2) directly adding them, i.e., $\mathbf{h}_m + \mathbf{h}_s$; (3) performing a linear projection to \mathbf{h}_s and then adding them, i.e., $\mathbf{h}_m + \text{Linear}(\mathbf{h}_s)$; (4) adding them and then performing a linear projection, i.e., $\text{Linear}(\mathbf{h}_m + \mathbf{h}_s)$.

(5) We also compare with the case where the long skip connection is dropped. As shown in Figure 2 (a), directly adding $\mathbf{h}_m, \mathbf{h}_s$ does not provide benefits. All other ways to combine the skip branch improve the performance compared to the case where no long skip connection is adopted, and the first way that applies concatenation and linear projection performs the best.

The way to feed the time into the network. We consider two ways to feed t into the network. (1) The first way is to treat it as a token as illustrated in Figure 1. (2) The second way is to incorporate the time after the layer normalization in the transformer block [19], which is similar to the adaptive group normalization [12] used in U-Net. The second way is referred to as adaptive layer normalization (AdaLN). Formally, $\text{AdaLN}(h, y) = y_s \text{LayerNorm}(h) + y_b$, where h is an embedding inside a transformer block, and y_s, y_b are obtained from a linear projection of the time embedding. As shown in Figure 2 (b), while simple, the first way that treats time as a token performs better than AdaLN.

The way to add an extra convolutional block after the transformer. We consider two ways to add an extra convolutional block after the transformer. (1) The first way is to add a 3×3 convolutional block after the linear projection that maps the token embeddings to image patches, as illustrated in Figure 1. (2) The second way is to add a 3×3 con-

volutional block before this linear projection, which needs to first rearrange the 1D sequence of token embeddings $\mathbf{h} \in \mathbb{R}^{L \times D}$ to a 2D feature of shape $H/P \times W/P \times D$, where P is the patch size. (3) We also compare with the case where we drop the extra convolutional block. As shown in Figure 2 (c), the first way that adds a 3×3 convolutional block after the linear projection performs slightly better than other two choices.

Variants of the patch embedding. We consider two variants of the patch embedding. (1) The original patch embedding adopts a linear projection that maps a patch to a token embedding, as illustrated in Figure 1. (2) Alternatively, [67] use a stack of 3×3 convolutional blocks followed by a 1×1 convolutional block to map an image to token embeddings. We compare the two design choices in Figure 2 (d), and we find that the original patch embedding performs better.

Variants of the position embedding. We consider two variants of the position embedding. (1) The first one is the 1-dimensional learnable position embedding proposed in the original ViT [15], which is the default setting in this paper. (2) The second one is the 2-dimensional sinusoidal position embedding, which is obtained by concatenating the sinusoidal embeddings [66] of i and j for a patch at position (i, j) . As shown in Figure 2 (e), the 1-dimensional learnable position embedding performs better. We also try not use any position embedding, and find the model fails to generate meaningful images, which implies the position information is critical in image generation.

4. Related Work

Transformers in diffusion models. A related work is GenViT [70]. GenViT employs a smaller ViT that does not employ long skip connections and the 3×3 convolutional block, and incorporates time before normalization layers for image diffusion models. Empirically, our U-ViT performs much better than GenViT (see Table 2) by carefully designing implementation details. Another related work is VQ-Diffusion [19] and its variants [55, 63]. VQ-Diffusion firstly obtains a sequence of discrete image tokens via a VQ-GAN [16], and then models these tokens using a discrete diffusion model [1, 56] with a transformer as its backbone. Time and condition are fed into the transformer through cross attention or adaptive layer normalization. In contrast, our U-ViT simply treats all inputs as tokens, and employs long skip connections between shallow and deep layers, which achieves a better FID (see Table 2 and Table 3). In addition to images, transformers in diffusion models are also employed to encode texts [44, 47, 49, 51], decode texts [7, 28, 36, 43] and generate CLIP embeddings [47].

U-Net in diffusion models. [59, 60] initially introduce CNN-based U-Net to model the gradient of log-likelihood function for continuous image data. After that, improvements on the CNN-based U-Net for (continuous) image diffusion models are made, including using group normalization [24], multi-head attention [45], improved residual block [12] and cross attention [49]. In contrast, our U-ViT is a ViT-based backbone with conceptually simple design, and meanwhile has a comparable performance if not superior to a CNN-based U-Net of a similar size (see Table 2 and Table 3).

Improvements of diffusion models. In addition to the backbone, there are also improvements on other aspects, such as fast sampling [3, 41, 52, 57, 68], improved training methodology [2, 14, 29, 31, 32, 40, 45, 58, 65] and controllable generation [4, 10, 12, 21, 26, 42, 54, 74].

5. Experiments

We evaluate the proposed U-ViT in unconditional and class-conditional image generation (Section 5.2), as well as text-to-image generation (Section 5.3). We also study the effect of depth, width and patch size of U-ViT (Section 5.4). Before presenting these results, we first list the experimental setup below (we also provide a summary table in Appendix A).

5.1. Experimental Setup

Datasets. For unconditional learning, we consider CIFAR10 [34], which contain 50K training images, and CelebA 64×64 [38], which contain 162,770 training images of human faces. For class-conditional learning, we consider ImageNet [11] at 64×64 , 256×256 and 512×512 resolutions, which contains 1,281,167 training images from 1K different classes. For text-to-image learning, we consider MS-COCO [37] at 256×256 resolution, which contains 82,783 training images and 40,504 validation images. Each image is annotated with 5 captions.

High resolution image generation. We follow latent diffusion models (LDM) [49] for high resolution image generation. Specifically, for images at 256×256 and 512×512 resolutions, we firstly convert them to latent representations at 32×32 and 64×64 resolutions respectively, using a pretrained image autoencoder provided by Stable Diffusion² [49]. Then we model these latent representations using the proposed U-ViT.

