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#### Context information is critical for vision tasks

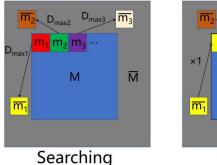
#### Representation Learning

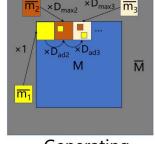
# Example: Question 1: Question 2:

Figure 1. Our task for learning patch representations involves randomly sampling a patch (blue) and then one of eight possible neighbors (red). Can you guess the spatial configuration for the two pairs of patches? Note that the task is much easier once you have recognized the object!

Unsupervised Visual Representation Learning by Context Prediction

#### Image Inpainting





Generating

Figure 3. Illustration of the CSA layer. Firstly, we search the most similar contextual patch  $\overline{m_i}$  of each generated patch  $m_i$  in the hole M, and initialize  $m_i$  with  $\overline{m_i}$ . Then, the previous generated patches and the most similar contextual patch are combined to generate the current one.

Coherent Semantic Attention for Image Inpainting

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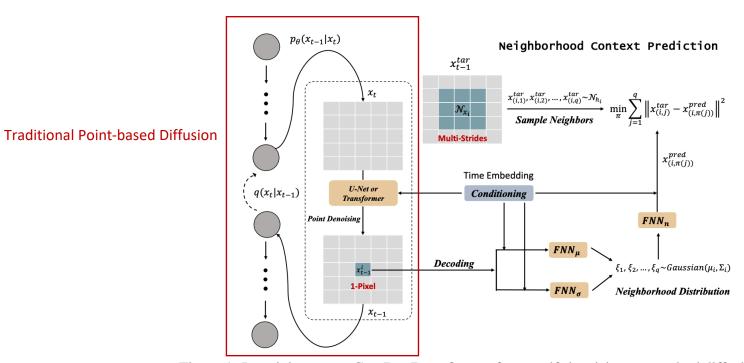


Figure 1: In training stage, ConPreDiff first performs self-denoising as standard diffusion models, then it conducts neighborhood context prediction based on denoised point  $\boldsymbol{x}_{t-1}^i$ . In inference stage, ConPreDiff only uses its self-denoising network for sampling.





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Training Objective

$$\mathcal{L}_{ ext{ConPreDiff}} = \sum_{i=1}^{x imes y} \left[ \underbrace{\mathcal{M}_p(oldsymbol{x}_{t-1}^i, oldsymbol{\hat{x}}^i)}_{point\ denoising} + \underbrace{\mathcal{M}_n(oldsymbol{H}_{\mathcal{N}_i^s}, oldsymbol{\hat{H}}_{\mathcal{N}_i^s})}_{context\ prediction} 
ight]$$

Mitigating Complexity Problem

$$\mathcal{L}_{ ext{ConPreDiff}} = \sum_{i=1}^{x imes y} \left[ \underbrace{\mathcal{M}_p(oldsymbol{x}_{t-1}^i, oldsymbol{\hat{x}}^i)}_{point\ denoising} + \underbrace{\mathcal{W}_2^2(\psi_n(oldsymbol{x}_{t-1}^i, t), \mathcal{P}_{\mathcal{N}_i^s})}_{neighborhood\ distribution\ prediction} 
ight]$$





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**Efficient Large Context Decoding** 

$$\psi_n(\boldsymbol{x}_{t-1}^i, t) = \text{FNN}_n(\xi), \ \xi \sim \mathcal{N}(\mu_i, \Sigma_i),$$

$$\mu_i = \text{FNN}_\mu(\boldsymbol{x}_{t-1}^i), \Sigma_i = \text{diag}(\exp(\text{FNN}_\sigma(\boldsymbol{x}_{t-1}^i))).$$

Final Loss for Both Discrete and Continuous Diffusion Backbones

$$\mathcal{L}_{ ext{ConPreDiff}}^{dis} = \mathcal{L}_{t-1}^{dis} + \lambda_t \cdot \sum_{i=1}^{x \wedge y} \mathcal{W}_2^2(\psi_n(m{x}_{t-1}^i, t), \mathcal{P}_{\mathcal{N}_i^s}),$$

$$\mathcal{L}_{ ext{ConPreDiff}}^{con} = \mathcal{L}_{t-1}^{con} + \lambda_t \cdot \sum_{i=1}^{x imes y} \mathcal{W}_2^2(\psi_n(m{x}_{t-1}^i, t), \mathcal{P}_{\mathcal{N}_i^s}),$$



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#### **Text-to-Image Synthesis**





ConPreDiff (Ours)



"The sunlight shines on "Some ancient stone pillars the leaves, and every stand upon the earth, arranged in an orderly manner and green leaf reflects light." spaced apart from each other."







