

Denoising Diffusion Probabilistic Models

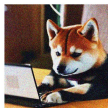
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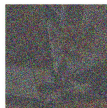
Yujin



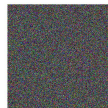
Xinke-
Wang



Changfeng-
Duan



JieLi



Yuhong-
Sun

Content

- 1 Background
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- 3 Features
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What is generative model?

Regardless of precise definition, the terminology is constitutional because a generative model can be used to "generate" random instances

Deep generative models

With the rise of deep learning, a new family of methods, called deep generative models (DGMs)

- Generative adversarial networks (GANs)
- Variational autoencoders (VAEs)
- Flow Based Model

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What is Diffusion Model?

We can say...

In machine learning, diffusion models, also known as diffusion probabilistic models, are a class of latent variable models.

Intuitive understanding

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DDPM Features

Name.	Likelihood	Speed	Methods	Stability	Others
GAN	None	fast	One-step	Unstable	high quality
VAE	Uncertain	fast	One-step	Stable	-
Flow Model	Exactly	fast	Multi-step	Stable	-
DDPM	Uncertain	slow	Multi-step	Stable	beat GANs

Table: Comparison of generative model

Beat GANs

Model	FID	sFID	Prec	Rec
LSUN Bedrooms 256×256				
DCTransformer [†] [42]	6.40	6.66	0.44	0.56
DDPM [25]	4.89	9.07	0.60	0.45
IDDPM [43]	4.24	8.21	0.62	0.46
StyleGAN [27]	2.35	6.62	0.59	0.48
ADM (dropout)	1.90	5.59	0.66	0.51
LSUN Horses 256×256				
StyleGAN2 [28]	3.84	6.46	0.63	0.48
ADM	2.95	5.94	0.69	0.55
ADM (dropout)	2.57	6.81	0.71	0.55
LSUN Cats 256×256				
DDPM [25]	17.1	12.4	0.53	0.48
StyleGAN2 [28]	7.25	6.33	0.58	0.43
ADM (dropout)	5.57	6.69	0.63	0.52
ImageNet 64×64				
BigGAN-deep* [5]	4.06	3.96	0.79	0.48
IDDPM [43]	2.92	3.79	0.74	0.62
ADM	2.61	3.77	0.73	0.63
ADM (dropout)	2.07	4.29	0.74	0.63
ImageNet 128×128				
BigGAN-deep [5]	6.02	7.18	0.86	0.35
LOGAN [†] [68]	3.36			
ADM	5.91	5.09	0.70	0.65
ADM-G (25 steps)	5.98	7.04	0.78	0.51
ADM-G	2.97	5.09	0.78	0.59
ImageNet 256×256				
DCTransformer [†] [42]	36.51	8.24	0.36	0.67
VQ-VAE-2 ^{††} [51]	31.11	17.38	0.36	0.57
IDDPM [†] [43]	12.26	5.42	0.70	0.62
SR3 ^{††} [53]	11.30			
BigGAN-deep [5]	6.95	7.36	0.87	0.28
ADM	10.94	6.02	0.69	0.63
ADM-G (25 steps)	5.44	5.32	0.81	0.49
ADM-G	4.59	5.25	0.82	0.52
ImageNet 512×512				
BigGAN-deep [5]	8.43	8.13	0.88	0.29
ADM	23.24	10.19	0.73	0.60
ADM-G (25 steps)	8.41	9.67	0.83	0.47
ADM-G	7.72	6.57	0.87	0.42

Figure: Some data about beat GANs

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The Process of DDPM

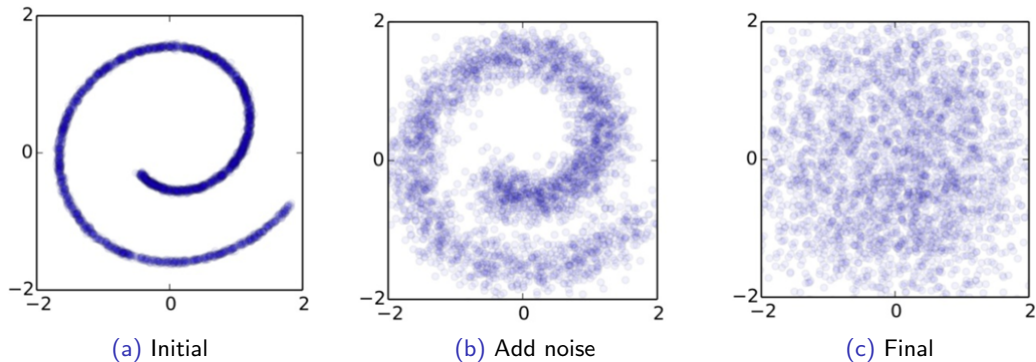


Figure: how the figure tranform to a Gaussian Distribution

Forward Equation

Forward

$$q(x_t|x_{t-1}) = N(x_t; x_{t-1}\sqrt{1-\beta_t}, \beta_t) \quad (1)$$

$$x_t = x_{t-1}\sqrt{1-\beta_t} + z_t\sqrt{\beta_t} \quad (2)$$

$$x_t = x_{t-1}\sqrt{1-\beta_t} + z_t\sqrt{\beta_t} \quad (\text{let } 1-\beta_t = \alpha_t) \quad (1a)$$

