DiVAE: Photorealistic Images Synthesis with Denoising Diffusion Decoder

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Abstract

Recently most successful image synthesis models are multi stage process to combine the advantages of different methods, which always includes a VAE-like model for faithfully reconstructing embedding to image and a prior model to generate image embedding. At the same time, diffusion models have shown be capacity to generate high-quality synthetic images. Our work proposes a VQ-VAE architecture model with a diffusion decoder (DiVAE) to work as the reconstructing component in image synthesis. We explore how to input image embedding into diffusion model for excellent performance and find that simple modification on diffusion’s UNet can achieve it. Training on ImageNet 256x256, Our model achieves state-of-the-art results and generates more photorealistic images specifically. In addition, we apply the DiVAE with an Auto-regressive generator on conditional synthesis tasks to perform more human-feeling and detailed samples.

1 Introduction

Recently, generative model of images, audio and videos have achieved rapid development and been capable of yielding impressive samples. With promising future in application, the research of visual synthesis (images and videos) is becoming more and more popular.

| Reconstruction | Text-to-Image |
|----------------|---------------|
| Input | DiVAE(f=16) FID: 4.07 | VQGAN(f=16) FID: 4.98 |

![Figure 1](image-url): DiVAE generates more photorealistic and detailed images.

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Visual Synthesis Several approaches have seen success in learning complex distributions of real vision, auto-regressive (AR) models\cite{2, 4, 12, 36, 10, 44, 26}, generative adversarial network (GANs)\cite{13, 48, 46, 40, 3}, variational autoencoders (VAEs)\cite{20, 32, 29, 28, 33, 1}, and flow-based models\cite{11, 6, 16, 21} have shown convincing generative ability. Based on VAE, VQVAE\cite{42} and VQGAN\cite{12} encode the image into a discrete latent space to learn the density of the hidden variables, and greatly improves the performance. In the past few years, GAN based model have shown their ability on high fidelity image generation and hold the state-of-the-art on many image generation tasks. However, GAN is often difficult to train and defective in capturing of diversity. Comparing with GAN, Auto-regressive (AR) generate model have advantages in density modeling and stable training. Based on the AR model, recent work like NUWA\cite{45}, DALL-E\cite{31} and DALL-E2\cite{30} have achieved impressive results on text-to-image, text-to-video generation, etc.

Diffusion models are a class of likelihood-based models and have achieved state-of-the-art results in density estimation as well as in sample quality\cite{18}. The diffusion probabilistic models was introduced firstly in 2015\cite{37}, as a class of generative models which learn to match a data distribution by reversing a multi-step, gradual noising process. Denoising diffusion probabilistic models (DDPM)\cite{17} shows that diffusion models can produce high-quality images and the promising prospect in visual synthesis. After that, Improved DDPM\cite{29} modified the learning of variance and optimization objectives to achieve better log-likelihoods. Denoising diffusion implicit models (DDIM)\cite{38} developed a approach to fast sampling. Guided Diffusion\cite{9} find that samples from a class conditional diffusion model with a independent classifier guidance can be significantly improved. Classifier-Free Diffusion\cite{19} propose classifier-free guidance that does not need to train a separate classifier model.

One stage and Two stage Image Synthesis Current visual generation work can be generalization into one-stage direct generation and two-stage generation\cite{7, 34, 47}. Visual auto-regressive models, such as PixelCNN\cite{41}, PixelRNN\cite{43}, and Image Transformer, diffusion model such as DDPM\cite{17} and Guided diffusion\cite{9}, performed visual synthesis in a “pixel-by-pixel” manner, optimization and inference often is with high computational cost. To mitigate the shortcomings of individual approaches, a lot of research combine the strengths of different methods. As Figure 2 shows, DALL-E\cite{31}, NUWA\cite{45}, VQ-Diffusion\cite{14} and Latent Diffusion\cite{33} first learn an encoder-decoder architecture, like VQ-GAN\cite{12} and VQ-VAE\cite{42}, which can compress image to latent representation and faithfully reconstruct it back to image, in second stage, AR based model: DALL-E\cite{31} and NUWA\cite{45} sequentially predict image token depends on the condition, while diffusion based model, VQ-Diffusion\cite{14} and Latent Diffusion\cite{33} predict it with a gradual denoising process.

