The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

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ADVANCED TOPICS IN COMPUTER VISION

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You reposted

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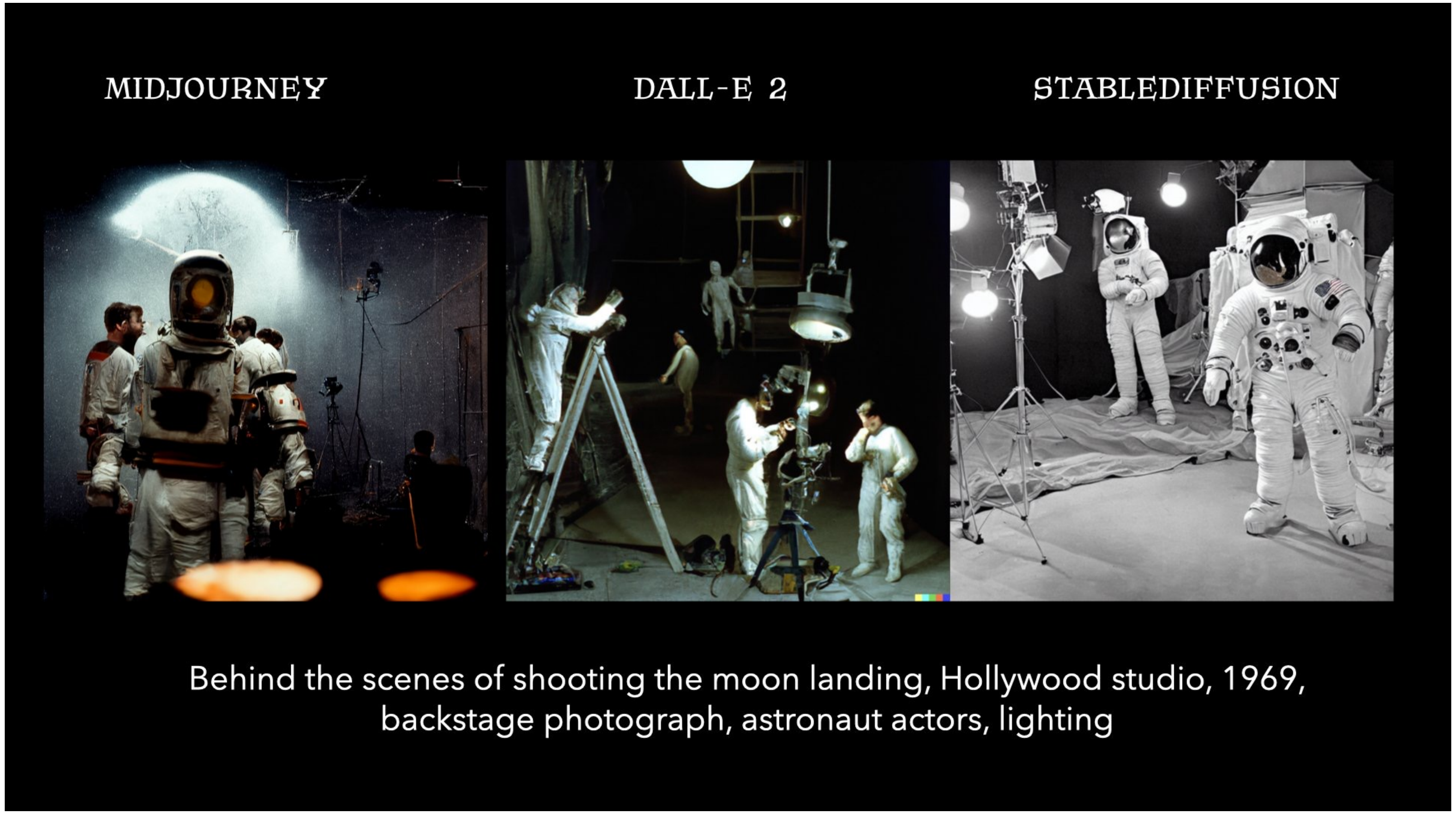
Research summary for the last 3 years...

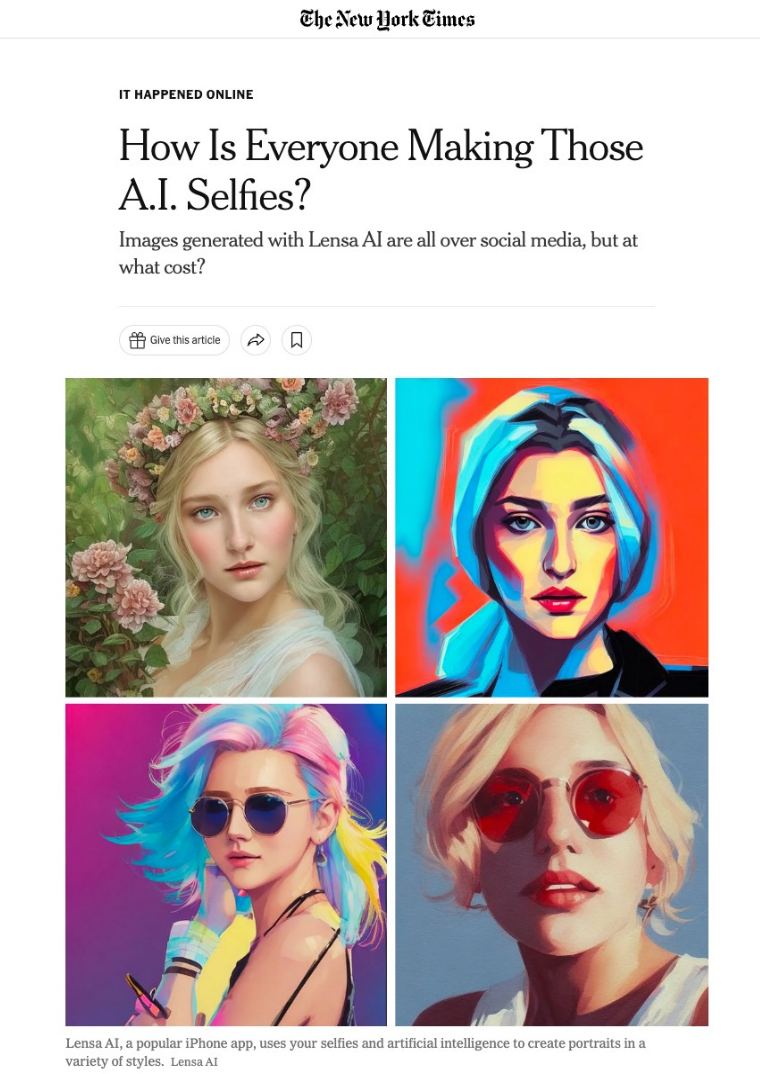
2021: Replace every CNN with a Transformer
2022: Replace every GAN with diffusion models
2023: Replace every NeRF with Gaussian splatting

9:02 AM · Oct 17, 2023 · **173.7K** Views

32 243 1.9K 404

$$$$$ market: Text2Image (video, 3D…)!




The New York Times

IT HAPPENED ONLINE

How Is Everyone Making Those A.I. Selfies?

Images generated with Lensa AI are all over social media, but at what cost?

Give this article

Lensa AI, a popular iPhone app, uses your selfies and artificial intelligence to create portraits in a variety of styles. Lensa AI

This part slides were **heavily borrowed from** https://cvpr2022-tutorial-diffusion-models.github.io/ and https://cvpr2023-tutorial-diffusion-models.github.io . **THANK YOU!**

DALL·E 2

"a teddy bear on a skateboard in times square"

"Hierarchical Text-Conditional Image Generation with CLIP Latents"
Ramesh et al., 2022

Imagen

A group of teddy bears in suit in a corporate office celebrating the birthday of their friend. There is a pizza cake on the desk.

"Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding", Saharia et al., 2022

The Workhorse: *Diffusion Models*

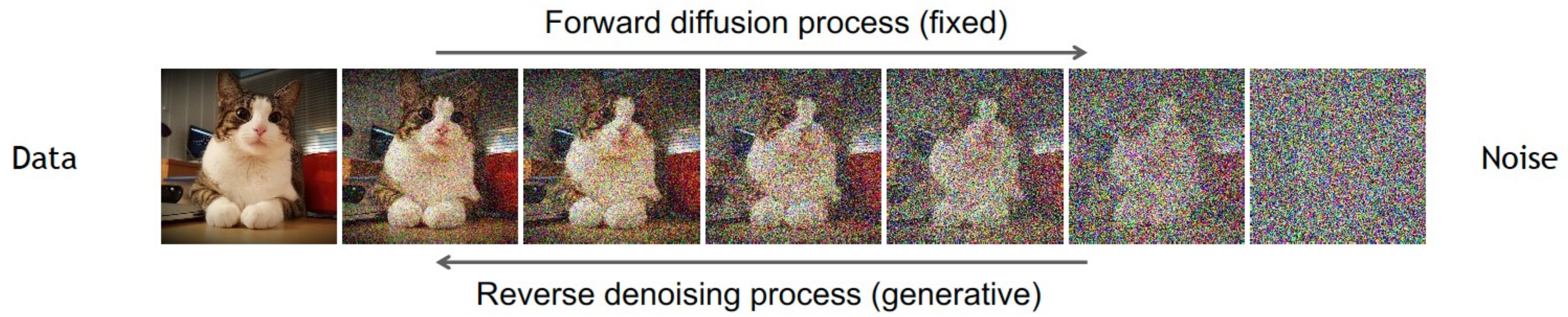
"Diffusion Models Beat GANs on Image Synthesis"
Dhariwal & Nichol, OpenAI, 2021