Text-to-image learning. On MS-COCO, we convert discrete texts to a sequence of embeddings using a CLIP text

²<https://github.com/CompVis/stable-diffusion>

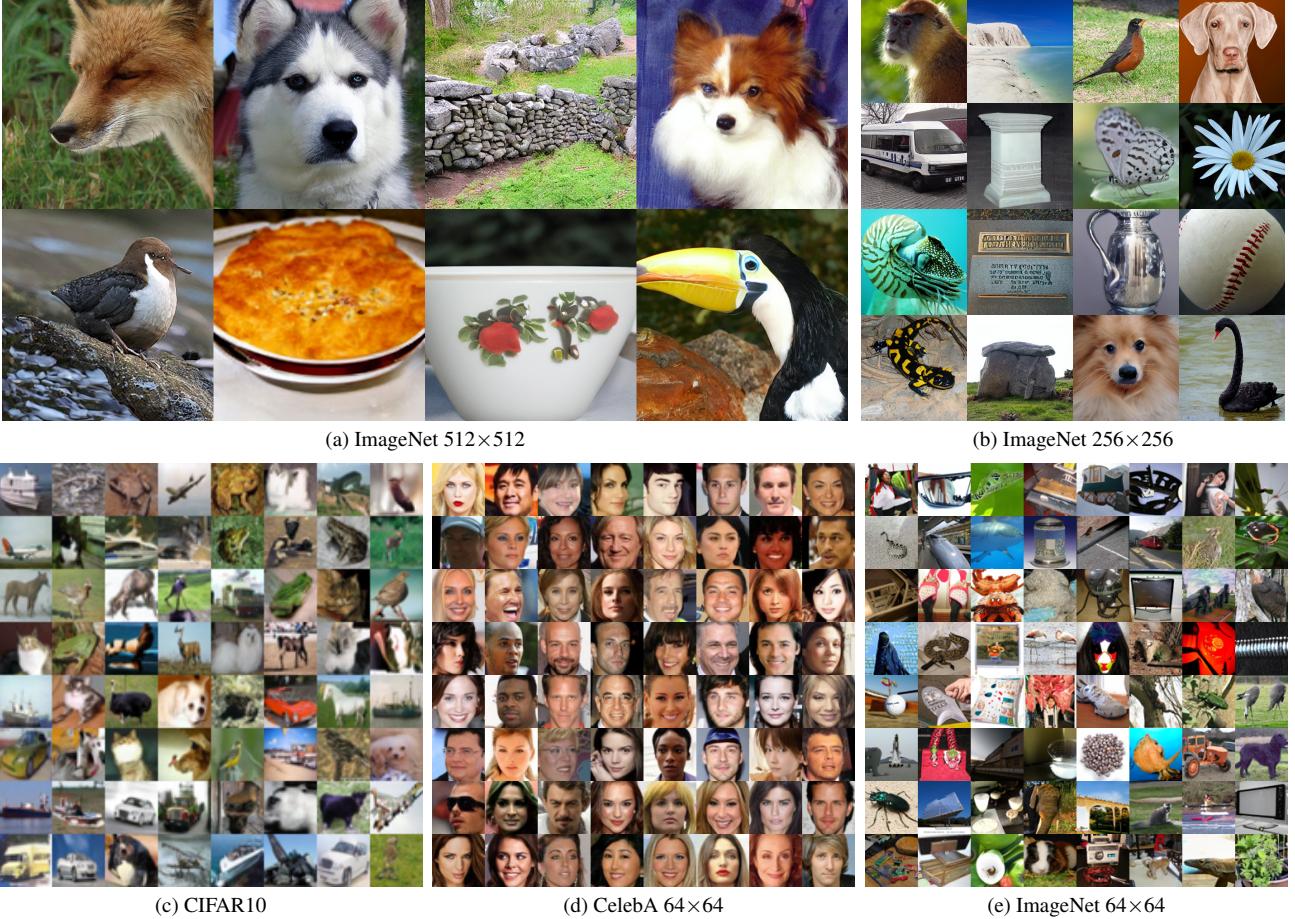


Figure 3. Image generation results of U-ViT: selected samples on ImageNet 512×512 and ImageNet 256×256, and random samples on CIFAR10, CelebA 64×64, and ImageNet 64×64.

encoder following Stable Diffusion. Then these embeddings are fed into U-ViT as a sequence of tokens.

U-ViT configurations. We identify four configurations of U-ViT with different number of parameters in Table 1.

Model	#Layers	Hidden size D	MLP size	#Heads	#Params
U-ViT-Small	13	512	2048	8	44M
U-ViT-Small-Deep	17	512	2048	8	58M
U-ViT-Mid	17	768	3072	12	131M
U-ViT-Large	21	1024	4096	16	287M

Table 1. Configurations of U-ViT.

By default, we adopt U-ViT-Small on CIFAR10, CelebA 64×64 and MS-COCO, adopt U-ViT-Mid on ImageNet 64×64, and adopt U-ViT-Large on ImageNet 256×256 and ImageNet 512×512.

Training. We use the AdamW optimizer [39] for all datasets. We try learning rates between 1e-4 and 5e-4,

and find that a learning rate of 2e-4 performs well for all datasets. On ImageNet 64×64, a learning rate of 3e-4 could further improve the performance. We try weight decay between 0.01 and 0.05, and find that a weight decay of 0.03 performs well for all datasets. We try the running coefficients β_1, β_2 of AdamW among {0.9, 0.99, 0.999}, and find that $(\beta_1, \beta_2) = (0.99, 0.99)$ performs well for all datasets. On CIFAR10, $\beta_2 = 0.999$ could further improve the performance. On MS-COCO, $(\beta_1, \beta_2) = (0.9, 0.9)$ could further improve the performance. We train 500K iterations on CIFAR10 and CelebA 64×64 with a batch size of 128. We train 300K iterations on ImageNet 64×64 and ImageNet 256×256, and 500K iterations on ImageNet 512×512, with a batch size of 1024. We train 1M iterations on MS-COCO with a batch size of 256. On ImageNet 256×256, ImageNet 512×512 and MS-COCO, we adopt classifier-free guidance [26] following [49].