Our work aims to propose a generality model to generate more detailed and photorealistic images to improve the reconstructing stage of multi stage image synthesis. The potential improvements of image embedding generating model is expecting for future works.

- We propose DiVAE, a vae generation framework with a diffusion decoder, which can generate more photorealistic images and achieved state-of-the-art results on image reconstruction from embeddings.
- We perform DiVAE with an Auto-regressive generator on Text-to-Image (T2I) synthesis tasks and generate high-quality and more detailed images.

Figure 2: Overall framework of SOTA two stage image synthesis models, comparing the approach with DiVAE.
2 Background

2.1 Diffusion Models’ Details

Diffusion generative models were first introduced by in 2015 [37] and improved in denoising diffusion probabilistic models (DDPM) [17] and Improved Denoising Diffusion Probabilistic Models [29], achieved state-of-the-art results on image generation. It has recently been shown that this class of models can produce high-quality images and have been researched in a series of recent visual [50] [28] [33] and audio [5] [22] synthesis tasks.

In diffusion model, the diffusion process (forward process) starts from data distribution $x_0 \sim q(x_0)$ and a Markovian noising process $q$ which gradually adds noise to the data to produce noised samples $x_1$ through $x_T$, each step of the noising process adds Gaussian noise according to variance schedule given by $\beta_t$, until $x_T$ is nearly an isotropic Gaussian distribution. We define $\alpha_t = 1 - \beta_t$ and $\hat{\alpha}_t = \prod_{s=0}^{t} \alpha_s$, the diffusion process can be expressed as:

$$q(x_t|x_{t-1}) \sim \mathcal{N}(x_t; \sqrt{1 - \beta_t} x_{t-1}; \beta_t I)$$

(1)

$$q(x_t|x_0) \sim \mathcal{N}(x_t; \sqrt{\hat{\alpha}_t} x_0; (1 - \hat{\alpha}_t) I) = \sqrt{\hat{\alpha}_t} x_0 + \sigma \sqrt{1 - \hat{\alpha}_t}, \sigma \sim \mathcal{N}(0, I)$$

(2)

$$x_t = \sqrt{\hat{\alpha}_t} x_0 + \sigma \sqrt{1 - \hat{\alpha}_t}, \sigma \sim \mathcal{N}(0, I)$$

(3)

$1 - \alpha_t$ is variance of the noise for an arbitrary timestep, and we could equivalently use this to define the noise schedule instead of $\beta_t$. With Bayes theorem, the posterior $q(x_{t-1}|x_t, x_0)$ in terms of $\beta_t$ and $\hat{\mu}(x_t, x_0)$ can be expressed as:

$$q(x_{t-1}|x_t, x_0) \sim \mathcal{N}(x_{t-1}; \hat{\mu}(x_t, x_0); \hat{\beta}_t I)$$

(4)

$$\hat{\beta}_t = \frac{1 - \hat{\alpha}_{t-1}}{1 - \hat{\alpha}_t} \beta_t$$

(5)

$$\mu(x_t, x_0) = \frac{\sqrt{\hat{\alpha}_{t-1}} \beta_t}{1 - \hat{\alpha}_t} x_0 + \frac{\sqrt{\alpha_t}(1 - \hat{\alpha}_{t-1})}{1 - \alpha_t} x_t$$

(6)

It can be seen from the above, when the exact reverse distribution $q(x_{t-1}|x_t)$ is known, $x_T$ can be sampled from $\mathcal{N}(0, I)$, and then we can get a sample from $q(x_0)$ from running the reverse process. In particular, sampling starts with noise $X_T$ and produces gradually less-noisy samples $x_{T-1}, x_{T-2}, ...$ until reaching a final sample $X_0$. However, since $q(x_{t-1}|x_t)$ depends on the entire data distribution, diffusion model approximate it using a neural network as follows $p_0(x_{t-1}|x_t)$. A diffusion model learns to produce a slightly more denoised $X_{t-1}$ from $X_t$.