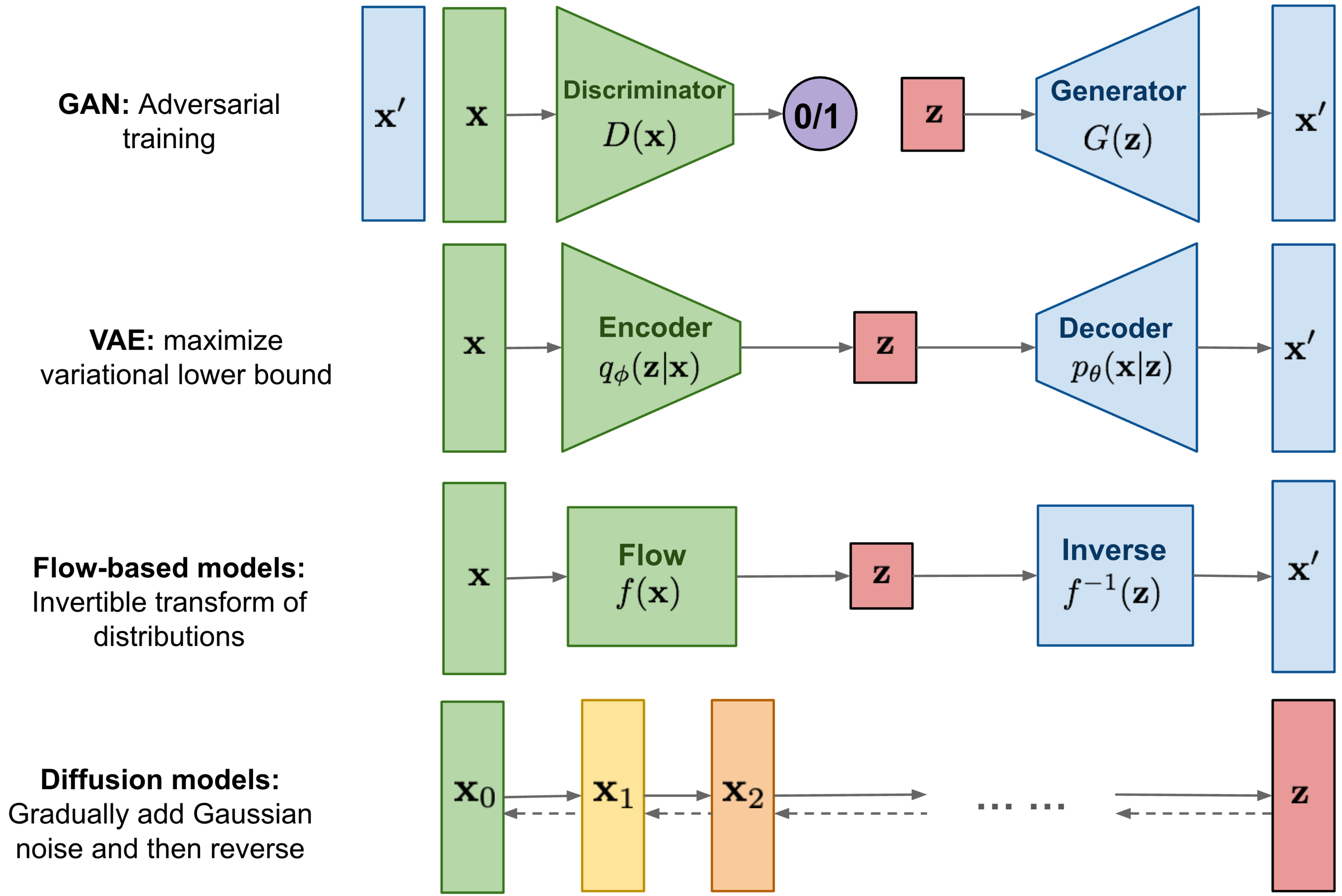
"Cascaded Diffusion Models for High Fidelity Image Generation"
Ho et al., Google, 2021

Learning to generate by denoising

Denoising diffusion models consist of two processes:

- Forward diffusion process that gradually adds noise to input
- Reverse denoising process that learns to generate data by denoising




GAN: Adversarial training
$\mathbf{x}'$
$\mathbf{x}$
Discriminator $D(\mathbf{x})$
0/1
$\mathbf{z}$
Generator $G(\mathbf{z})$
$\mathbf{x}'$
VAE: maximize variational lower bound
$\mathbf{x}$
Encoder $q_\phi(\mathbf{z}|\mathbf{x})$
$\mathbf{z}$
Decoder $p_\theta(\mathbf{x}|\mathbf{z})$
$\mathbf{x}'$
Flow-based models: Invertible transform of distributions
$\mathbf{x}$
Flow $f(\mathbf{x})$
$\mathbf{z}$
Inverse $f^{-1}(\mathbf{z})$
$\mathbf{x}'$
Diffusion models: Gradually add Gaussian noise and then reverse
$\mathbf{x}_0$
$\mathbf{x}_1$
$\mathbf{x}_2$
... ...
$\mathbf{z}$

Variational Autoencoders (VAEs)

- We introduce an **inference model** q(z|x)

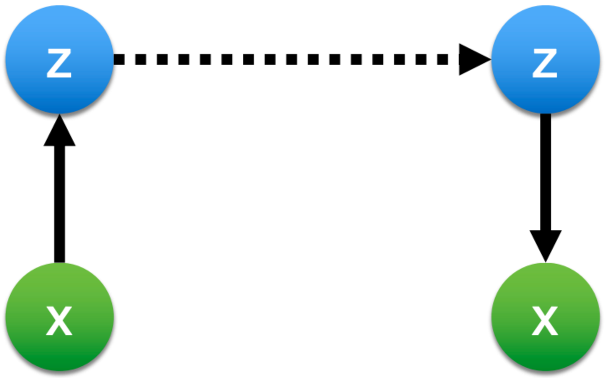
$$q_\phi(\mathbf{z}|\mathbf{x}) = \mathcal{N}(\boldsymbol{\mu}_\phi(\mathbf{x}), \boldsymbol{\Sigma}_\phi(\mathbf{x}))$$

- This allows us to efficiently optimize the log-likelihood, through the **evidence lower bound** (ELBO).

$$\log p_{\theta,\phi}(\mathbf{x}) \geq \mathrm{ELBO}(\mathbf{x}) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[\log \frac{p_\theta(\mathbf{x},\mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})}\right]$$

- We optimize q(z|x) and p(x,z) jointly w.r.t. ELBO

- Bound is tight with the right q(z|x)



Inference model
q(z|x)

Generative model
p(x,z)

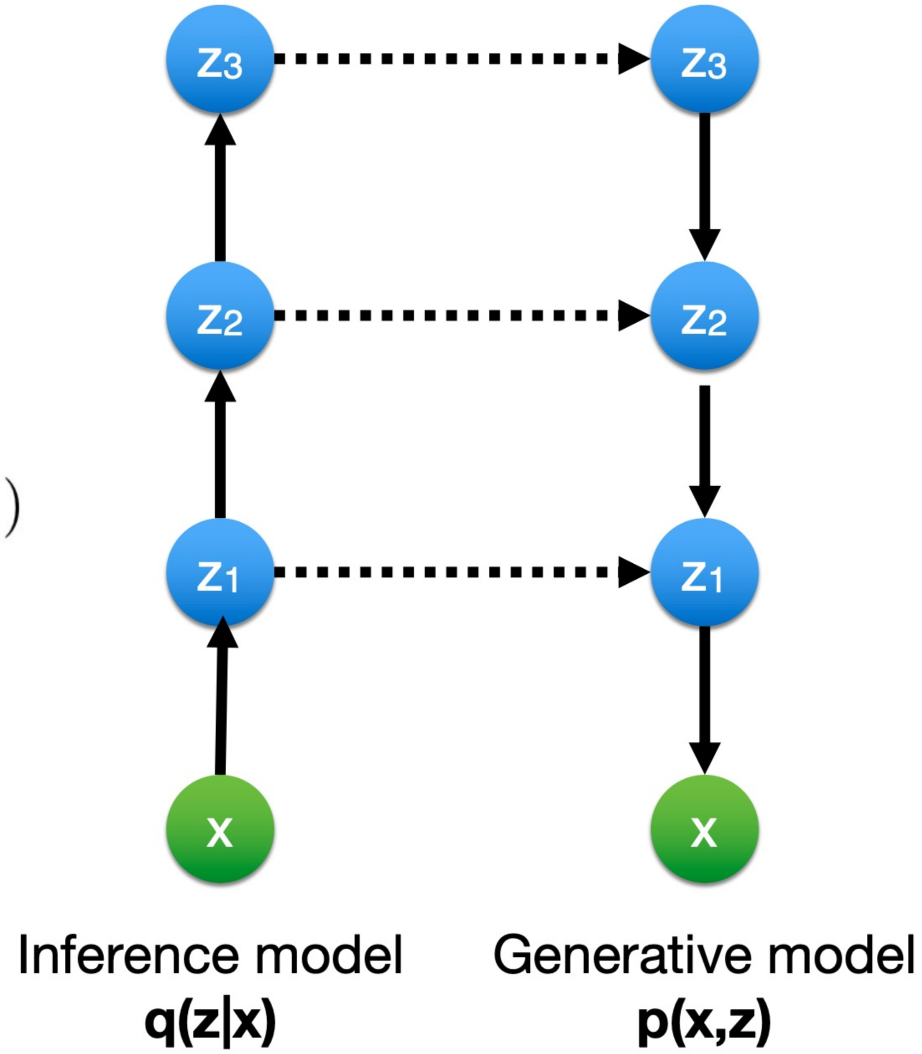
Hierarchical VAEs

- "Flat" VAEs suffer from simple priors
- Making both inference model and generative model hierarchical

$$q_\phi(\mathbf{z}_{1,2,3}|\mathbf{x}) = q_\phi(\mathbf{z}_1|\mathbf{x})q_\phi(\mathbf{z}_2|\mathbf{z}_1)q_\phi(\mathbf{z}_3|\mathbf{z}_2)$$

