Deep Learning for Vision & Language

Text-to-Scene Models

RICE UNIVERSITY

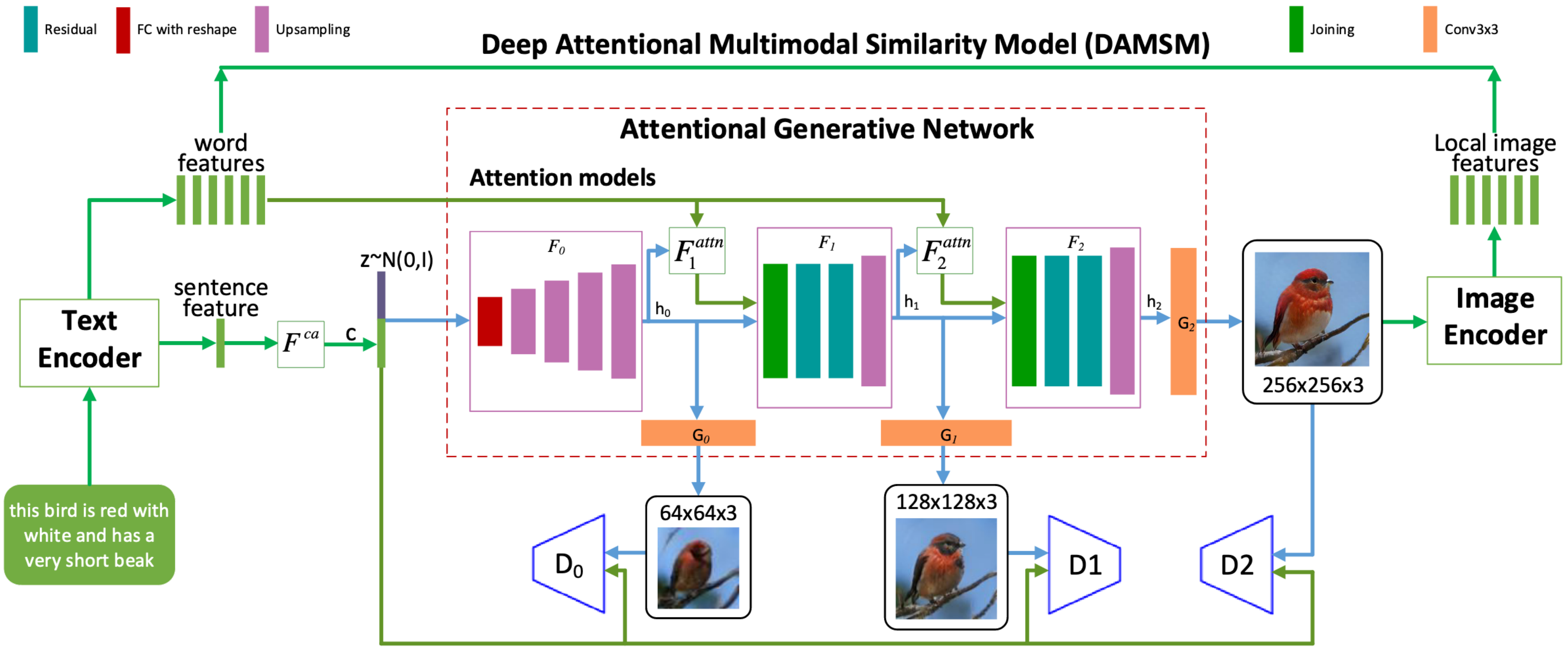
Last Class

- Text to image Models
- Sequence-to-sequence based text-to-image models
- Detour: Style Transfer – Input Feature Optimization.