We train with mixed precision for efficiency. The training on CIFAR10 or CelebA with U-ViT-Small takes around 24 hours with 4 GeForce RTX 2080 Ti. The training on

Model on CIFAR10		FID ↓
GAN		
StyleGAN2-ADA [30]		2.92
Diff. based on U-Net	#Params	
DDPM [24]	36M	3.17
IDDPM [45]	53M	2.90
DDPM++ cont. [61]	62M	2.55
EDM [†] [29]	56M	1.97
Diff. based on ViT	#Params	
GenViT [70]	11M	20.20
U-ViT-Small (ours)	44M	3.11
Model on CelebA 64×64		FID ↓
Diff. based on U-Net	#Params	
DDIM [57]	79M	3.26
Soft Truncation [†] [31]	62M	1.90
Diff. model based on ViT	#Params	
U-ViT-Small (ours)	44M	2.87
Model on ImageNet 64×64		FID ↓
GAN		
BigGAN-deep [5]		4.06
StyleGAN-XL [53]		1.51
Diff. based on U-Net	#Params	
IDDPM (small) [45]	100M	6.92
IDDPM (large) [45]	270M	2.92
CDM [25]	Unknown	1.48
ADM [12]	296M	2.07
EDM [†] [29]	296M	1.36
Diff. based on ViT	#Params	
U-ViT-Mid (ours)	131M	5.85
U-ViT-Large (ours)	287M	4.26
Model on ImageNet 256×256		FID ↓
GAN		
BigGAN-deep [5]		6.95
StyleGAN-XL [53]		2.30
Discrete diff. based on transformer		
VQ-Diffusion [19]		11.89
VQ-Diffusion (acc0.05) [19]		5.32
Diff. based on U-Net	#Params	
IDDPM [45]	270M + 280M (SR)	12.26
CDM [25]	Unknown	4.88
ADM [12]	554M	10.94
ADM-U [12]	296M + 312M (SR)	7.49
ADM-G [12]	554M + 54M (Cls)	4.59
ADM-G, ADM-U [12]	296M + 65M (Cls) + 312M (SR)	3.94
LDM [‡] [49]	400M + 55M (AE)	3.60
Diff. based on ViT	#Params	
U-ViT-Large [‡] (ours)	287M + 84M (AE)	3.40
Model on ImageNet 512×512		FID ↓
GAN		
BigGAN-deep [5]		8.43
StyleGAN-XL [53]		2.41
Diff. based on U-Net	#Params	
ADM [12]	559M	23.24
ADM-U [12]	422M + 309M (SR)	9.96
ADM-G [12]	559M + 54M (Cls)	7.72
ADM-G, ADM-U [12]	422M + 43M (Cls) + 309M (SR)	3.85
Diff. based on ViT	#Params	
U-ViT-Large [‡] (ours)	287M + 84M (AE)	4.67

Table 2. FID results of unconditional image generation on CIFAR10 and CelebA 64×64, and class-conditional image generation on ImageNet 64×64, 256×256 and 512×512. We mark the best results *among diffusion models* in **bold**. We also include GAN results (gray) for completeness. Methods marked with [†] use advanced training techniques for diffusion models. Methods marked with [‡] model latent representations of images [49] and use classifier free guidance [26]. We also present the number of parameters of auxiliary components for diffusion models, where SR represents a super-resolution module, AE represents an image autoencoder, and Cls represents a classifier.

MS-COCO with U-ViT-Small takes around 60 hours with 4 A100. The training on ImageNet 64×64 with U-ViT-Mid takes around 59 hours with 8 A100. The training on ImageNet 64×64 and ImageNet 256×256 with U-ViT-Large takes around 100 hours with 8 A100. The training on ImageNet 512×512 with U-ViT-Large takes around 166 hours with 8 A100. These training time of U-ViT is comparable to U-Net.

Sampling. On CIFAR10 and CelebA 64×64, we apply Euler-Maruyama SDE sampler [61] with 1K sampling steps to generate samples from the diffusion model. On other

datasets, we apply DPM-Solver [41] with 50 sampling steps. With 1 A100, generating 500 samples with DPM-Solver takes around 19 seconds, 34 seconds, 59 seconds, with U-ViT-Small, U-ViT-Mid, U-ViT-Large respectively. The time would double if classifier-free guidance is used.

5.2. Unconditional and Class-Conditional Image Generation

We compare U-ViT with prior diffusion models based on U-Net. We also compare with GenViT [70], a smaller ViT which does not employ long skip connections and the 3×3 convolutional block, and incorporates time before normal-