$$= x_{t-2}\sqrt{\alpha_t}(\sqrt{\alpha_{t-1}} + z_{t-2}\sqrt{1-\alpha_{t-1}}) + z_{t-1}\sqrt{1-\alpha_t} \quad (2a)$$

$$= x_{t-2}\sqrt{\alpha_t\alpha_{t-1}} + z_{t-2}\sqrt{\alpha_t - \alpha_t\alpha_{t-1}} + z_{t-1}\sqrt{1-\alpha_t} \quad (3a)$$

$$= x_{t-2}\sqrt{\alpha_t\alpha_{t-1}} + z\sqrt{1-\alpha_t\alpha_{t-1}} \quad (4a)$$

$$= \dots$$

$$= x_0\sqrt{\bar{\alpha}_t} + z\sqrt{1-\bar{\alpha}_t} \quad (5a)$$

Backward Equation

$$\begin{aligned}
 q(x_{t-1}|x_t, x_0) &= q(x_t|x_{t-1}, x_0) \frac{q(x_{t-1}|x_0)}{q(x_t|x_0)} \\
 &\propto \exp \left(-\frac{1}{2} \left(\left(\frac{\alpha_t}{\beta_t} + \frac{1}{1 - \bar{\alpha}_{t-1}} \right) x_{t-1}^2 - \left(\frac{2\sqrt{\alpha_t}}{\beta_t} x_t + \frac{2\sqrt{\bar{\alpha}_{t-1}}}{1 - \bar{\alpha}_{t-1}} \right) x_{t-1} + C(x_t, x_0) \right) \right) \\
 &= \exp \left(-\frac{1}{2} (A x_{t-1}^2 + B x_{t-1} + C) \right) \\
 \mu &= -\frac{B}{2A}, \sigma^2 = \frac{1}{A}
 \end{aligned} \tag{3}$$

Backward

$$p(x_t|x_{t-1}) = N(x_{t-1}; f_\mu(x_t, t), f_\sigma^2(x_t, t)) \tag{4}$$

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Text2Image

Generate images that match the description from the text, give some descriptions, and generate pictures that meet the description.

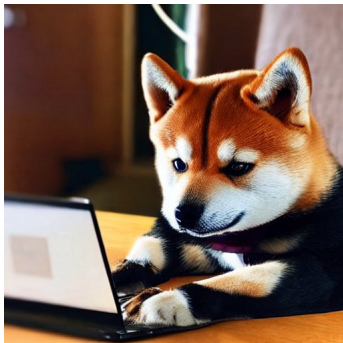


Figure: A dog is reading book

Image Refinement

Refine the blurry image to give the picture more detail.

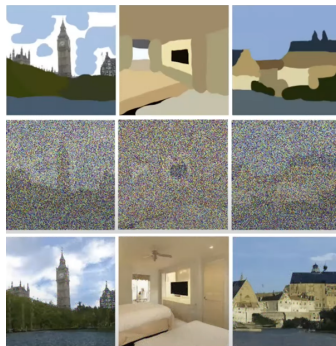


Figure: Image Refinement with Diffusion

Inpainting

Padding the missing image can complement the details and content of the image.

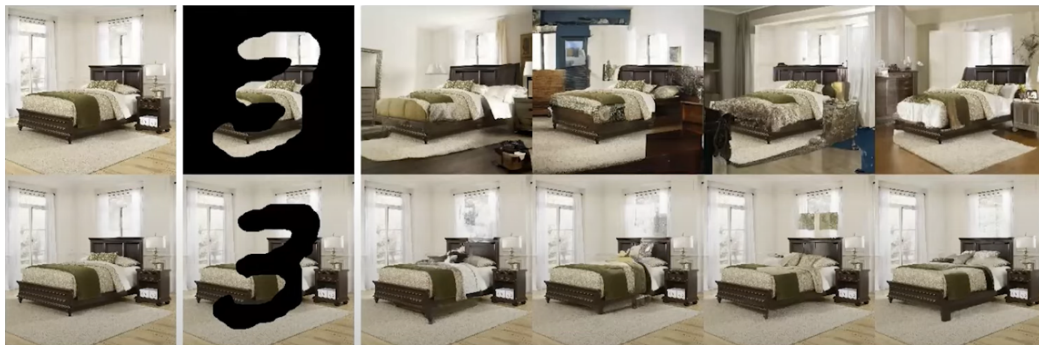


Figure: inpainting with Diffusion

Colorization

Color fill images with missing colors.



Figure: Colorization with Diffusion

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Worries and Prospect

Worries

malicious uses for political purposes

Prospect

uses in art, photography, and music

References

Thank you for watching!

Here is the **References**

- Ho J, Jain A, Abbeel P. Denoising diffusion probabilistic models[J]. Advances in Neural Information Processing Systems, 2020, 33: 6840-6851.
- Dhariwal P, Nichol A. Diffusion models beat gans on image synthesis[J]. Advances in Neural Information Processing Systems, 2021, 34: 8780-8794.

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