Today:

- Reverse Diffusion Models
- Other Topics

(1) Hierarchical Conditional GANs / Text-conditioned (AttnGAN)



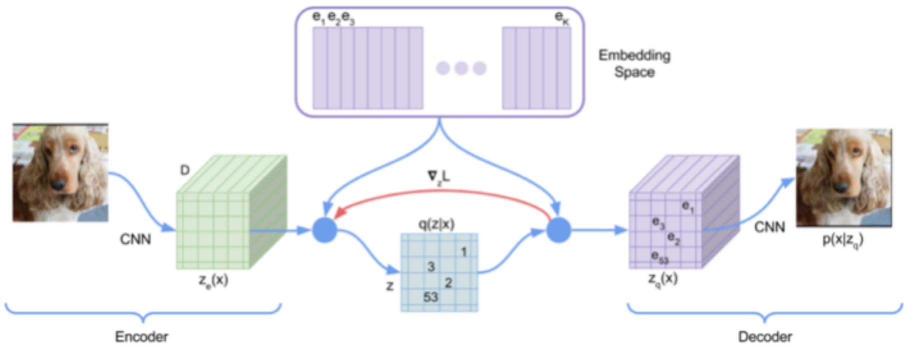
AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks

Tao Xu, Pengchuan Zhang, Qiuyuan Huang, Han Zhang, Zhe Gan, Xiaolei Huang, Xiaodong He

(2) Visual Token Learning (VQGAN) + Seq2Seq Machine Translation (e.g. BART)

Step 1:

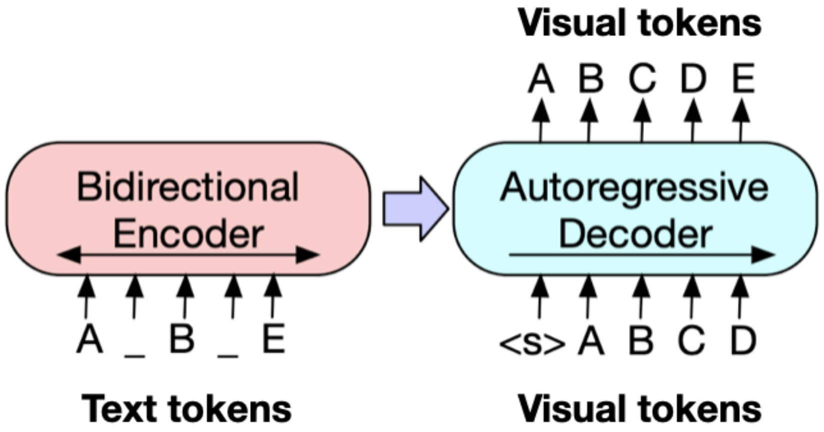
Learn Discrete Dictionary of Visual Tokens



VQVAE — Oord, Vinyals, Kavukcuoglu, 2017
VQGAN — Esser, Rombach, Ommer, 2021
dVAE - DALL-E — Ramesh et al 2021

Step 2:

Build a scene as a composition of discrete visual tokens



BART, GPT-3, etc

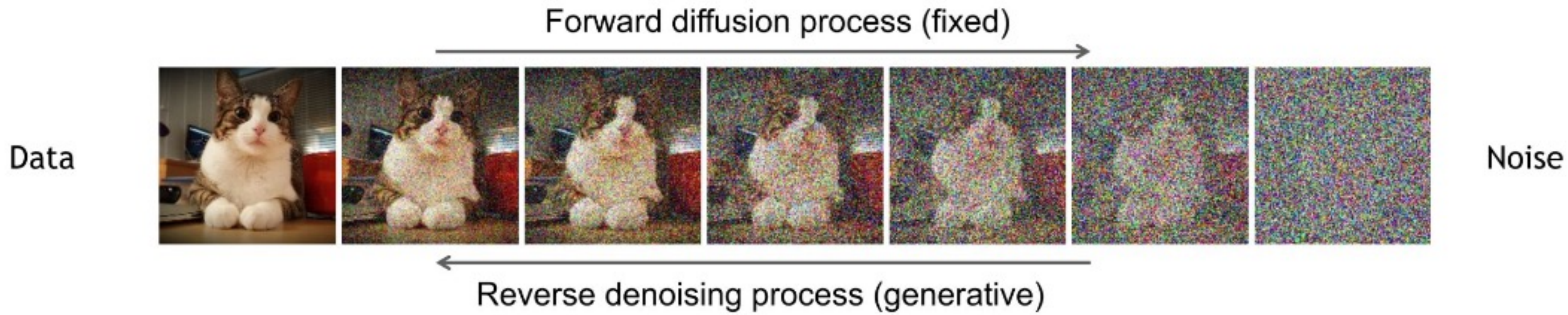
Zero-Shot Text-to-Image Generation

Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, Ilya Sutskever

Denoising Diffusion Probabilistic Models (DDPM)