$$p_0(x_{t-1}|x_t) \sim \mathcal{N}(x_{t-1}; \mu(x_t, t), \sum(x_t, t))$$

(7)

The most obvious option is to predict $\mu_0(x_t, t)$ directly with a neural network. Alternatively, the network could predict $X_0$, and this output could be used in Equation 5 to produce $\mu_0(x_t, t)$. DDPM found that a different objective produces better samples in practice. In particular, they do not directly parameterize $\mu_0(x_t, t)$ as a neural network, but instead train a model $\theta(x_t, t)$ to predict.

$$\mu(x_t, x_0) = \frac{1}{\sqrt{\alpha_t}} (x_t - \frac{1 - \alpha_t}{\sqrt{1 - \alpha_t}} \epsilon_t(x_t, x_0))$$

(8)

In obvious works, $\sum_{\theta}(x_t, t)$ often is constraints not learned, DDPM finds that its reasonable range is very small, and it would be hard for a neural network to predict $\sum(x_t, t)$ directly. Improved Denoising Diffusion Probabilistic Models proposes to parameterize the variance as an interpolation between
In this work, model outputs a vector $v$ containing one component per dimension, and we turn this output into variances as follows:

$$\sum_{\theta} (x_i, t) = \exp(v \log \beta_t + (1 - v) \log \hat{\beta}_t)$$

(9)

### 2.2 VQ-VAE Architectures Models

Auto-regressive transformer architectures have shown great promise in image synthesis due to their outstanding expressivity. Since the computation cost is quadratic to the sequence length, it is computationally prohibitive to directly model raw pixels. To reduce the description length of compositions, recent works propose to represent an image by discrete image tokens with reduced sequence length. Hereafter a transformer generator can be effectively trained upon this reduced context length or image tokens. With an encoder-decoder architectures and a codebook, the image can be compressed to latent representation via the CNN encoder and then faithfully reconstructed via the CNN decoder.

Vector quantized variational autoencoder (VQ-VAE)[42] consists of an encoder $E$, a decoder $G$ and a codebook $Z = z_{kk} = 1^K \in R^K$ containing a finite number of embedding vectors, where $K$ is the size of the codebook and $d$ is the dimension of codes. Given an image $x \in R^{HW3}$, VQ-VAE obtain a spatial collection of image tokens $z_q$ with the encoder $z = E(x) = R^{hwd}$ and a subsequent spatial-wise quantizer $Q()$ which maps each spatial feature $z_{ij}$ into its closest codebook entry $z_k$:

$$z_q = Q(z) = (\arg \min_{z_k \in Z} ||\hat{z}_{ij} - z_k||) \in R^{hwz}$$

(10)

The reconstructing is performed by a CNN decoder, and reconstruction $\hat{x} = x$ is

$$\hat{x} = G(z_q) = G(q(E(x)))$$

(11)

Backpropagation through the non-differentiable quantization operation is achieved by a straight-through gradient estimator (STE) to train encoder and decoder, as well as learning an effective codebook.

$$L_{VQ}(E, G, Z) = ||x - \hat{x}||^2 + ||sg(E(x)) - z_q||^2 + \beta ||sg(z_q) - E(x)||^2$$

(12)

In order to learn a richer codebook, VQ-GAN[12], a variant of the original VQ-VAE, and use a discriminator and perceptual loss to keep good perceptual quality at increased compression rate, was proposed. An adversarial training with a patch-based discriminator $D$ that aims to differentiate between real and reconstructed images was used:

$$L_{GAN}(E, G, Z, D) = [\log D(x) + \log(1 - D(\hat{x}))]$$

(13)