Model	FID	Type	Training datasets	#Params
Generative model trained on external large dataset (zero-shot)				
DALL-E [48]	~ 28	Autoregressive	DALL-E dataset (250M)	12B
CogView [13]	27.1	Autoregressive	Internal dataset (30M)	4B
LAFITE [76]	26.94	GAN	CC3M (3M)	75M + 151M (TE)
GLIDE [44]	12.24	Diffusion	DALL-E dataset (250M)	3.5B + 1.5B (SR)
Make-A-Scene [18]	11.84	Autoregressive	Union datasets (without MS-COCO) (35M)	4B
DALL-E 2 [47]	10.39	Diffusion	DALL-E dataset (250M)	4.5B + 700M (SR)
Imagen [51]	7.27	Diffusion	Internal dataset (460M) + LAION (400M)	2B + 4.6B (TE) + 600M (SR)
Parti [71]	7.23	Autoregressive	LAION (400M) + FIT (400M) + JFT (4B)	20B + 630M (AE)
Re-Imagen [8]	6.88	Diffusion	KNN-ImageText (50M)	2.5B + 750M (SR)
Generative model trained on external large dataset with access to MS-COCO				
VQ-Diffusion [†] [19]	13.86	Discrete diffusion	Conceptual Caption Subset (7M)	370M
Make-A-Scene [18]	7.55	Autoregressive	Union datasets (with MS-COCO) (35M)	4B
Re-Imagen [‡] [8]	5.25	Diffusion	KNN-ImageText (50M)	2.5B + 750M (SR)
Parti [†] [71]	3.22	Autoregressive	LAION (400M) + FIT (400M) + JFT (4B)	20B + 630M (AE)
Generative model trained on MS-COCO				
AttnGAN [69]	35.49	GAN	MS-COCO (83K)	230M
DM-GAN [77]	32.64	GAN	MS-COCO (83K)	46M
VQ-Diffusion [19]	19.75	Discrete diffusion	MS-COCO (83K)	370M
DF-GAN [64]	19.32	GAN	MS-COCO (83K)	19M
XMC-GAN [73]	9.33	GAN	MS-COCO (83K)	166M
Friro [17]	8.97	Diffusion	MS-COCO (83K)	512M + 186M (TE) + 68M (AE)
LAFITE [76]	8.12	GAN	MS-COCO (83K)	75M + 151M (TE)
U-Net*	7.32	Latent diffusion	MS-COCO (83K)	53M + 123M (TE) + 84M (AE)
U-ViT-Small (ours)	5.95	Latent diffusion	MS-COCO (83K)	45M + 123M (TE) + 84M (AE)
U-ViT-Small-Deep (ours)	5.48	Latent diffusion	MS-COCO (83K)	58M + 123M (TE) + 84M (AE)

Table 3. FID results of different models on MS-COCO validation (256×256). U-ViT-Small-Deep increases the number of layers from 13 to 17 compared to U-ViT-Small. We also present the number of parameters of auxiliary components for a model when it is reported in the corresponding paper, where SR represents a super-resolution module, AE represents an image autoencoder, and TE represents a text encoder. Methods marked with [†] finetune on MS-COCO. Methods marked with [‡] use MS-COCO as a knowledge base for retrieval. The U-Net* is trained by ourselves to serve as a direct baseline of U-ViT, where we leave other parts unchanged except for the backbone.

ization layers. Consistent with previous literature, we report the FID score [22] on 50K generated samples to measure the image quality.

As shown in Table 2, U-ViT is comparable to U-Net on unconditional CIFAR10 and CelebA 64×64 , and meanwhile performs much better than GenViT.

On class-conditional ImageNet 64×64 , we initially try the U-ViT-Mid configuration with 131M parameters. As shown in Table 2, it gets a FID of 5.85, which is better than 6.92 of IDDPM that employs a U-Net with 100M parameters. To further improve the performance, we employ the U-ViT-Large configuration with 287M parameters, and the FID improves from 5.85 to 4.26.

Meanwhile, we find that our U-ViT performs especially well in the latent space [49], where images are firstly converted to their latent representations before applying diffusion models. On class-conditional ImageNet 256×256 , our U-ViT even outperforms the original latent diffusion model (LDM), which employs a U-Net of 400M parameters to model these latent representations. Note that our U-ViT also outperforms VQ-Diffusion, which is a discrete diffusion model [1] that employs a transformer as its back-

bone. On class-conditional ImageNet 256×256 and ImageNet 512×512 , our U-ViT also outperforms ADM-G that directly models the pixels of images. In Figure 3, we provide selected samples on ImageNet 256×256 and ImageNet 512×512 , and random samples on other datasets, which have good quality and clear semantics. We provide more generated samples including class-conditional and random ones in Appendix C.

5.3. Text-to-Image Generation on MS-COCO

We evaluate U-ViT for text-to-image generation on the standard benchmark dataset MS-COCO. We train our U-ViT in the latent space of images [49] as detailed in Section 5.1. We also train another latent diffusion model that employs a U-Net of comparable model size to U-ViT-Small, and leave other parts unchanged. Its hyperparameters and training details are provided in Appendix B. We report the FID score [22] to measure the image quality. Consistent with previous literature, we randomly draw 30K prompts from the MS-COCO validation set, and generate samples on these prompts to compute FID.

As shown in Table 3, our U-ViT-Small already achieves a



Figure 4. Text-to-image generation on MS-COCO. All the other settings except the backbone are the same. U-Net and U-ViT generate samples using the same random seed for a fair comparison. The random seed is unselected.

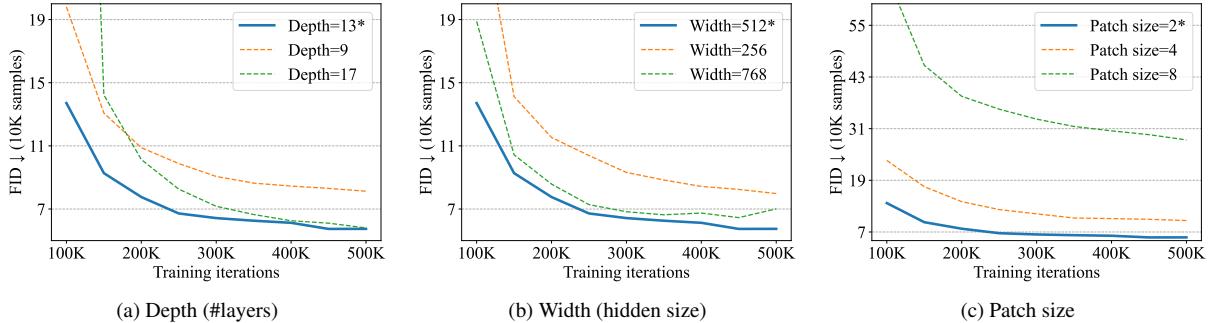


Figure 5. Effect of depth, width and patch size. The one marked with * corresponds to the setting of U-ViT-Small. We evaluate FID on 10K generated samples (instead of 50K samples for efficiency).