Forward diffusion: Markov chain of diffusion steps to slowly add gaussian noise to data

Reverse diffusion: A model is trained to generate data from noise by iterative denoising



Denoising Diffusion Probabilistic Models

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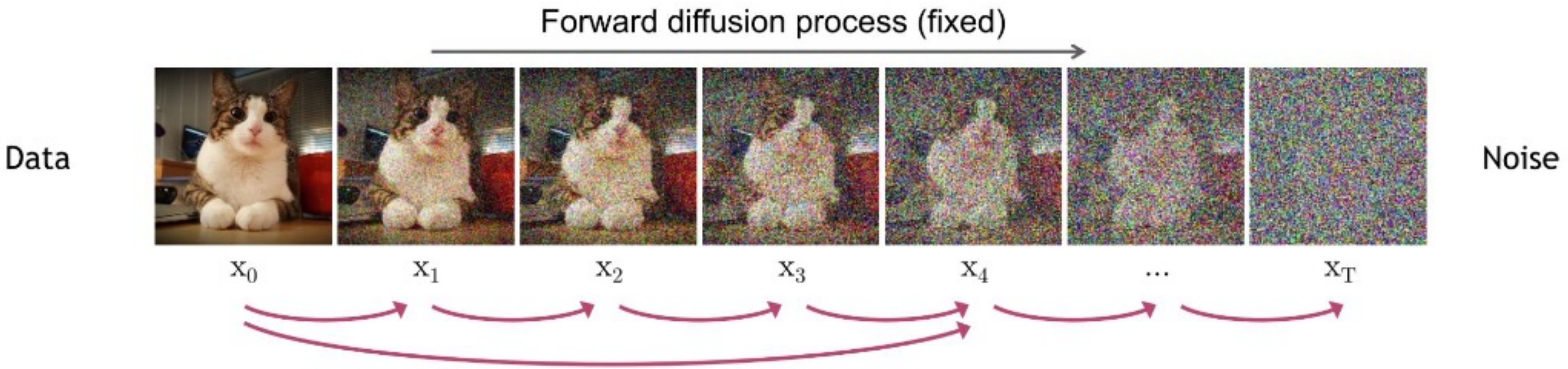
https://cvpr2022-tutorial-diffusion-models.github.io/