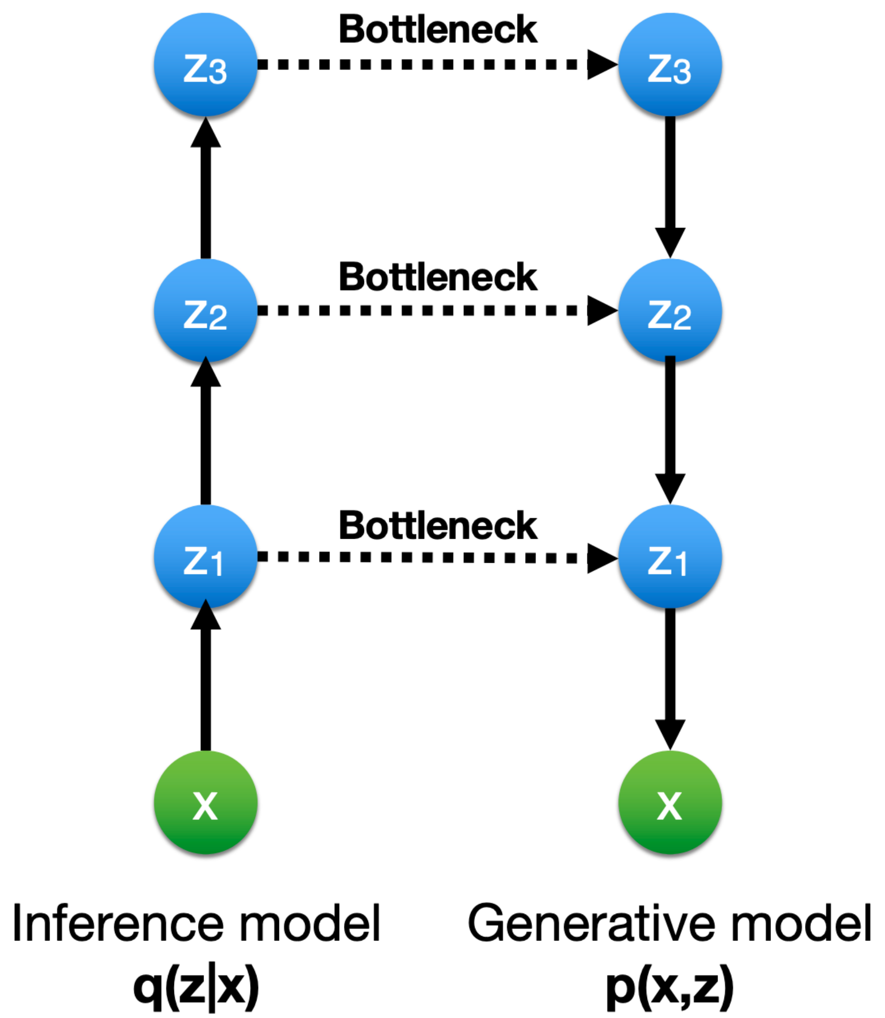
$$p_\theta(\mathbf{z}_{1,2,3}) = p_\theta(\mathbf{z}_3)p_\theta(\mathbf{z}_2|\mathbf{z}_3)p_\theta(\mathbf{z}_1|\mathbf{z}_2)p_\theta(\mathbf{x}|\mathbf{z}_1)$$

- Better likelihoods are achieved with hierarchies of latent variables



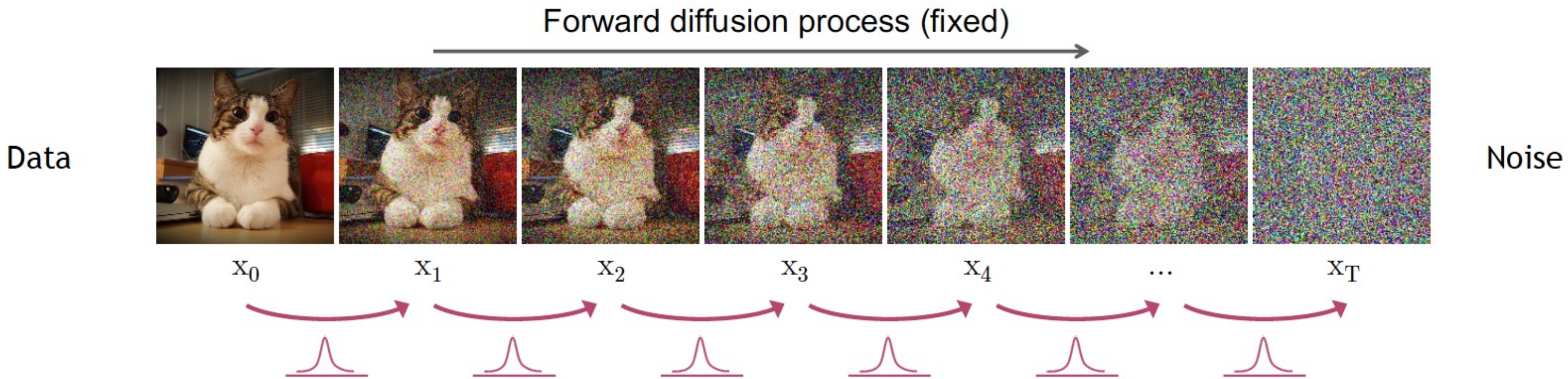
VAEs: challenges

- Optimization can be difficult for large models
- The ELBO enforces an **information bottleneck** (through its loss function) at the latent variables 'z', making VAE optimization prone to **bad local minima**.
- **Posterior collapse** is a dreaded bad local minimum where the latents do not transmit any information.

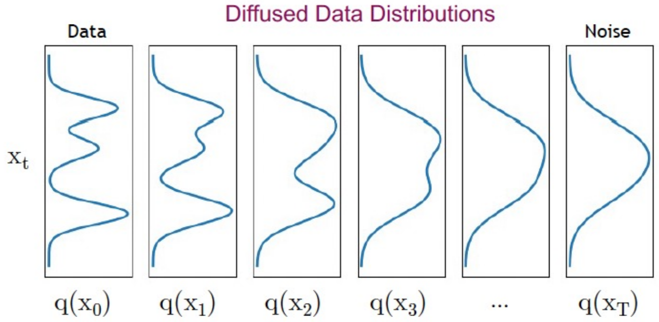


Forward Diffusion Process

The formal definition of the forward process in T steps:

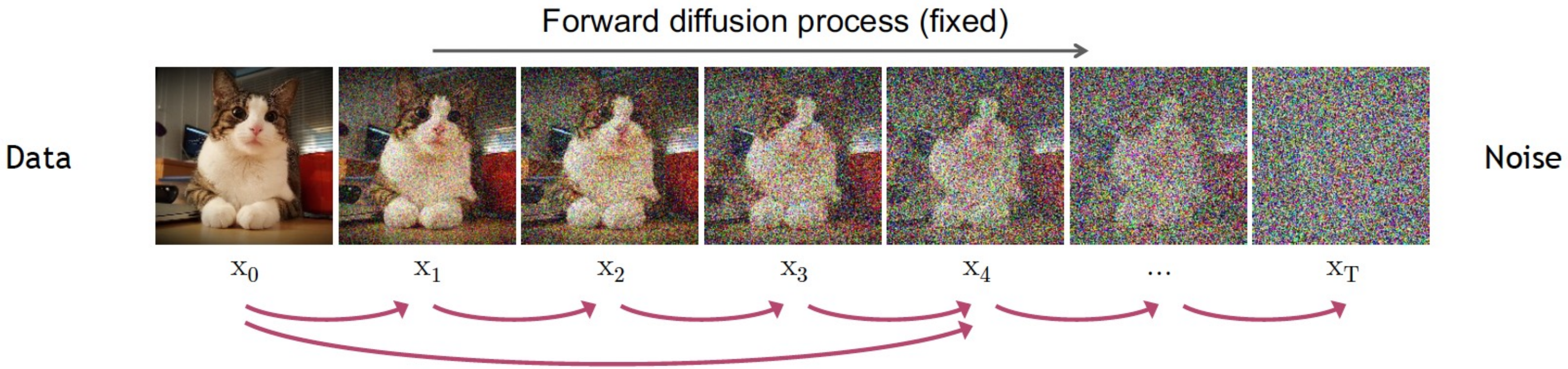


$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x_t}; \sqrt{1-\beta_t}\mathbf{x_{t-1}}, \beta_t\mathbf{I}) \quad \Rightarrow \quad q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$



Similar to the inference model in hierarchical VAEs

Sampling at arbitrary time step with “reparameterization trick”



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 $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

The diffusion kernel is Gaussian convolution.