state-of-the-art FID among methods without accessing large external datasets during the training of generative models. By further increasing the number of layers from 13 to 17, our U-ViT-Small-Deep can even achieve a better FID of 5.48. Figure 4 shows generated samples of U-Net and U-ViT using the same random seed for a fair comparison. We find U-ViT generates more high quality samples, and meanwhile the semantics matches the text better. For example, given the text ‘‘a baseball player swinging a bat at a ball’’, U-Net generates neither the bat nor the ball. In contrast, our U-ViT-Small generates the ball with even a smaller number of parameters, and our U-ViT-Small-Deep further generates the bat. We hypothesize this is because texts and images interact at every layer in our U-ViT, which is more frequent than U-Net that only interact at cross attention layer. We provide more samples in Appendix C.

5.4. Effect of Depth, Width and Patch Size

We study the effect of the depth (i.e., the number of layers), width (i.e., the hidden size D) and patch size of U-ViT. We evaluate on CIFAR10 with U-ViT-Small as the default setting. As shown in Figure 5, the performance improves as the depth (i.e., the number of layers) increases from 9 to 13. Nevertheless, U-ViT does not gain from a larger depth like 17 in 50K training iterations. Similarly, increasing the width (i.e., the hidden size) from 256 to 512 improves the performance, and further increase to 768 brings no gain. On the other hand, a smaller patch size consistently improves the performance.

6. Conclusion

This work presents U-ViT, a simple and general ViT-based architecture for image generation with diffusion mod-

els. U-ViT treats all inputs including the time, condition and noisy image patches as tokens and employs long skip connections between shallow and deep layers. We evaluate U-ViT in tasks including unconditional and class-conditional image generation, as well as text-to-image generation, and experiments demonstrate U-ViT is comparable if not superior to a CNN-based U-Net of a similar size. These results suggest that, for diffusion-based image modeling, the long skip connection is crucial while the down-sampling and up-sampling operators in CNN-based U-Net are not always necessary. We believe that U-ViT can provide insights for future research on backbones in diffusion models and benefit generative modeling on large scale cross-modality datasets.

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A. Summary of Experimental Setup

We present the summary of experimental setup in Table 4.

Dataset	CIFAR10	CelebA 64×64	ImageNet 64×64	ImageNet 256×256	ImageNet 512×512	MS-COCO
Latent space	×	×	×	✓	✓	✓
Latent shape	-	-	-	32×32×4	64×64×4	32×32×4
Patch size	2	4	4	2	4	2
#Layers	13	13	17 / 21	21	21	13 / 17
Hidden size	512	512	768 / 1024	1024	1024	512
MLP size	2048	2048	3072 / 4096	4096	4096	2048
#Heads	8	8	12 / 16	16	16	8
#Params of U-ViT	44M	44M	131M / 287M	287M	287M	45M / 58M
Batch size	128	128	1024	1024	1024	256
Training iterations	500K	500K	300K	300K	500K	1M
Warm-up steps	2.5K	5K	5K	5K	5K	5K
Optimizer	AdamW	AdamW	AdamW	AdamW	AdamW	AdamW
Learning rate	2e-4	2e-4	3e-4	2e-4	2e-4	2e-4
Weight decay	0.03	0.03	0.03	0.03	0.03	0.03
Betas	(0.99, 0.999)	(0.99, 0.99)	(0.99, 0.99)	(0.99, 0.99)	(0.99, 0.99)	(0.9, 0.9)
Sampler	EM	EM	DPM-Solver	DPM-Solver	DPM-Solver	DPM-Solver
Sampling steps	1K	1K	50	50	50	50
CFG	×	×	×	✓	✓	✓
p_{uncond}	-	-	-	0.15	0.15	0.1
Guidance strength	-	-	-	0.4	0.7	1

Table 4. The experimental settings. EM represents the Euler-Maruyama sampler. p_{uncond} represents the unconditional training probability in classifier free guidance (CFG).

B. Details of the U-Net Baseline on MS-COCO

We employ the U-Net with cross attention provided by LDM [49] for the baseline. The U-Net is performed on the 32×32 resolution latent representation, and down-samples it to 16×16, 8×8 and 4×4 resolution. The number of channels is 128 at 32×32 resolution, and 256 at other resolutions. Each resolution has 2 residual blocks. The U-Net performs self attention and cross attention at 16×16 and 8×8 resolution. Such a configuration leads to a total of 53M parameters, which is comparable to 45M of U-ViT-Small for a fair comparison. We use the AdamW optimizer with weight decay set to 0.01 and running coefficients β_1 , β_2 set to (0.9, 0.999), which are the setting used across LDM [49]. We tune the learning rate of U-Net and find 2e-4 performs the best. The training iterations and the batch size of U-Net are the same to U-ViT for a fair comparison.

C. Additional Samples



Figure 6. Generated samples on ImageNet 512×512, conditioned on goldfish (1), arctic fox (279), monarch butterfly (323), african elephant (386), flamingo (130), tennis ball (852).