Slides compiled by my student Aman Shrivastava

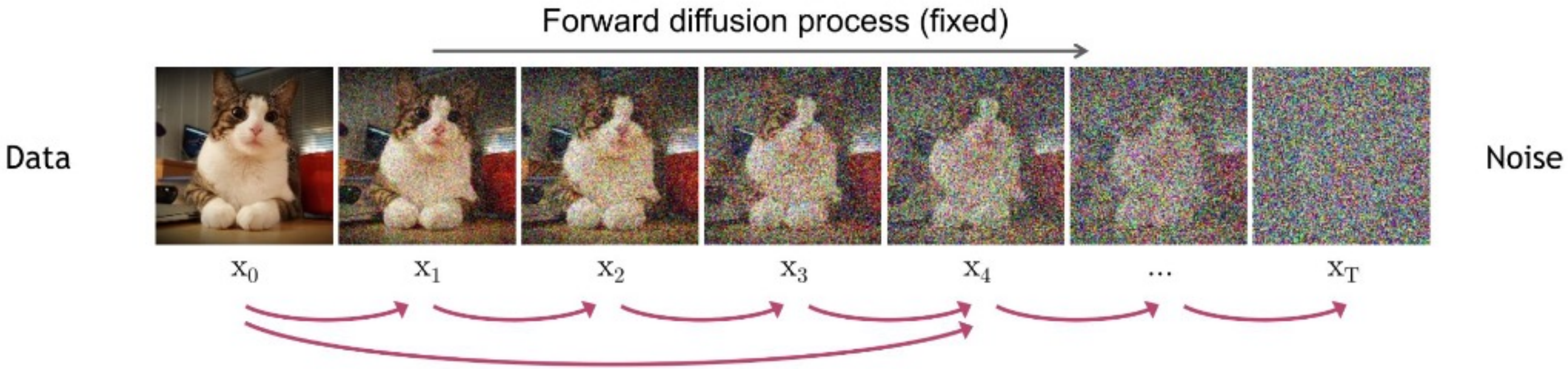
DDPM | Forward diffusion



We add a small amount of gaussian noise to a sample $\mathbf{x_0}$ in **T** timesteps to produces noised samples, $\{\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_T}\}$. The steps are controlled by the noise schedule as follows:

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}) \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

https://cvpr2022-tutorial-diffusion-models.github.io/



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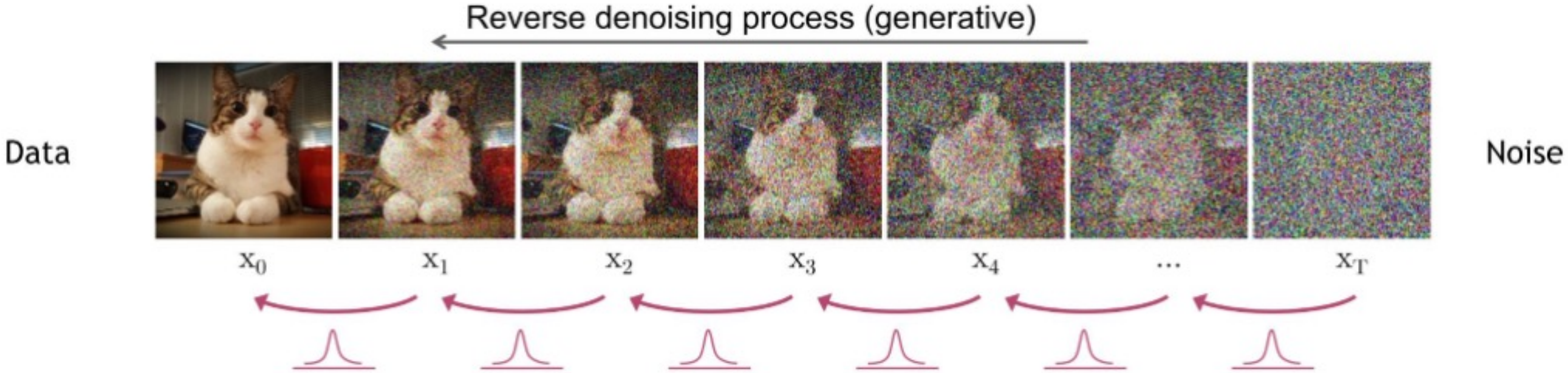
Define $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$ ➡ $q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I}))$ (Diffusion Kernel)

For sampling: $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\,\mathbf{x}_0 + \sqrt{(1-\bar{\alpha}_t)}\,\epsilon$ where $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

DDPM | Reverse Diffusion



We learn a neural network model **(p_θ)** to approximate these conditional probabilities **$q(x_{(t-1)} \mid x_t)$** in order to run the reverse diffusion process as follows:

$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) \quad p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