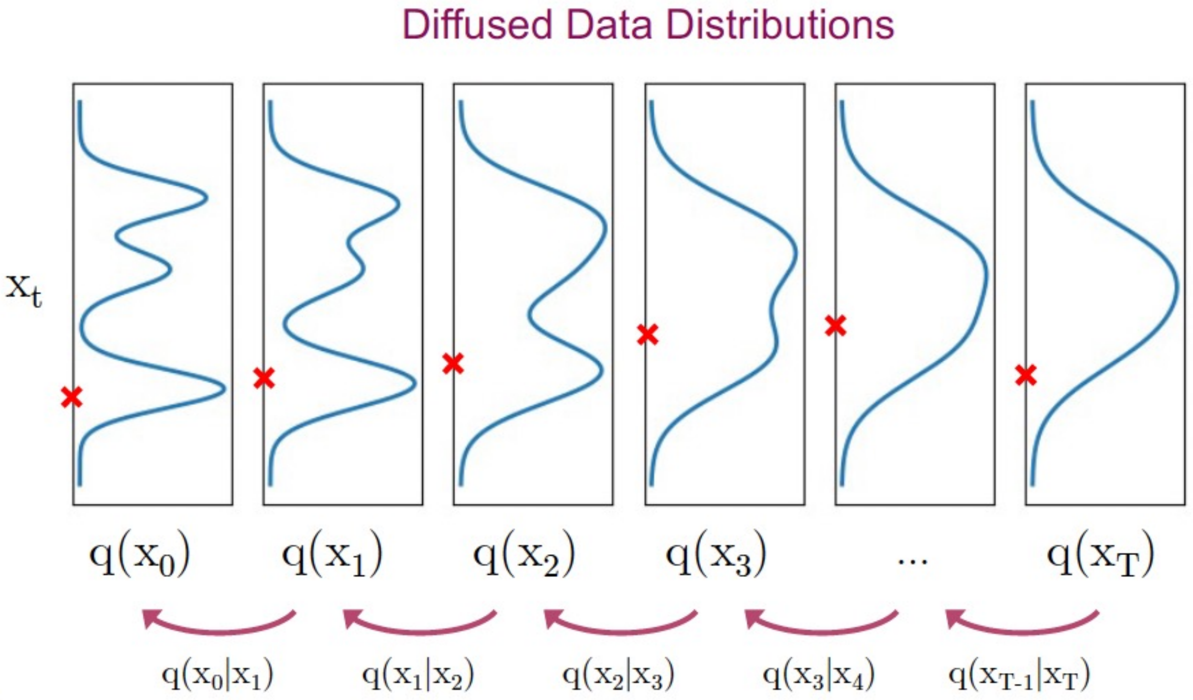
β_t values schedule (i.e., the noise schedule) is designed such that $\bar{\alpha}_T \to 0$ and $q(\mathbf{x}_T|\mathbf{x}_0) \approx \mathcal{N}(\mathbf{x}_T; \mathbf{0}, \mathbf{I}))$

Key trick: what happens if we add/merge two Gaussians?

If X_1 and X_2 are two independent normal random variables, with means μ_1, μ_2 and standard deviations σ_1, σ_2, then their sum $X_1 + X_2$ will also be normally distributed,[proof] with mean $\mu_1 + \mu_2$ and variance $\sigma_1^2 + \sigma_2^2$

Generative Learning by Denoising

Recall, that the diffusion parameters are designed such that $q(\mathbf{x}_T) \approx \mathcal{N}(\mathbf{x}_T; \mathbf{0}, \mathbf{I})$



Generation:

Sample $\mathbf{x}_T \sim \mathcal{N}(\mathbf{x}_T; \mathbf{0}, \mathbf{I})$

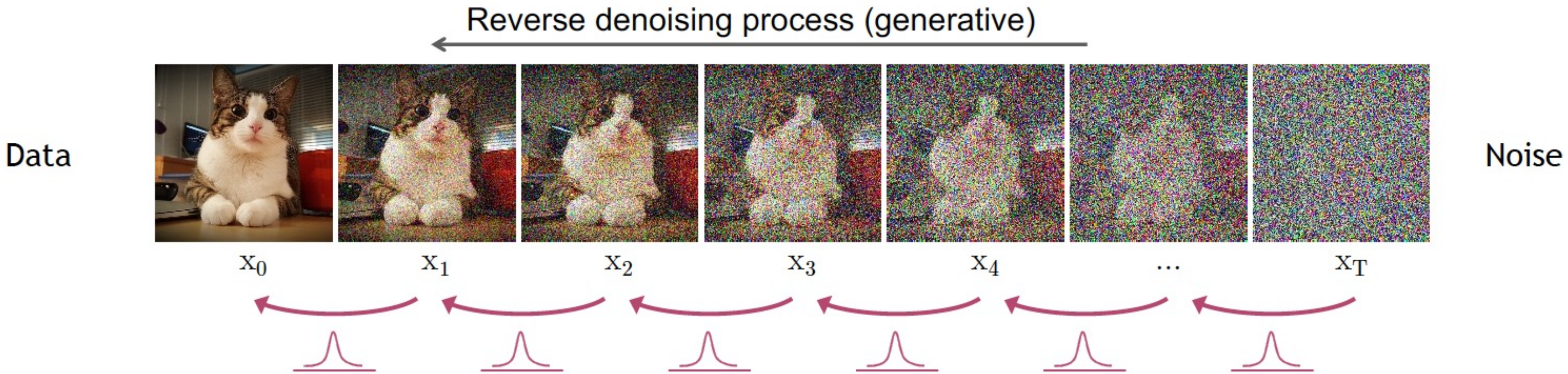
Iteratively sample $\mathbf{x}_{t-1} \sim \underbrace{q(\mathbf{x}_{t-1}|\mathbf{x}_t)}_{\text{True Denoising Dist.}}$

In general, $q(\mathbf{x}_{t-1}|\mathbf{x}_t) \propto q(\mathbf{x}_{t-1})q(\mathbf{x}_t|\mathbf{x}_{t-1})$ is intractable.

Can we approximate $q(\mathbf{x}_{t-1}|\mathbf{x}_t)$? Yes, we can use a Normal distribution if β_t is small in each forward diffusion step.

Reverse Denoising Process

Formal definition of forward and reverse processes in T steps:



$$p(\mathbf{x}_T) = \mathcal{N}(\mathbf{x}_T; \mathbf{0}, \mathbf{I})$$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \underbrace{\mu_\theta(\mathbf{x}_t, t)}_{\substack{\text{Trainable network} \\ \text{(U-net, Denoising Autoencoder)}}}, \sigma_t^2\mathbf{I})$$

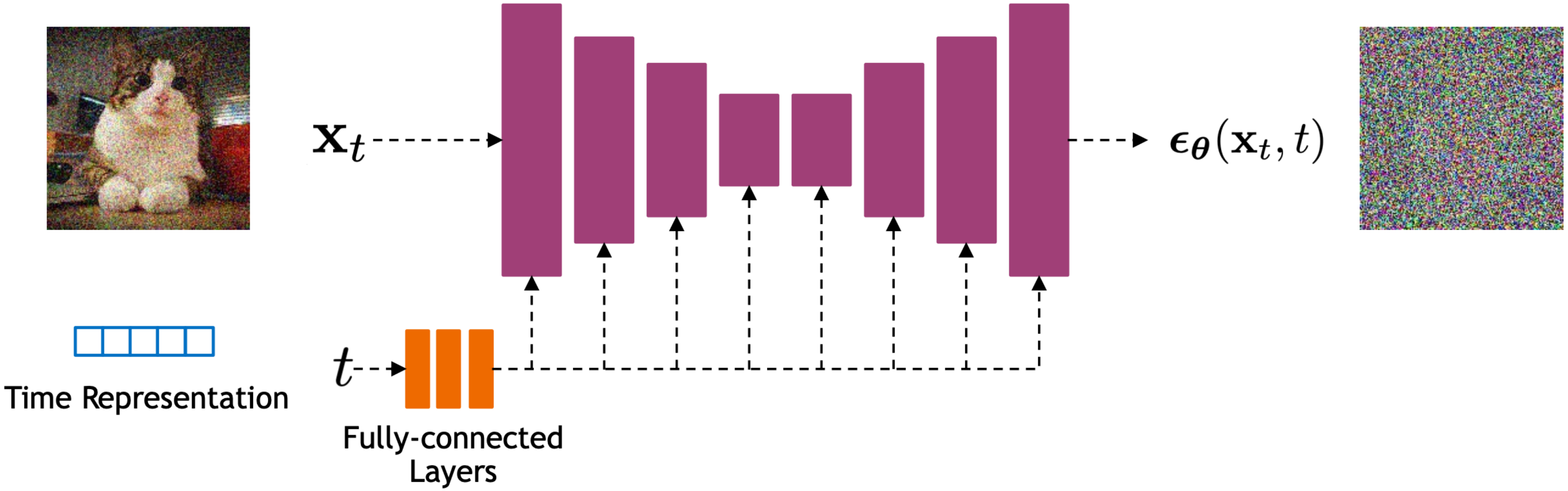
$$\frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t} \cdot \beta_t$$

$$\Rightarrow \quad p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$$

Similar to the generative model in hierarchical VAEs

Reverse Denoising Process

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)