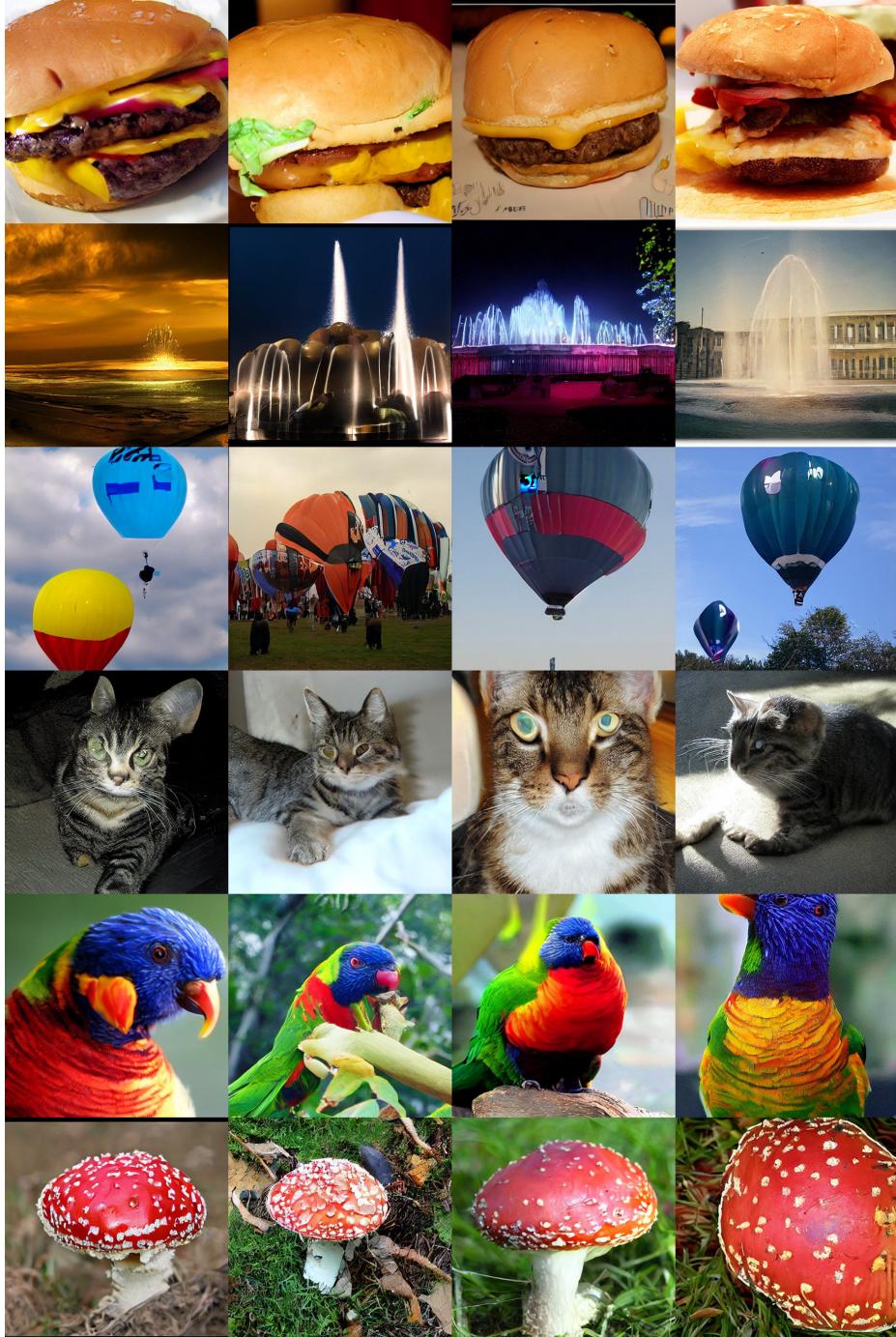


Figure 7. Generated samples on ImageNet 512×512, conditioned on cheeseburger (933), fountain (562), balloon (417), tabby cat (281), lorikeet (90), agaric (992).

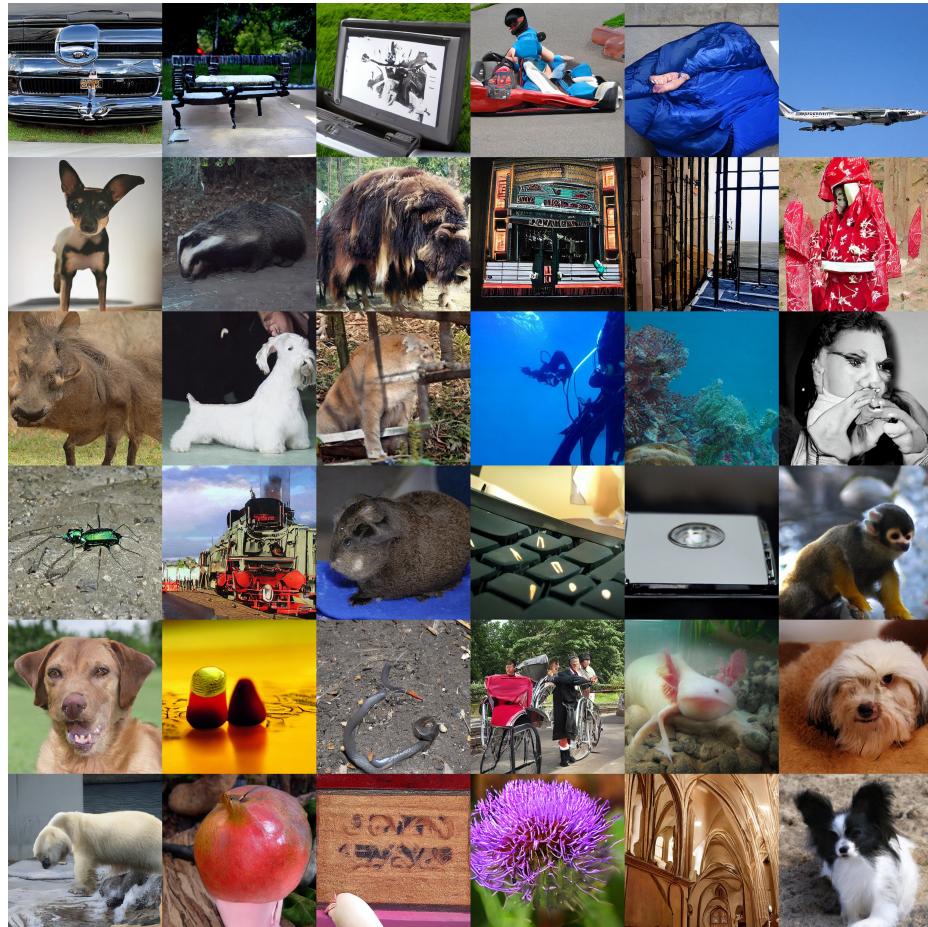


Figure 8. Random samples on ImageNet 512×512.