And the complete object of VQGAN is:

$$[L_{VQ}(E, G, Z) + \lambda L_{GAN}(E, G, Z, D)]$$

(14)

### 3 DiVAE

#### 3.1 Denoising Diffusion Decoder in DiVAE

Perhaps the work most related to our approach are VQ-VAE[42] and VQ-GAN[12], which consist of the following parts: a CNN encoder which parameterizes a posterior distribution $q(z|x)$ of discrete latent variables $z$ from input data $x$, a Codebook $Z$ containing a finite number of embedding vectors, and a decoder with a distribution $p(x|z)$, and the image can be faithfully reconstructed via the CNN decoder. In multi-stage image synthesis, the reconstructing decoder greatly influence the quality of results.

Different from VQ-GAN and VQ-VAE, DiVAE parameterizes $p(x|z)$ through a denoising diffusion model, take DDPM’s denoising process for instance, $p(x|z)$ can be obtained by $T$ times’ iterative
We aim to model the denoise diffusion process which works better in practice than the actual variational lower bound $L$. The current timestep $t$ is injected into the network with Adaptive Group Normalization (AdaGN) operator, i.e., $AdaGN(h, t) = a_iLayerNorm(h) + b_i$, where $h$ is the intermediate activations, at and $b_i$ are obtained from a linear projection of the timestep embedding.

$$p_0(x_{t-1}|x_t, z) \sim \mathcal{N}(x_{t-1}; \mu(x_t, t), \sum(x_t, t))$$

Essentially the work is to parameterize the model as a function to predict $\mu_0(x_t, t)$ which define the noise component of a noisy sample $x_t$ and the $\sum(x_t, t)$ define the variance. DDPM observe that the simple mean-squared error objective, $L_{simple}$, which can be seen as a reweighted form of $L_{vrb}$, works better in practice than the actual variational lower bound $L_{vrb}$.

$$L_{simple} = E_{\epsilon \sim (0, t), x_0 \sim \mathcal{N}(z_0, t)}[||e - \epsilon_t(x_t, x_0)||^2]$$

$$L_{vrb} = L_0 + L_1 + L_2 + \ldots + L_{T-1} + L_T$$

$$L_0 = -logp_0(x_0|x_1, y)$$
\[ L_{t-1} = D_{KL}(q(x_{t-1}|x_t, x_0)||p_\theta(x_{t-1}|x_t, z)) \]  \hspace{1cm} (20)
\[ L_T = D_{KL}(q(x_T|x_0)||p(x_T)) \]  \hspace{1cm} (21)

Our work follows the hybrid objective in Improved DDPM, as early DDPM set \( \sum(x_t, t) \) not learned. Improved DDPM experiments and considers two opposite extremes, parameterized the variance as an interpolation and achieved their best results. Since \( L_{simple} \) doesn’t depend on \( \sum(x_t, t) \), they use an new hybrid objective:
\[ L_{hybrid} = L_{simple} + \lambda L_{vb} \]  \hspace{1cm} (22)

### 3.2 Application in Conditional Images Synthesis Tasks

Previous multi stage image synthesis models e.g. DALL-E, NUWA, includes a VAE structure model for faithfully reconstructing image embedding to image and an auto-regressive model sequentially predict image tokens to generate image embedding. Our work prevents such two stage visual synthesis trade-offs, improves the first stage ability by realizing a diffusion decoder based on Denoising Diffusion Model. With a denoising diffusion decoder, DiVAE can reconstruct more high-quality and detailed image from a latent representation \( z \). We apply the DiVAE with an auto-regressive generator on Text-to-Image tasks to evaluate our model’s ability and generality of better and more human-feeling samples. The auto-regressive generator is an transformer encoder-decoder framework covering language and image to realize conditioned synthesis. The model’s target is to model \( p(x|y) \), which can be mainly divided into the modeling and optimization of token generation and image reconstruction:
\[
p(x|y) : \begin{cases} 
p(z|y) = \prod_{i=1}^{N} p(z^i|z^{i-1},...,z^1, y) \\
p(x|z) = \prod_{t=T}^{1} p(x_{t-1}|x_t, z) 
\end{cases} \]  \hspace{1cm} (23)

Auto-regressive generator produce \( z \) from captions to enable image embedding generations from text captions, and then diffusion decoder of DiVAE reconstruct it to synthesis image.