Training Loss (simplified)

After applying the variational lower bound …

(see details here)

$$
\begin{aligned}
L_t &= \mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon}}\Big[\frac{1}{2\|\boldsymbol{\Sigma}_\theta(\mathbf{x}_t,t)\|_2^2}\|\tilde{\boldsymbol{\mu}}_t(\mathbf{x}_t,\mathbf{x}_0)-\boldsymbol{\mu}_\theta(\mathbf{x}_t,t)\|^2\Big] \\
&= \mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon}}\Big[\frac{1}{2\|\boldsymbol{\Sigma}_\theta\|_2^2}\|\frac{1}{\sqrt{\alpha_t}}\Big(\mathbf{x}_t-\frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_t\Big)-\frac{1}{\sqrt{\alpha_t}}\Big(\mathbf{x}_t-\frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t,t)\Big)\|^2\Big] \\
&= \mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon}}\Big[\frac{(1-\alpha_t)^2}{2\alpha_t(1-\bar{\alpha}_t)\|\boldsymbol{\Sigma}_\theta\|_2^2}\|\boldsymbol{\epsilon}_t-\boldsymbol{\epsilon}_\theta(\mathbf{x}_t,t)\|^2\Big] \\
&= \mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon}}\Big[\frac{(1-\alpha_t)^2}{2\alpha_t(1-\bar{\alpha}_t)\|\boldsymbol{\Sigma}_\theta\|_2^2}\|\boldsymbol{\epsilon}_t-\boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0+\sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}_t,t)\|^2\Big]
\end{aligned}
$$

Empirically, Ho et al. (2020) found that training the diffusion model works better with a simplified objective that ignores the weighting term:

$$
\begin{aligned}
L_t^{\text{simple}} &= \mathbb{E}_{t\sim[1,T],\mathbf{x}_0,\boldsymbol{\epsilon}_t}\Big[\|\boldsymbol{\epsilon}_t-\boldsymbol{\epsilon}_\theta(\mathbf{x}_t,t)\|^2\Big] \\
&= \mathbb{E}_{t\sim[1,T],\mathbf{x}_0,\boldsymbol{\epsilon}_t}\Big[\|\boldsymbol{\epsilon}_t-\boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0+\sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}_t,t)\|^2\Big]
\end{aligned}
$$

Denoising diffusion probabilistic models (DDPM)

Algorithm 1 Training

repeat
  $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
  $t \sim \mathrm{Uniform}(\{1, \ldots, T\})$
  $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  Take gradient descent step on
  $$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\boxed{\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}}, t) \right\|^2$$
until converged

Algorithm 2 Sampling

$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
for $t = T, \ldots, 1$ **do**
  $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  $\mathbf{x}_{t-1} = \boxed{\frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right)} + \sigma_t \mathbf{z}$
end for
return $\mathbf{x}_0$

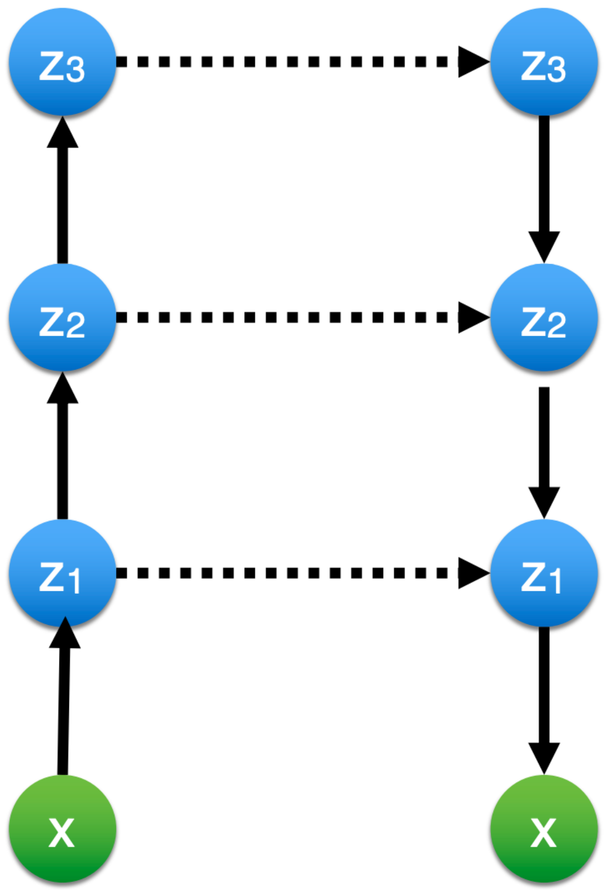
Full derivation: https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

Connection to VAEs

Diffusion models can be considered as a special form of hierarchical VAEs.

However, in diffusion models:

- The inference model is fixed: easier to optimize
- The latent variables have the same dimension as the data.
- The ELBO is decomposed to each time step: fast to train
    - Can be made extremely deep (even infinitely deep)
- The model is trained with some reweighting of the ELBO.

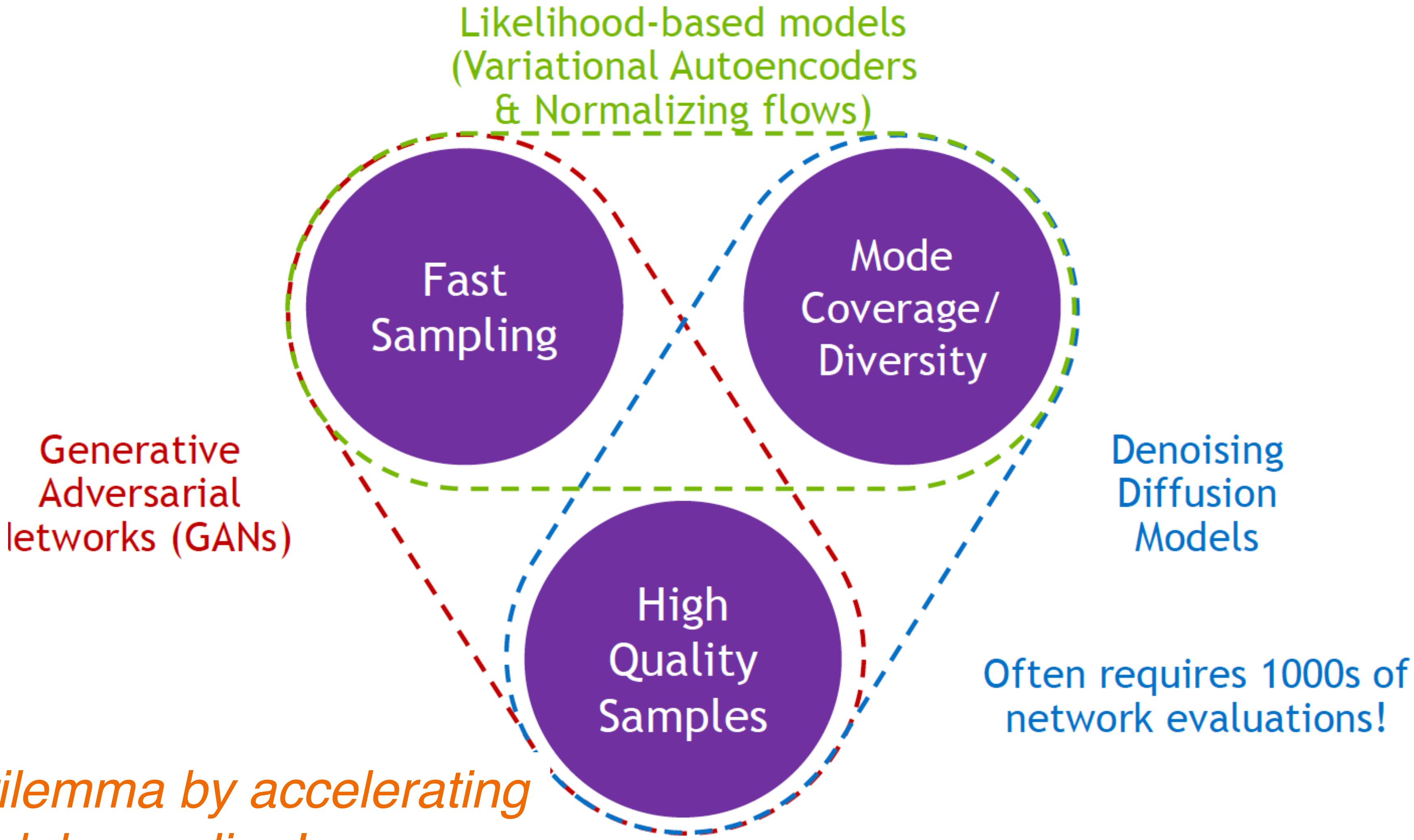


Inference model
q(z|x)