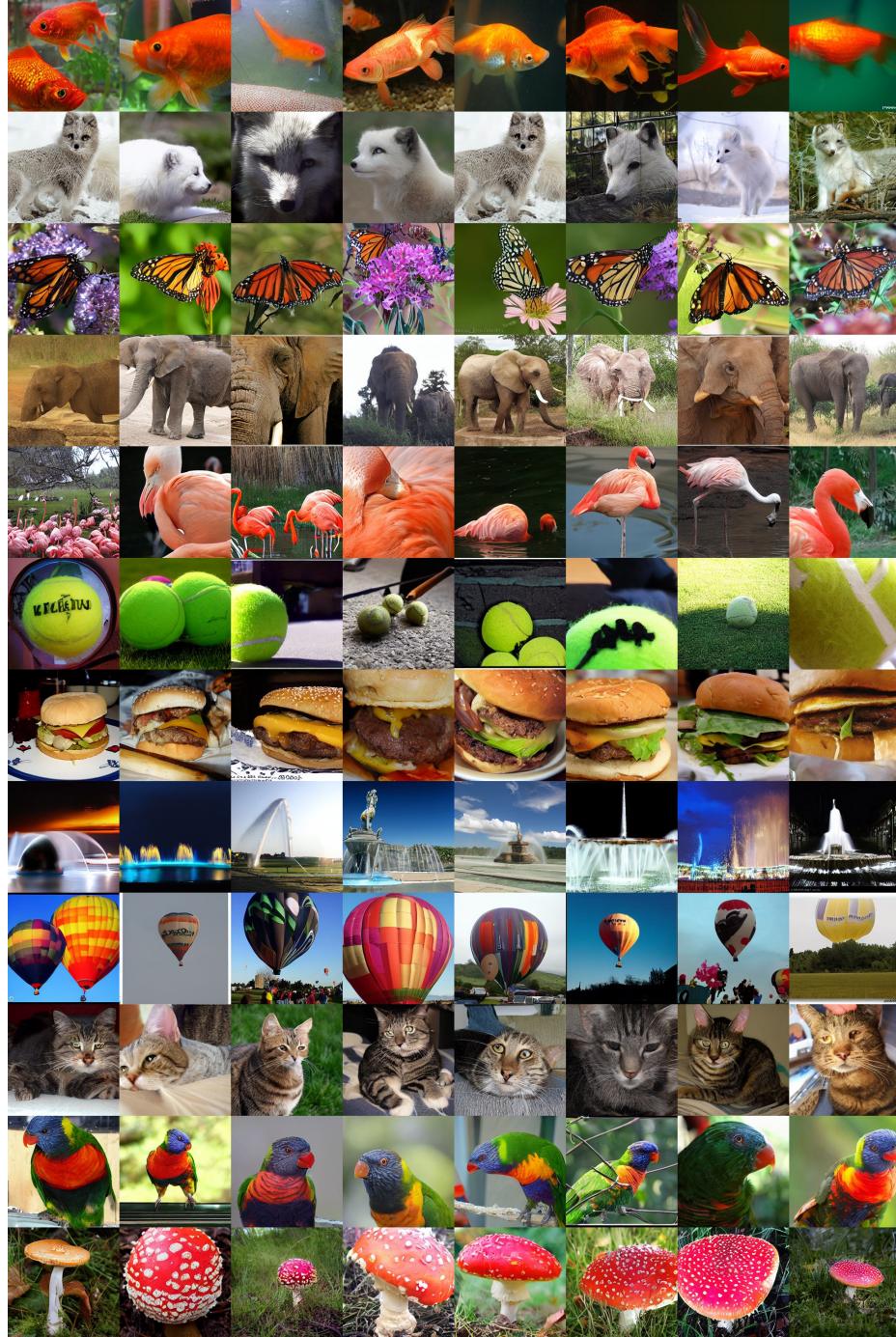


Figure 9. Generated samples on ImageNet 256×256, conditioned on goldfish (1), arctic fox (279), monarch butterfly (323), african elephant (386), flamingo (130), tennis ball (852), cheeseburger (933), fountain (562), balloon (417), tabby cat (281), lorikeet (90), agaric (992).