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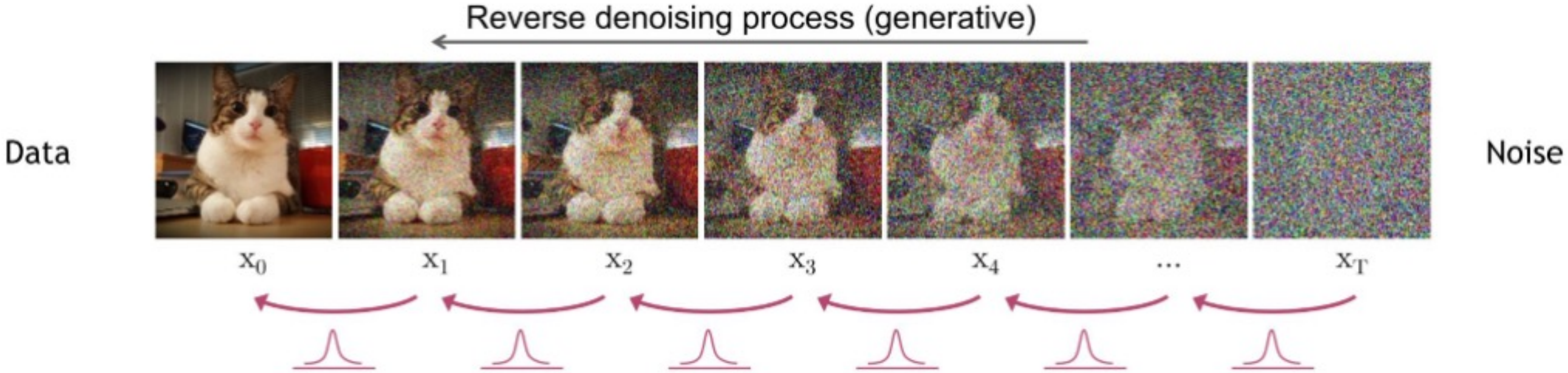
DDPM | Reverse Diffusion



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U-Net

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boxed{\mu_\theta(\mathbf{x}_t, t)}, \sigma_t^2\mathbf{I})$$

Objective:

$$L_{t-1} = D_{\mathrm{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0)||p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t))$$

$$= \mathbb{E}_q\left[\frac{1}{2\sigma_t^2}||\tilde{\mu}_t(\mathbf{x}_t, \mathbf{x}_0) - \mu_\theta(\mathbf{x}_t, t)||^2\right] + C$$

Given that: $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\,\mathbf{x}_0 + \sqrt{(1-\bar{\alpha}_t)}\,\epsilon$

$$\tilde{\mu}_t(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{1-\beta_t}}\left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon\right)$$

$$\mu_\theta(\mathbf{x}_t, t) = \frac{1}{\sqrt{1-\beta_t}}\left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\,\epsilon_\theta(\mathbf{x}_t, t)\right)$$

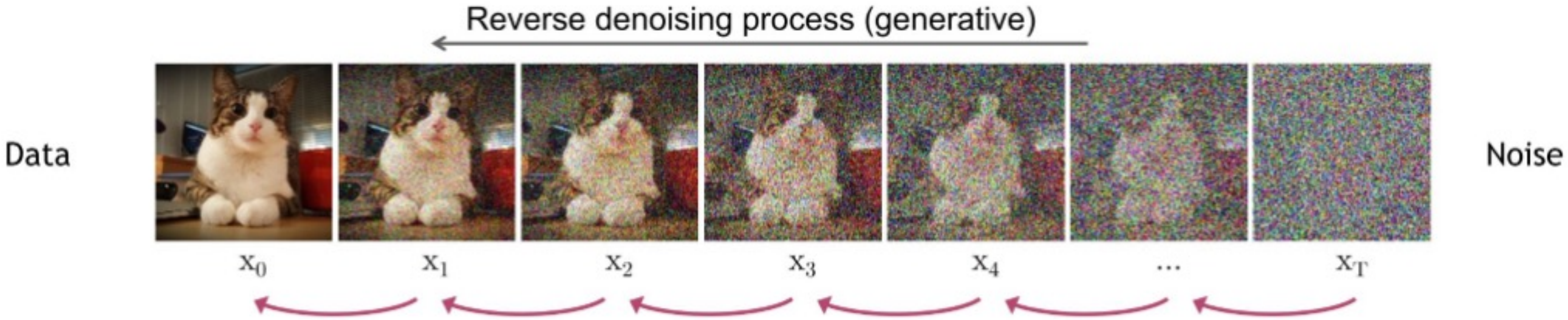
Replacing on the equation

$$L_{t-1} = \mathbb{E}_{\mathbf{x}_0 \sim q(\mathbf{x}_0), \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})} \left[\underbrace{\frac{\beta_t^2}{2\sigma_t^2 (1-\beta_t)(1-\bar{\alpha}_t)}}_{\lambda_t} ||\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t}\, \mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\, \epsilon, t)||^2 \right]$$

Used in practice:

$$L_{\text{simple}} = \mathbb{E}_{\mathbf{x}_0 \sim q(\mathbf{x}_0), \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), t \sim \mathcal{U}(1,T)} \left[||\epsilon - \epsilon_\theta(\underbrace{\sqrt{\bar{\alpha}_t}\, \mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\, \epsilon}_{\mathbf{x}_t}, t)||^2 \right]$$

How do we train?



Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \mathrm{Uniform}(\{1, \ldots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on

$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$

6: **until** converged

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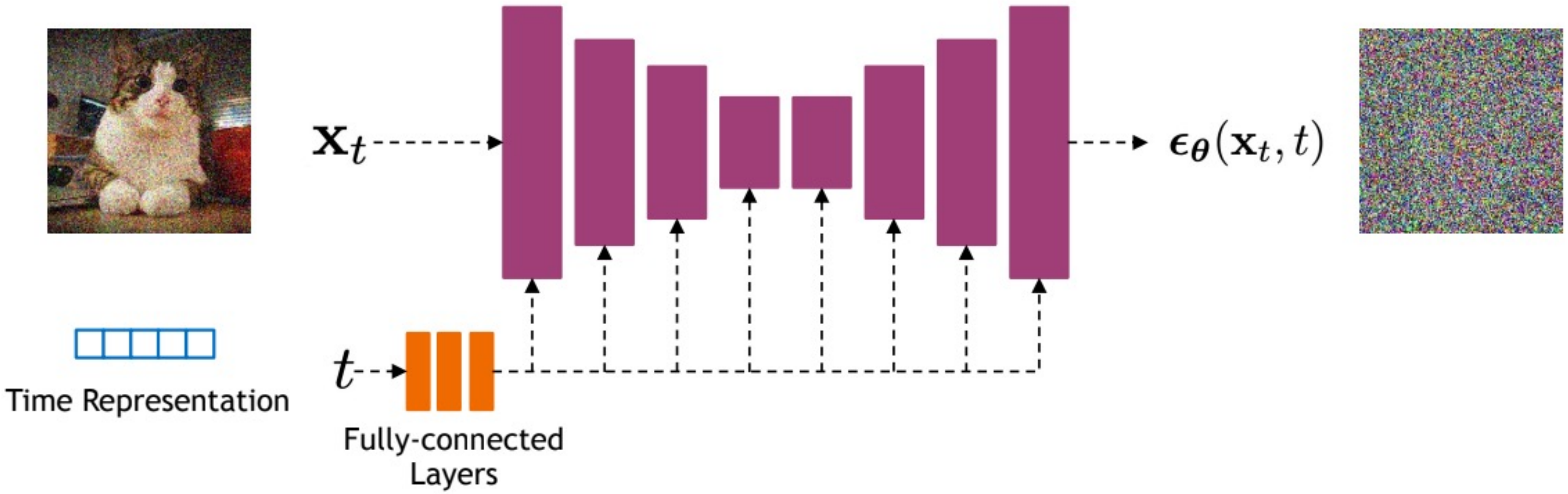
Unet to model transition

Diffusion models often use U-Net architectures with ResNet blocks and self-attention layers to represent $\epsilon_\theta(\mathbf{x}_t, t)$



Time representation: sinusoidal positional embeddings or random Fourier features.

Time features are fed to the residual blocks using either simple spatial addition or using adaptive group normalization layers. (see Dharivwal and Nichol NeurIPS 2021)