Generative model
p(x,z)

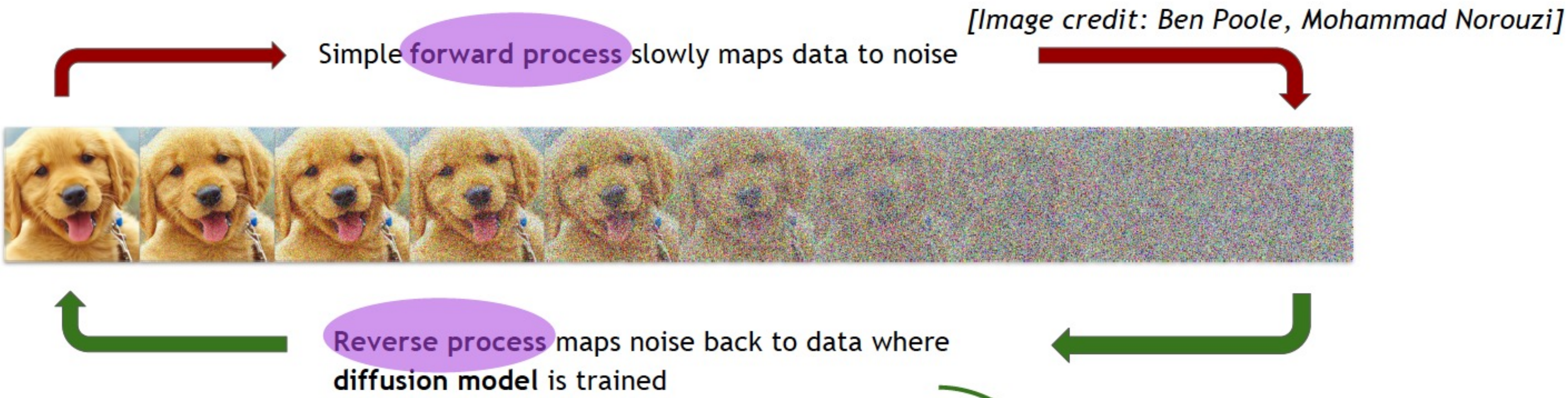
[Vahdat and Kautz, NVAE: A Deep Hierarchical Variational Autoencoder, NeurIPS 2020]
[Sønderby, et al.. Ladder variational autoencoders, NeurIPS 2016.]

The generative learning trilemma

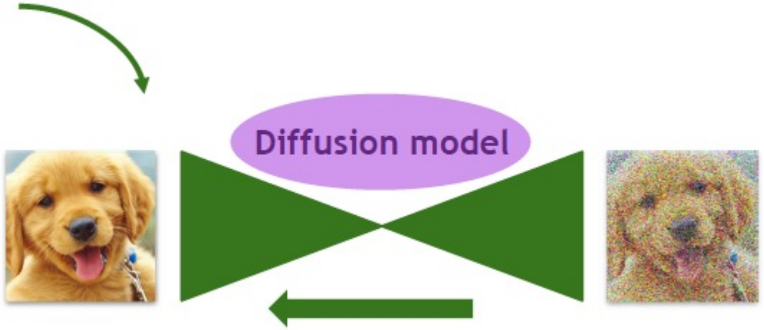


Tackle the trilemma by accelerating diffusion model sampling!

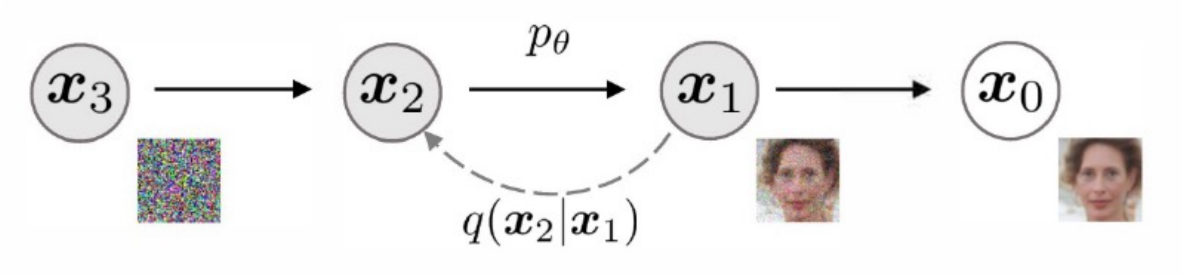
How to accelerate diffusion models?

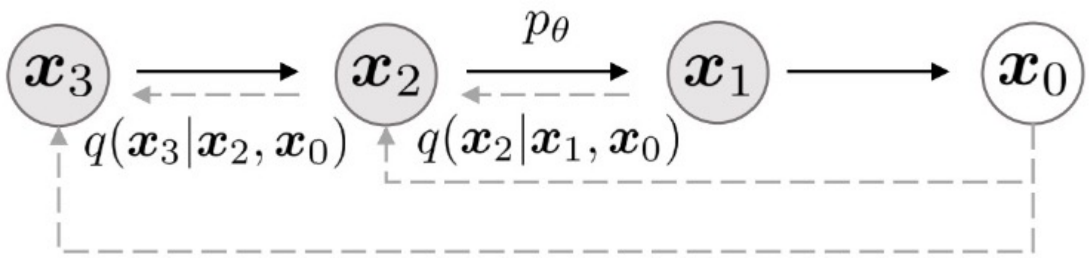


- Naïve acceleration methods, such as reducing diffusion time steps in training or sampling every k time step in inference, lead to immediate worse performance.
- We need something cleverer.
- Given a limited number of functional calls, usually much less than 1000s, how to improve performance?



From DDPM to DDIM: *Denoising diffusion implicit models*





Main Idea

Design a family of non-Markovian diffusion processes and corresponding reverse processes.

The process is designed such that the model can be optimized by the same surrogate objective as the original diffusion model.

$$L_{\text{simple}}(\theta) := \mathbb{E}_{t,\mathbf{x}_0,\boldsymbol{\epsilon}}\left[\left\|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t)\right\|^2\right]$$

Therefore, can take a pretrained diffusion model but with more choices of sampling procedure.

From DDPM to DDIM: *Denoising diffusion implicit models*

$$p(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}\left(\sqrt{\bar{\alpha}_{t-1}}\hat{\mathbf{x}}_0 + \sqrt{1-\bar{\alpha}_{t-1}-\tilde{\sigma}_t^2}\cdot\frac{\mathbf{x}_t-\sqrt{\bar{\alpha}_t}\hat{\mathbf{x}}_0}{\sqrt{1-\bar{\alpha}_t}}, \tilde{\sigma}_t^2\mathbf{I}\right)$$

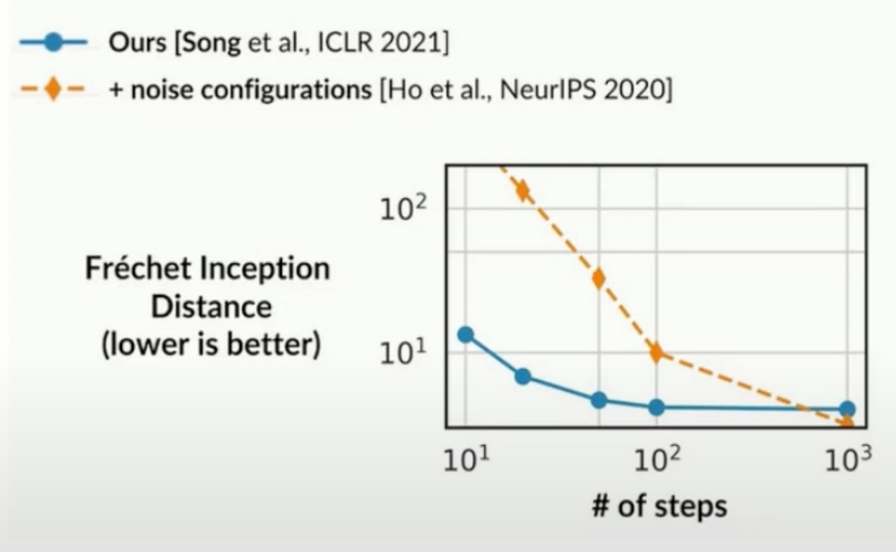
- … often using its **deterministic form**: $\tilde{\sigma}_t^2 = 0, \forall t$
- With DDIM, it is possible to train the diffusion model up to any arbitrary number of forward steps but only **sample from a subset of steps in the generative process**

- **During Generation ($s < k$):** DDIM is not a new model, just a special sampling way