### 4 Experiments

This section evaluates the ability of our approach to reconstruct high-quality image from image embedding, we use Fréchet Inception Distance (FID)\[[15]\] as our default metric as the other state-of-the-art generative modeling works. Firstly, We compare the DiVAE’s performance of reconstructing with the state-of-the-art generative models in Sec \[4.1\]. In addition, we apply the DiVAE with a pre-trained Auto-regressive generator on Text-to-Image (T2I) synthesis task to evaluate its generality in visual synthesis tasks in Sec \[4.2\]. Ablation Study in Sec \[4.3\] explores how to add image embedding into diffusion model for excellent performance. We train our model on ImageNet datasets\[[8]\] with a training batch size of 256 for total 10k training steps, AdamW optimizer is used with the learning rate linearly warming up to a peak value of 1e-4 over 1000 steps.

#### 4.1 Comparison with state-of-the-art

| Model       | Dataset   | \( D \rightarrow R \) | Rate | dim Z | FID   |
|-------------|-----------|------------------------|------|-------|-------|
| DALL-E dVAE| Web data  | \( 32^2 \rightarrow 256^2 \) | f8   | 8192  | 32.0  |
| VQGAN       | ImageNet  | \( 16^2 \rightarrow 256^2 \) | f16  | 1024  | 7.94  |
| VQGAN       | ImageNet  | \( 16^2 \rightarrow 256^2 \) | f16  | 16384 | 4.98  |
| VQGAN       | ImageNet  | \( 32^2 \rightarrow 256^2 \) | f8   | 8192  | 1.49  |
| DiVAE(ours) | ImageNet  | \( 16^2 \rightarrow 256^2 \) | f16  | 16384 | 4.07  |
| DiVAE(ours) | ImageNet  | \( 32^2 \rightarrow 256^2 \) | f8   | 8192  | 1.24  |

Table 1: FID between reconstructed validation split and original validation with 50000 images split on ImageNet.
We investigate how our approach quantitatively and qualitatively compares to existing state-of-the-art models (VQVAE, VQGAN) for generative image synthesis. The models are trained in two compression rates (f16 and f8). In our training, model built with 1000 diffusion steps, in inference, DiVAE model use 1000 steps DDPM sampling approaches. Table 5 shows FID between reconstructed images and original images in the validation split on ImageNet. DiVAE is able to achieve better FID compared with VQGAN in case of both $32^2 \rightarrow 256^2$ and $16^2 \rightarrow 256^2$ generating, achieving state-of-the-art results. The diffusion model brings its ability of high-quality sampling to DiVAE. Specifically, as shown as Figure 4, improvement is more obvious in human-feeling quality and details of images. DiVAE's synthesis sample is more photo-realistic and reconstructing well more details, like eyes and small target, the improvement is significantly especially in Rate of f16.

4.2 Text-to-Image (T2I) Task

Our work aims to propose a generality model to generate more realistic and photo-realistic images to improve the reconstructing stage of multi stage image synthesis, so the first stage of text-to-image model in our experiment still is an auto-regressive transformer to generate image embedding conditioned on text. We pre-train an auto-regressive transformer on Conceptual Captions[27] for text-to-image (T2I) generation. The auto-regressive model produces image embedding from text, and the $32^2 \rightarrow 256^2$ diffusion decoder reconstructs image conditioned on $z$ inverting the compressing process of encoder.