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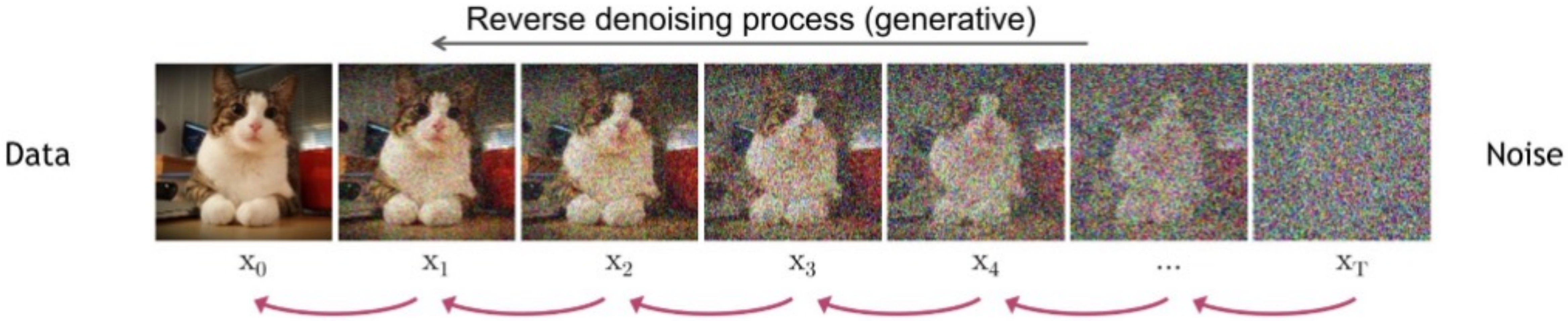
How do we train?

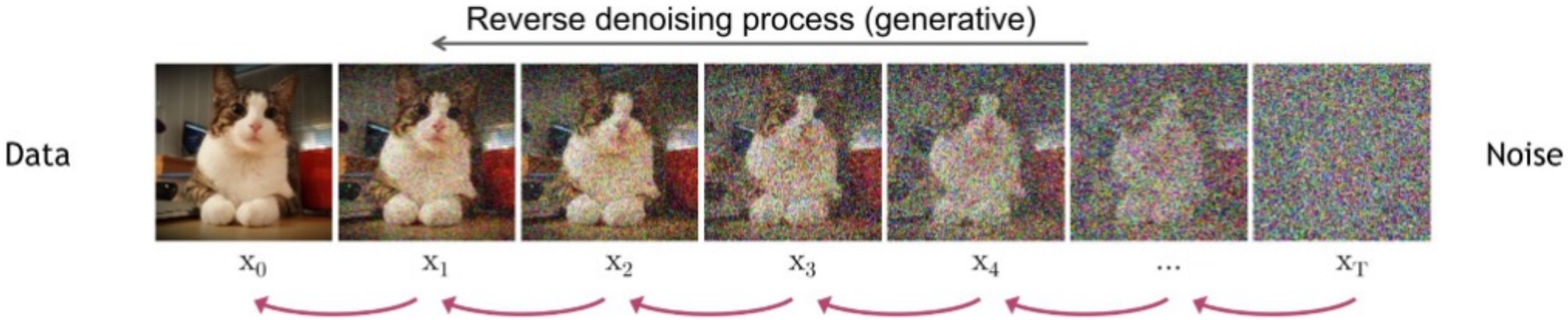


Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \ldots, 1$ **do**
3: $\quad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\quad \mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

https://cvpr2022-tutorial-diffusion-models.github.io/

How do we train?



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5: Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