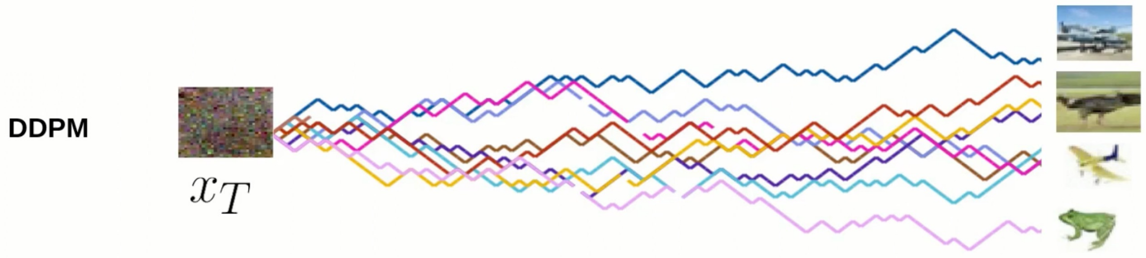
$$\boxed{x_s = \sqrt{\bar{\alpha}_s}\left(\frac{x_k - \sqrt{1-\bar{\alpha}_k}\epsilon_\theta(x_k)}{\sqrt{\bar{\alpha}_k}}\right) + \sqrt{1-\bar{\alpha}_s-\sigma^2}\epsilon_\theta(x_k) + \sigma\epsilon}$$

Quick DDIM Facts:

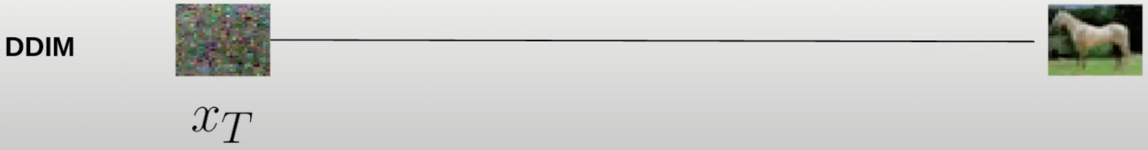
- Not a new model, just a new sampling way – **can apply to any pre-trained diffusion model** e.g. DDPM!
- Generate good samples (maybe slightly worse than DDPM) using a much fewer number of steps (**20-100**); DDPM won't work well with T<100!
- Have "**consistency**" property since the generative process is deterministic, meaning that multiple samples conditioned on the same latent *z* should have similar high-level features.
- Because of the consistency, DDIM can do **semantically meaningful latent interpolation**.
- The default sampler in Stable Diffusion v1 (now we have more!)



- When sigma =! 0 : stochastic process



- When sigma = 0 (DDIM case) : deterministic process
  - The same original noise Xt leads to the same image X0



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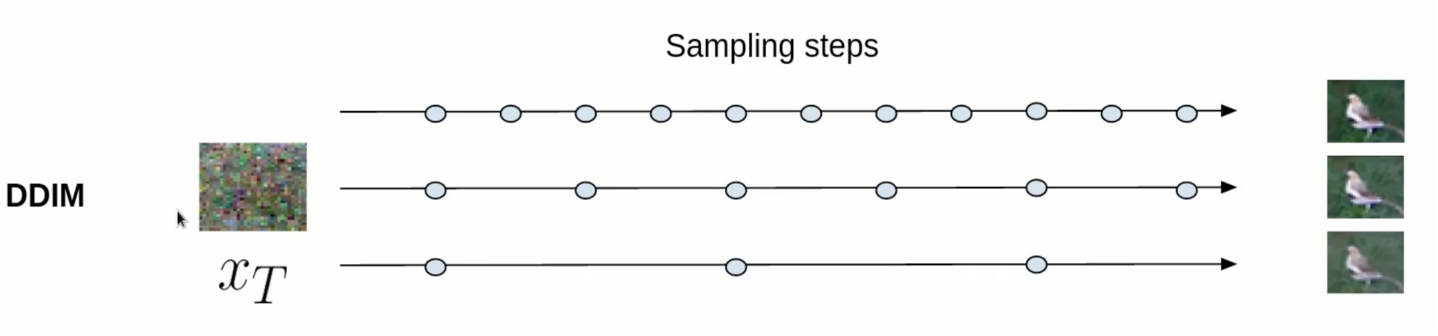
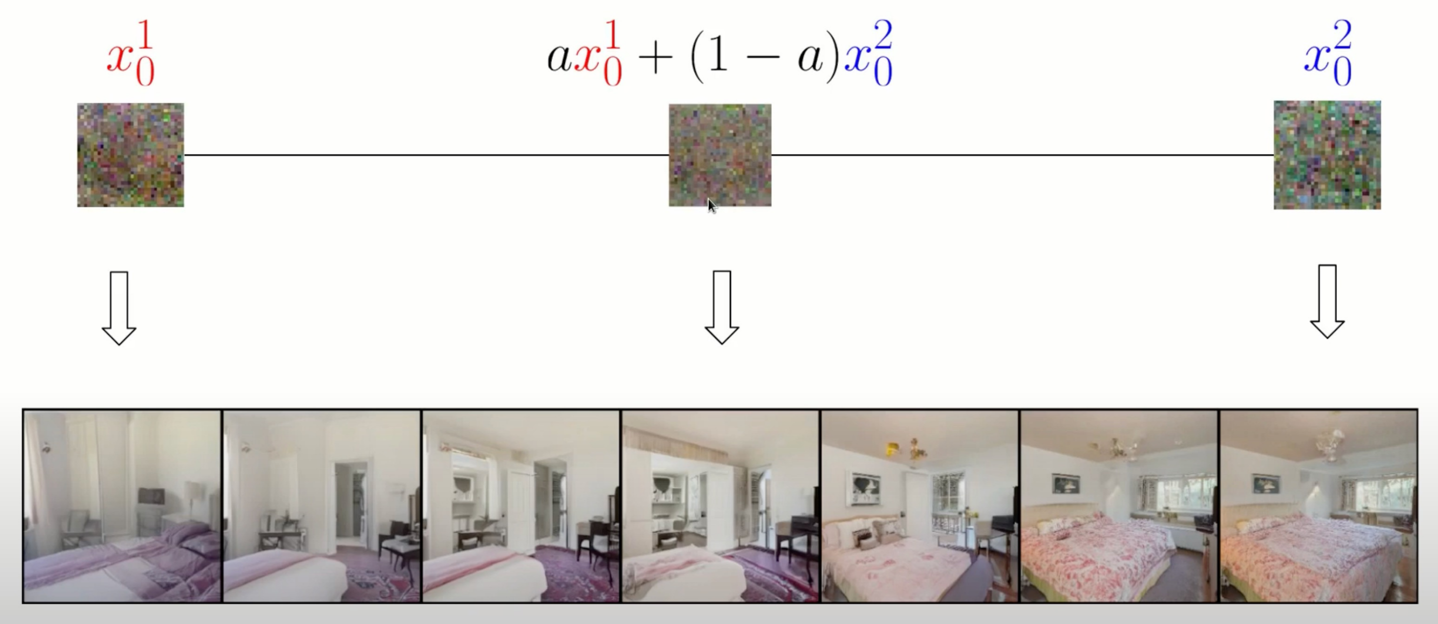
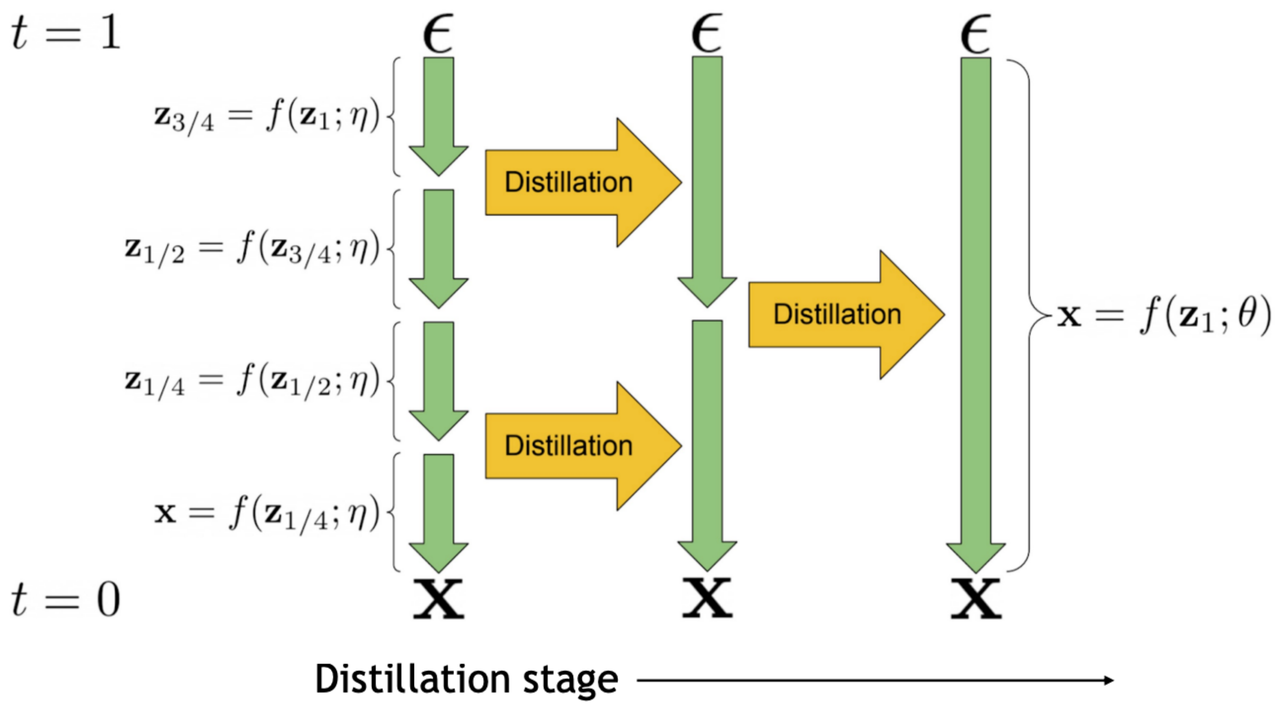