Comparing in Table 2, we perform text-to-image prediction quantitatively on MSCOCO (256×256) datasets[27] and qualitatively show results in Figure 5. As shown in Table 2, FID of GLIDE and DALLE-2 is really perfect, GLIDE is an one-stage classifier-free guidance diffusion model, DALLE-2 is an multi stage visual synthesis model with an excellent prior and an classifier-free guidance diffusion[19] decoder. Both of them have an better generator from text and huge high-quality training datasets. Except them, DiVAE achieves FID 11.53, is better than previous models. Figure shows the synthesized images of DiVAE conditioned on text in MSCOCO validation, obviously, the samples are realistic and have fine-grained details.

NUWA is an two stage visual synthesis model, which also contains an auto-regressive generator and an embedding decoder. As comparison in NUWA, although reporting a significant FID score of 9.3, XMC-GAN’s sampling images are not realistic like NUWA, so we compare our synthesis images with NUWA in same condition in Figure 6. In the experiment, we take the $16^2$ image embeddings from
Figure 5: Samples of Text-to-Image (T2I) task generated by DiVAE.

| Model          | FID  | Zero-shot FID |
|----------------|------|---------------|
| AttnGAN        | 35.49|               |
| DM-GAN         | 32.64|               |
| DF-GAN         | 21.42|               |
| DALL-E         | 27.50|               |
| CogView        | 27.10|               |
| NUWA           | 12.9 | 22.6          |
| VQ-Diffusion   | 13.86|               |
| XMC-GAN        | 9.33 |               |
| GLIDE          | 12.24|               |
| DALL-E2        | 10.39|               |
| **DIVAE (Ours)** | **11.53** |             |

Table 2: Qualitative comparison with the state-of-the-art models for Text-to-Image (T2I) task on the MSCOCO (256x256) dataset.

NUWA’s auto-regressive model to DiVAE’s decoder to reconstruct 256² size for clearer comparison in Figure. DiVAE’s synthesis images is more photorealistic and reconstructing well more details, as the eyes and hair are significantly fine-reconstructed. The phenomenon will be more obvious in 16² → 256² decoder’s comparison as show in Table 5 and Figure 4. The ability of DiVAE allows larger compressing ratio of image in multi stage visual synthesis model, leading to more efficient and large-scale pre-training.

4.3 Ablation Study

The key of DiVAE is how to add image embeddings to diffusion model’s Network, our work explores several approaches to make it work better. In this section we comparing the FID of different setting on 5000 validation of ImageNet. UNet for diffusion modeling is an encoder-decoder Network, so we investigate to concat embeddings to the encoding blocks, middle blocks and decoding blocks to train the model. As the results in Table 4, the FID score of adding to middle block is better than the others, considering the middle block of U-Net is the bottom of features with more concentrated information.
A baby girl chews on a stick with a teddy bear in hand. A big zebra and a small zebra are standing in a grassy field. A boy with a hat wearing a tie. A brown cat is sitting on a plastic bag. A beautiful child.

Figure 6: Qualitative comparison NUWA for Text-to-Image (T2I) task, with the same image embeddings from NUWA.

| Method       | Concat | Add | Attention |
|--------------|--------|-----|-----------|
| FID          | 11.58  | 11.61 | 13.35     |

Table 3: Method of inputting embeddings.

| Position   | Encoder | Middle | Decoder |
|------------|---------|--------|---------|
| FID        | 13.08   | 11.58  | 13.06   |

Table 4: Position of inputting embeddings.

Figure 7: Comparison of different method and position to input embeddings into UNet.

As show in Figure 7, inputting the image embeddings in the encoding blocks or decoding blocks instead of the middle block, DVAE reconstruction nearly exactly the same style image as the VQGAN, maybe model gets too much information from the skip connections when putting into encoding blocks and it’s too late to input when putting into decoding blocks. So it is optimal to add embeddings to the middle layer. Based on above, we investigate to add or concat embeddings to middle block, in addition we try to input the embedding by an attention block. As Table 3 shows, we find that adding and concatting don’t have much difference, while attention block has poorer performance, maybe it needs more design. Both of adding and concatting is effective as show in Figure 7. So the position of inputting embeddings is greatly crucial and concatting and adding have little difference.