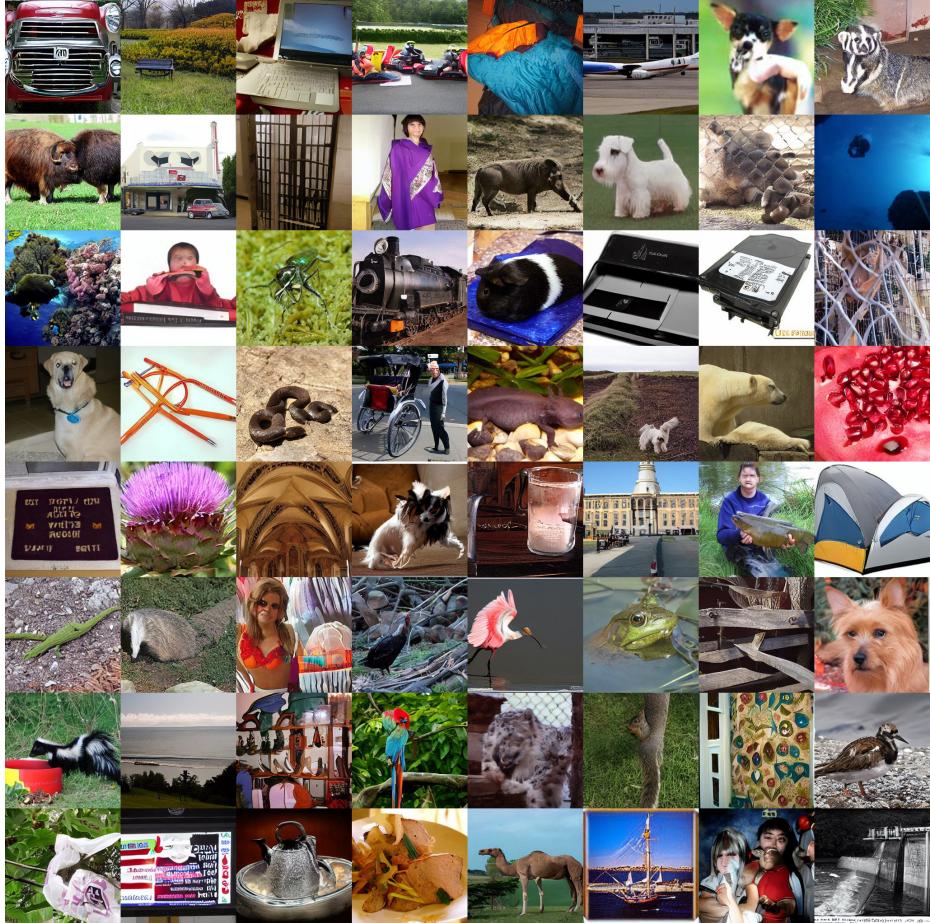


Figure 10. Random samples on ImageNet 256×256.

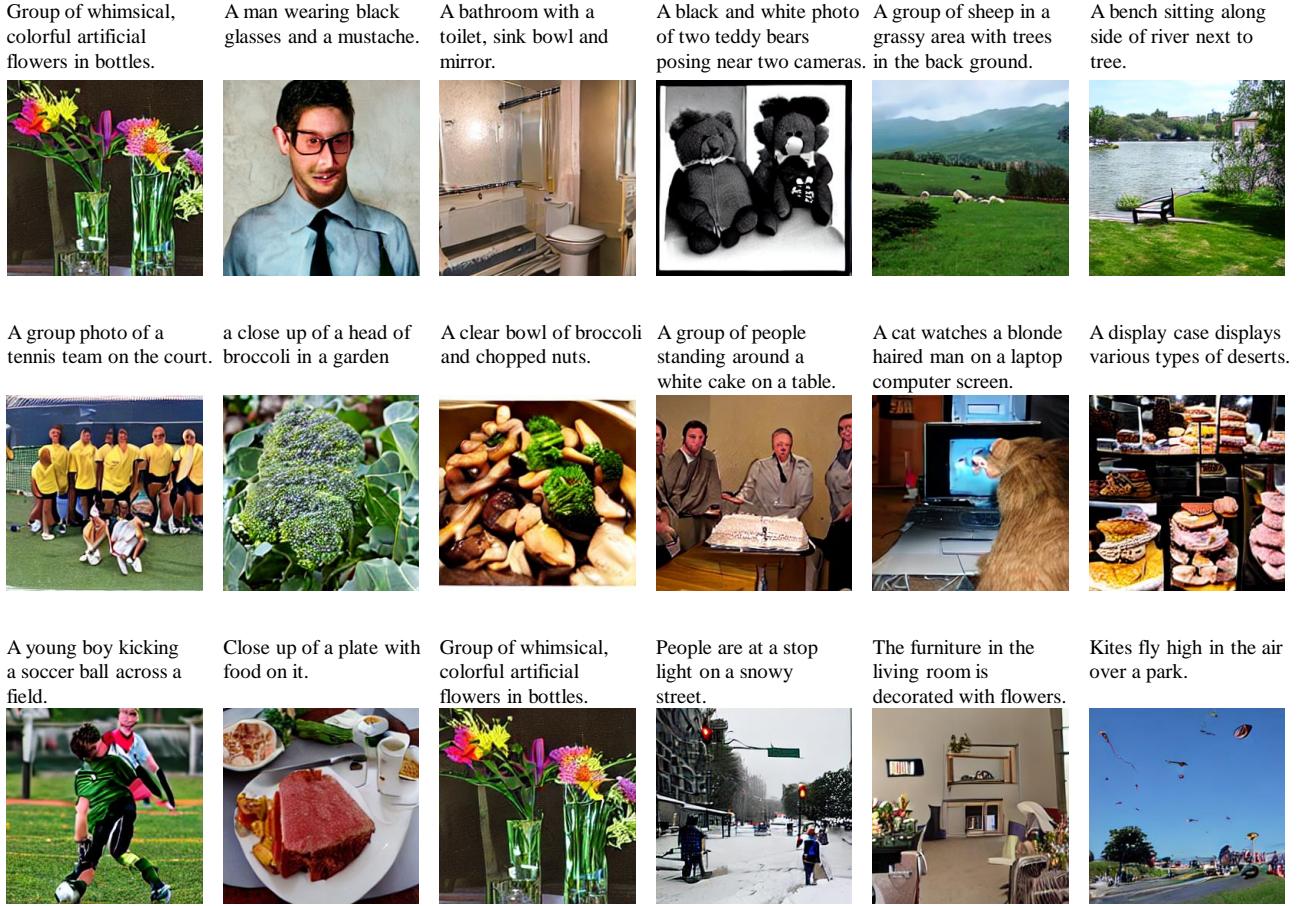


Figure 11. Random samples on MS-COCO. Prompts are randomly drawn from the validation set.