"There are black suits and white pants hanging in the wardrobe."







"On a rainy day street, the air near the ground is filled with raindrops."







"A bunch of flowers bloomed in the grass, with dewdrops on each petal."







"The sky was blanketed with thick snow, while the ground lay adorned with stones."







"A box contains apples, each displaying a touch of green







"An elderly fisherman sits in a "A rainbow rise after the boat, his fishing rod set aside, rain, a group of cows and sheep graze in the fields. gazing towards the distant Cows are black and sheep horizon. The last rays of the are white." sun reflect off the ripples on

the water's surface."







"On a town's nighttime streets, light strips were pulled up on the busy streets. People dressed in various attire and holding umbrellas strolled along the streets."

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Table 1: Quantitative evaluation of FID on MS-COCO for  $256 \times 256$  image resolution.

| Approach                   | Model Type           | FID-30K | Zero-shot<br>FID-30K |  |
|----------------------------|----------------------|---------|----------------------|--|
| AttnGAN [96]               | GAN                  | 35.49   | _                    |  |
| DM-GAN [113]               | GAN                  | 32.64   | -                    |  |
| DF-GAN [86]                | GAN                  | 21.42   | =                    |  |
| DM-GAN + CL [100]          | GAN                  | 20.79   | -                    |  |
| XMC-GAN [107]              | GAN                  | 9.33    | -                    |  |
| LAFITE [112]               | GAN                  | 8.12    |                      |  |
| Make-A-Scene [22]          | Autoregressive       | 7.55    | -                    |  |
| DALL-E [61]                | Autoregressive       | -       | 17.89                |  |
| LAFITE [112]               | GAN                  | -       | 26.94                |  |
| LDM [65]                   | Continuous Diffusion | -       | 12.63                |  |
| GLIDE [54]                 | Continuous Diffusion | -       | 12.24                |  |
| DALL-E 2 [62]              | Continuous Diffusion | -       | 10.39                |  |
| Improved VQ-Diffusion [85] | Discrete Diffusion   | -       | 8.44                 |  |
| Simple Diffusion [31]      | Continuous Diffusion | -       | 8.32                 |  |
| Imagen [69]                | Continuous Diffusion | -       | 7.27                 |  |
| Parti [104]                | Autoregressive       | -       | 7.23                 |  |
| Muse [7]                   | Non-Autoregressive   | -       | 7.88                 |  |
| eDiff-I [3]                | Continuous Diffusion | -       | 6.95                 |  |
| CONPREDIFF <sub>dis</sub>  | Discrete Diffusion   | -       | 6.67                 |  |
| ${f ConPreDiff}_{con}$     | Continuous Diffusion | -       | 6.21                 |  |



**Image Inpainting** 

# Improving Diffusion-Based Image Synthesis with Context Prediction

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Figure 3: Inpainting examples generated by our CONPREDIFF.

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Table 2: Quantitative evaluation of image inpainting on CelebA-HQ and ImageNet.

| CelebA-HQ<br>Method | Wide<br>  LPIPS↓  | Narrow<br>LPIPS ↓ | Super-Resolve 2×<br>LPIPS ↓ | Altern. Lines<br>LPIPS ↓ | Half<br>LPIPS↓ | Expand<br>LPIPS ↓ |
|---------------------|-------------------|-------------------|-----------------------------|--------------------------|----------------|-------------------|
| AOT [105]           | 0.104             | 0.047             | 0.714                       | 0.667                    | 0.287          | 0.604             |
| DSI [56]            | 0.067             | 0.038             | 0.128                       | 0.049                    | 0.211          | 0.487             |
| ICT [91]            | 0.063             | 0.036             | 0.483                       | 0.353                    | 0.166          | 0.432             |
| DeepFillv2 [103]    | 0.066             | 0.049             | 0.119                       | 0.049                    | 0.209          | 0.467             |
| LaMa [84]           | 0.045             | 0.028             | 0.177                       | 0.083                    | 0.138          | 0.342             |
| RePaint [49]        | 0.059             | 0.028             | 0.029                       | 0.009                    | 0.165          | 0.435             |
| CONPREDIFF          | 0.042             | 0.022             | 0.023                       | 0.022                    | 0.139          | 0.297             |
| ImageNet<br>Method  | Wide<br>  LPIPS ↓ | Narrow<br>LPIPS ↓ | Super-Resolve 2×<br>LPIPS ↓ | Altern. Lines LPIPS ↓    | Half<br>LPIPS↓ | Expand LPIPS ↓    |
| DSI [56]            | 0.117             | 0.072             | 0.153                       | 0.069                    | 0.283          | 0.583             |
| ICT [91]            | 0.107             | 0.073             | 0.708                       | 0.620                    | 0.255          | 0.544             |
| LaMa [84]           | 0.105             | 0.061             | 0.272                       | 0.121                    | 0.254          | 0.534             |
| RePaint [49]        | 0.134             | 0.064             | 0.183                       | 0.089                    | 0.304          | 0.629             |
| CONPREDIFF          | 0.098             | 0.057             | 0.129                       | 0.107                    | 0.285          | 0.506             |