5 Conclusion

In this paper, we propose a DiVAE with a diffusion decoder to generate more photorealistic and detailed images to improve the reconstructing stage of multi stage image synthesis. Our model achieves state-of-the-art results on reconstruction of images comparing with existing approach and samples more detailed images on Text-to-Image tasks. And the potential improvements of the first stage multi stage image synthesis which generates images embedding is expecting to future works.
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A  Training

We train the model on ImageNet datasets on 32 A100 GPUs with a training batch size of 256 for total 10k training steps, AdamW optimizer is used with the learning rate linearly warming up to a peak value of 1e-4 over 1000 steps.

B  Limitations

We note that our model still has more time consumption than un-diffusion model, so we also experiment DDIM sample approach with 25 steps. From the comparison on reconstructing tasks, we find that the FID of DiVAE with DDIM 25 steps can’t be better than DDPM 1000 steps. However, in comparison of visual effect, DiVAE is more detailed than VQGAN no matter in DDPM or DDIM sample mode. The time consuming problem of diffusion model need to be further solved. In addition, the size of generative image is stationary, which is determined by training data. A trained model can’t accept and output various size images as VQ-GAN. The variability of synthesis image’s size is worth exploring in further works.

| Model       | Dataset          | $D \rightarrow R$ | Rate | dim Z | FID  |
|-------------|------------------|-------------------|------|-------|------|
| DALL-E dVAE | Web data         | $32^2 \rightarrow 256^2$ | f8   | 8192  | 32.0 |
| VQGAN       | ImageNet         | $16^2 \rightarrow 256^2$ | f16  | 1024  | 7.94 |
| VQGAN       | ImageNet         | $16^2 \rightarrow 256^2$ | f16  | 16384 | 4.98 |
| VQGAN       | ImageNet         | $32^2 \rightarrow 256^2$ | f8   | 8192  | 1.49 |
| DiVAE       | ImageNet         | $16^2 \rightarrow 256^2$ | f16  | 16384 | 4.07 |
| DiVAE       | ImageNet         | $32^2 \rightarrow 256^2$ | f8   | 8192  | 1.24 |
| DiVAE(ddim25) | ImageNet       | $16^2 \rightarrow 256^2$ | f16  | 16384 | 7.07 |
| DiVAE(ddim25) | ImageNet       | $32^2 \rightarrow 256^2$ | f8   | 8192  | 3.14 |

Table 5: FID between reconstructed validation split and original validation with 50000 images split on ImageNet.

C  Additional Results

In this part, we provide more samples of comparison on reconstruction in Figure 8 and Text-to-Image task in Figure 10.
Figure 9: Comparison with VQGAN in $32^2 \rightarrow 256^2$ and $16^2 \rightarrow 256^2$ reconstruction with same codebook dimension $Z$. 
Clouds can be seen beyond the wing of the plane
A gray and white cat sitting in blue bowl
A collection of books and knick-knacks on shelves
A sloping street in a small mountain community
A pine apple on top of a pile of mixed fruit

A man wearing a tie, jacket and white shirt
A dog with goggles is in a motorcycle side car
A man with white hair and a beard wearing priestly robes
A street intersection at night with no vehicles on the road
A spotted dog sitting underneath the kitchen counter

Cityscape of a train stopping traffic on a street
Full grown cat laying down and sleeping on top of a car
The giraffe is sticking out its long tongue, perhaps tasting the fence rail.
Two blue bowls of food next to a bottle of cinnamon and sugar
An adorable cat attempts to hide in a purse to steal the persons identity

A cat sitting on a desk next to a window
A double decker bus driving while it snows
An adorable small dog wearing sunglasses while sitting in a back seat
A teddy bear in a pink dress and pink shoes
A giraffe is nursing its young in the zoo

A city with a river in the middle with boats docked
A modern kitchen with a fridge, an island counter, hardwood floor, and deco ceiling artwork
A cat looking off to its right with bright blue eyes
A large orange sitting on a glass plate

Figure 10: Text-to-Image 256x256 samples.