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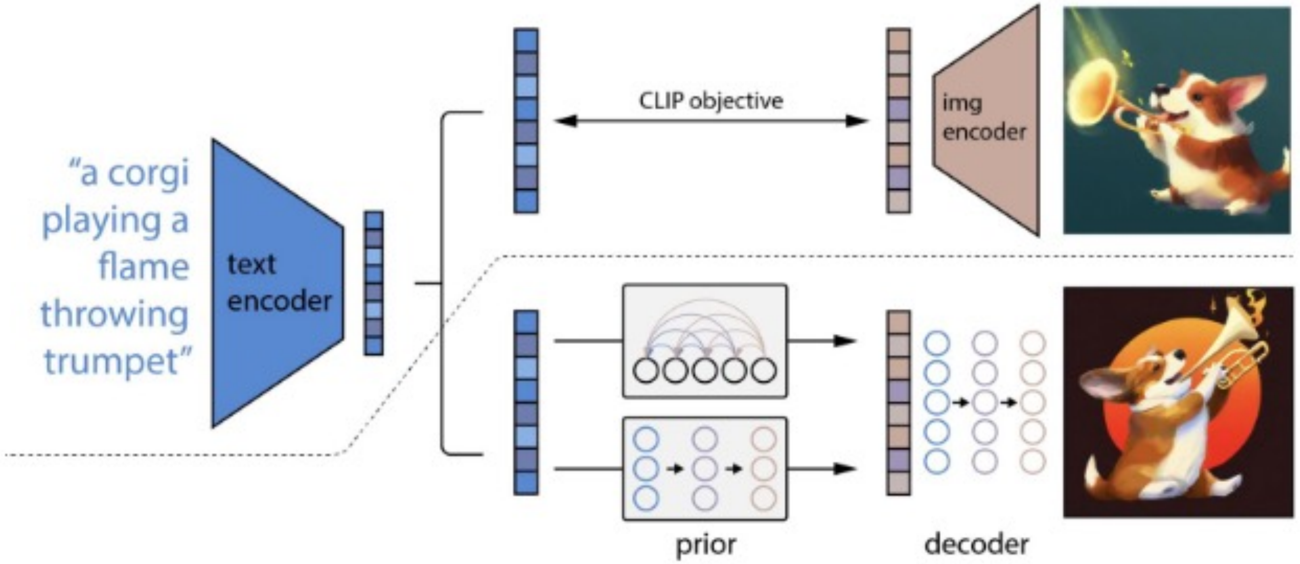
DALL.E 2 | Open AI

Conditioning on CLIP-embeddings

- Helps capture multimodal representations

- The bi-partite latent enables several text-controlled image manipulation tasks



Ramesh, Aditya, et al. "Hierarchical text-conditional image generation with clip latents." *arXiv preprint arXiv:2204.06125* (2022).

DALL.E 2 | OpenAI

- 1kx1k text-conditioned image generation
- Uses a **prior** to produce CLIP embeddings conditioned on the text-caption
- Uses a **decoder** to produce images conditioned on the CLIP embeddings


a shiba inu wearing a beret and black turtleneck


a close up of a handpalm with leaves growing from it


panda mad scientist mixing sparkling chemicals, artstation


a corgi's head depicted as an explosion of a nebula

Slides compiled by my student Aman Shrivastava

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Imagen by Google

A cute corgi lives in a house made out of sushi.

A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

Imagen by Google

2.2 Diffusion models and classifier-free guidance

Here we give a brief introduction to diffusion models; a precise description is in Appendix A. Diffusion models [63, 28, 65] are a class of generative models that convert Gaussian noise into samples from a learned data distribution via an iterative denoising process. These models can be conditional, for example on class labels, text, or low-resolution images [e.g. 16, 29, 59, 58, 75, 41, 54]. A diffusion model $\hat{\mathbf{x}}_\theta$ is trained on a denoising objective of the form

$$\mathbb{E}_{\mathbf{x},\mathbf{c},\boldsymbol{\epsilon},t}\left[w_t \|\hat{\mathbf{x}}_\theta(\alpha_t \mathbf{x} + \sigma_t \boldsymbol{\epsilon}, \mathbf{c}) - \mathbf{x}\|_2^2\right] \tag{1}$$

where $(\mathbf{x}, \mathbf{c})$ are data-conditioning pairs, $t \sim \mathcal{U}([0, 1])$, $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, and α_t, σ_t, w_t are functions of t that influence sample quality. Intuitively, $\hat{\mathbf{x}}_\theta$ is trained to denoise $\mathbf{z}_t := \alpha_t \mathbf{x} + \sigma_t \boldsymbol{\epsilon}$ into $\mathbf{x}$ using a squared error loss, weighted to emphasize certain values of t. Sampling such as the ancestral sampler [28] and DDIM [64] start from pure noise $\mathbf{z}_1 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ and iteratively generate points $\mathbf{z}_{t_1}, \ldots, \mathbf{z}_{t_T}$, where $1 = t_1 > \cdots > t_T = 0$, that gradually decrease in noise content. These points are functions of the $\mathbf{x}$-predictions $\hat{\mathbf{x}}_0^t := \hat{\mathbf{x}}_\theta(\mathbf{z}_t, \mathbf{c})$.

https://arxiv.org/pdf/2205.11487.pdf

Questions