Recall ↑

0.49

0.57

Recall ↑

0.44 0.52

0.61

| FFHQ $256 \times 256$   |   |                              | CelebA-He                     | CelebA-HQ $256 \times 256$  |   |                                       |
|---|---|------------------------------|-------------------------------|---|---|---------------------------------------|
|   |   |                              | Pagel1 ↑                      | Method  | FID↓  | Prec. ↑                               |
| Method  ImageBART[16] U-Net GAN (+aug) [72] UDM [39] StyleGAN [36] ProjectedGAN [71] LDM [65] | 9.57<br>7.6<br>5.54<br>4.16<br>3.08<br>4.98 | Prec. ↑  0.71 0.65 0.73      | Recall ↑  0.46 0.46 0.50      | DC-VAE [55]<br>VQGAN+T. [17] (k=400)<br>PGGAN [43]<br>LSGM [87]<br>UDM [39]<br>LDM [65]     | 15.8<br>10.2<br>8.0<br>7.22<br>7.16<br>5.11 | -<br>-<br>-<br>-<br>-<br>0.72         |
| CONPREDIFF  | 2.24  | 0.81                         | 0.50                          | CONPREDIFF  LSUN-Churc  | 3.22<br>ches 256                            | 0.83<br>× 256                         |
| LSUN-Bedrooms $256 \times 256$  |   |                              | Method                        | FID↓  | Prec. ↑                                     |                                       |
| Method  ImageBART [16] DDPM [28] UDM [39] StyleGAN [36] ADM [14] ProjectedGAN [71] LDM-4 [65] | FID ↓ 5.51 4.9 4.57 2.35 1.90 1.52 2.95     | Prec. ↑  0.59 0.66 0.61 0.66 | Recall ↑  0.48 0.51 0.34 0.48 | DDPM [28] ImageBART [16] PGGAN [43] StyleGAN [36] StyleGAN2 [37] ProjectedGAN [71] LDM [65] | 7.89 7.32 6.42 4.21 3.86 1.59 4.02          | -<br>-<br>-<br>-<br>-<br>0.61<br>0.64 |
| ConPreDiff  | 1.12  | 0.73                         | 0.59                          | CONPREDIFF  | 1.78  | 0.74                                  |





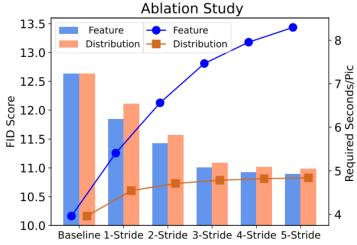


Figure 4: Bar denotes FID and line denotes time cost.

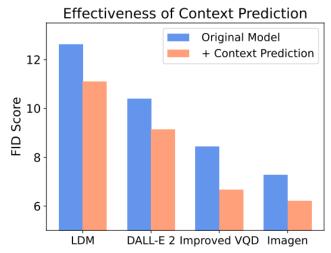


Figure 5: Equip diffusion models with our context prediction.



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"A photo of a dark Goth house"

"A group of elephants walking in muddy water."



"A teddy bear sitting on a chair."



"A person holding a bunch of bananas on a table."



"Green frog on green grass"



"The plane wing above the clouds."





"Trees on African grassland"



"Pancakes with ketchup"



"Cat fell asleep on the owner's bed"



"A photo of an adult lion."



"A red hydrant sitting in the snow."



"A photo of an white garlic ice cream"





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Thanks for Listening!

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