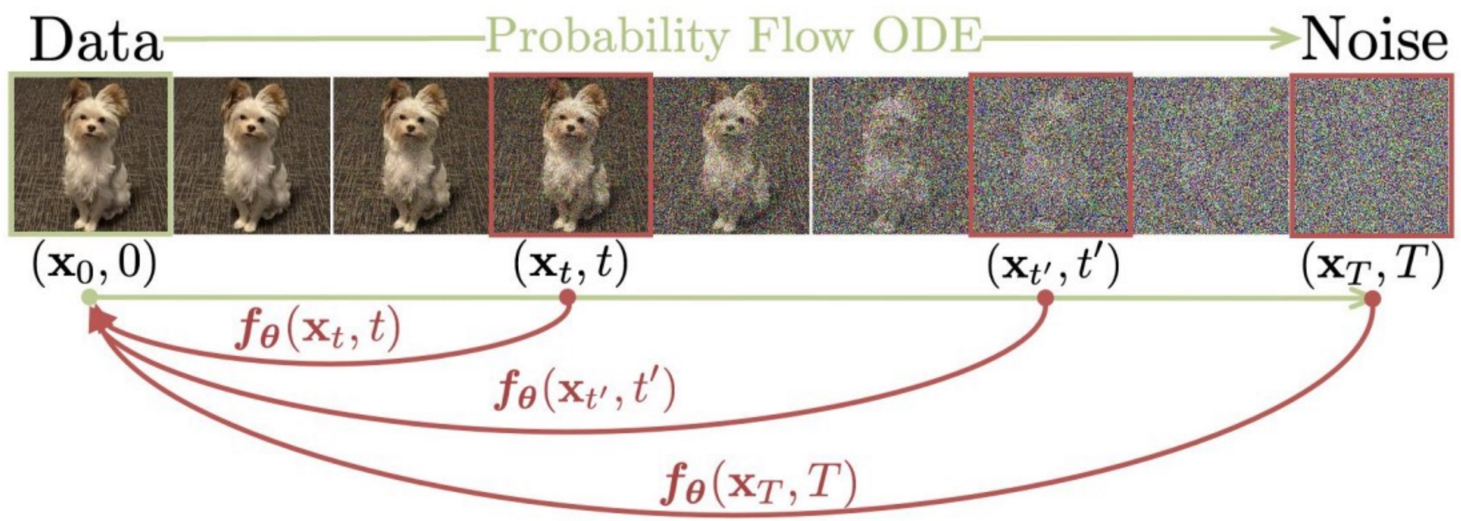
Distill diffusion models into models using just 4-8 sampling steps!

- Distill a deterministic ODE sampler (i.e. DDIM sampler) to the same model architecture.
- At each stage, a “student” model is learned to distill two adjacent sampling steps of the “teacher” model to one sampling step.
- At next stage, the “student” model from previous stage will serve as the new “teacher” model.



Salimans & Ho, “Progressive distillation for fast sampling of diffusion models”, ICLR 2022.

Consistency Model (a special distillation)



- Given a Probability Flow ODE that smoothly converts data to noise, Consistency model learns to map any point on the ODE trajectory to its origin for generative modeling.
- Models of these mappings are called consistency models, as *their outputs are trained to be consistent for points on the same trajectory.*
- They support **fast one-step generation** by design, while still allowing multistep sampling to trade compute for sample quality

Conditional Generation

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

Variational upper bound: $L_\theta(\mathbf{x}_0|\mathbf{c}) = \mathbb{E}_q\left[L_T(\mathbf{x}_0) + \sum_{t>1} D_{\mathrm{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) \parallel p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{c})) - \log p_\theta(\mathbf{x}_0|\mathbf{x}_1, \mathbf{c})\right].$

Incorporate conditions into U-Net

- Scalar conditioning: encode scalar as a vector embedding, simple spatial addition or adaptive group normalization layers.
- Image conditioning: channel-wise concatenation of the conditional image.
- Text conditioning: single vector embedding - spatial addition or adaptive group norm / a seq of vector embeddings - cross-attention.

Classifier guidance: Guiding Sampling usin the gradient of a trained classifier

Algorithm 1 Classifier guided diffusion sampling, given a diffusion model $(\mu_\theta(x_t), \Sigma_\theta(x_t))$, classifier $p_\phi(y|x_t)$, and gradient scale s.

Input: class label y, gradient scale s
$x_T \leftarrow$ sample from $\mathcal{N}(0, \mathbf{I})$
for all t from T to 1 **do**
  $\mu, \Sigma \leftarrow \mu_\theta(x_t), \Sigma_\theta(x_t)$
  $x_{t-1} \leftarrow$ sample from $\mathcal{N}(\mu + s\Sigma \nabla_{x_t} \log p_\phi(y|x_t), \Sigma)$
end for
return x_0

Main Idea

For class-conditional modeling of $p(\mathbf{x}_t|\mathbf{c})$, train an extra classifier $p(\mathbf{c}|\mathbf{x}_t)$

Mix its gradient with the diffusion/score model during sampling

Sample with a modified score: $\nabla_{\mathbf{x}_t}[\log p(\mathbf{x}_t|\mathbf{c}) + \omega \log p(\mathbf{c}|\mathbf{x}_t)]$

Classifier-free guidance: Implicit trick via Bayesian rule

- Instead of training an additional classifier, get an "implicit classifier" by jointly training a conditional and unconditional diffusion model:

$$p(\mathbf{c}|\mathbf{x}_t) \propto p(\mathbf{x}_t|\mathbf{c})/p(\mathbf{x}_t)$$

Conditional diffusion model   Unconditional diffusion model

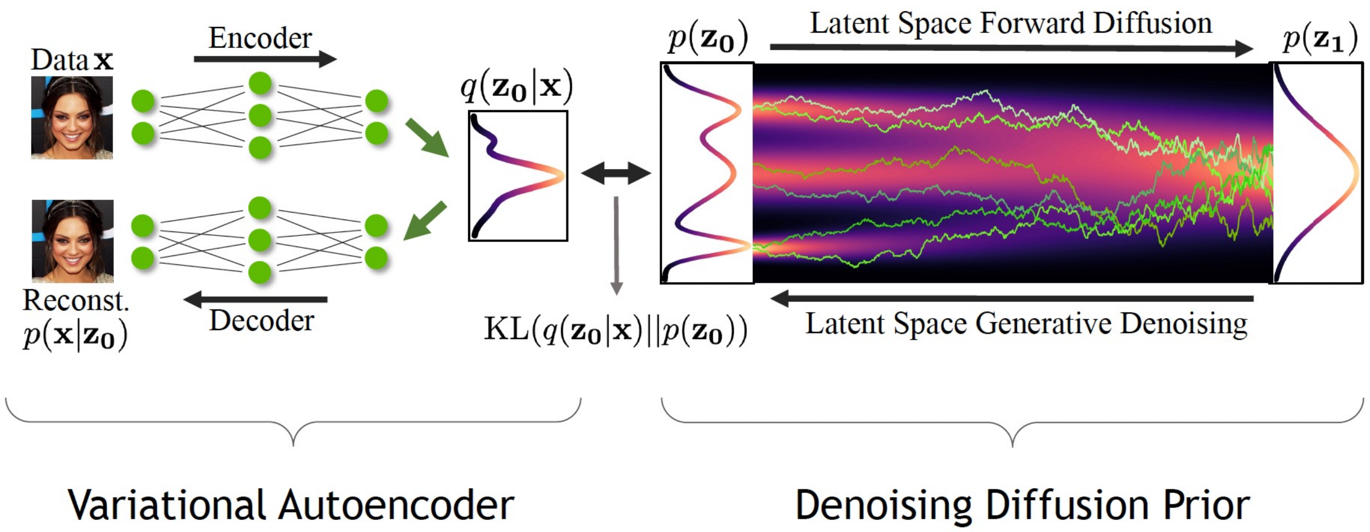
- In practice, $p(\mathbf{x}_t|\mathbf{c})$ and $p(\mathbf{x}_t)$ by randomly dropping the condition of the diffusion model at certain chance.

- The modified score with this implicit classifier included is:

$$\begin{aligned}\nabla_{\mathbf{x}_t}[\log p(\mathbf{x}_t|\mathbf{c}) + \omega \log p(\mathbf{c}|\mathbf{x}_t)] &= \nabla_{\mathbf{x}_t}[\log p(\mathbf{x}_t|\mathbf{c}) + \omega(\log p(\mathbf{x}_t|\mathbf{c}) - \log p(\mathbf{x}_t))] \\ &= \nabla_{\mathbf{x}_t}[(1+\omega)\log p(\mathbf{x}_t|\mathbf{c}) - \omega \log p(\mathbf{x}_t)]\end{aligned}$$

Latent Diffusion Models

Variational autoencoder + score-based prior



Advantages:

(1) The distribution of latent embeddings close to Normal distribution → *Simpler denoising, Faster synthesis!*

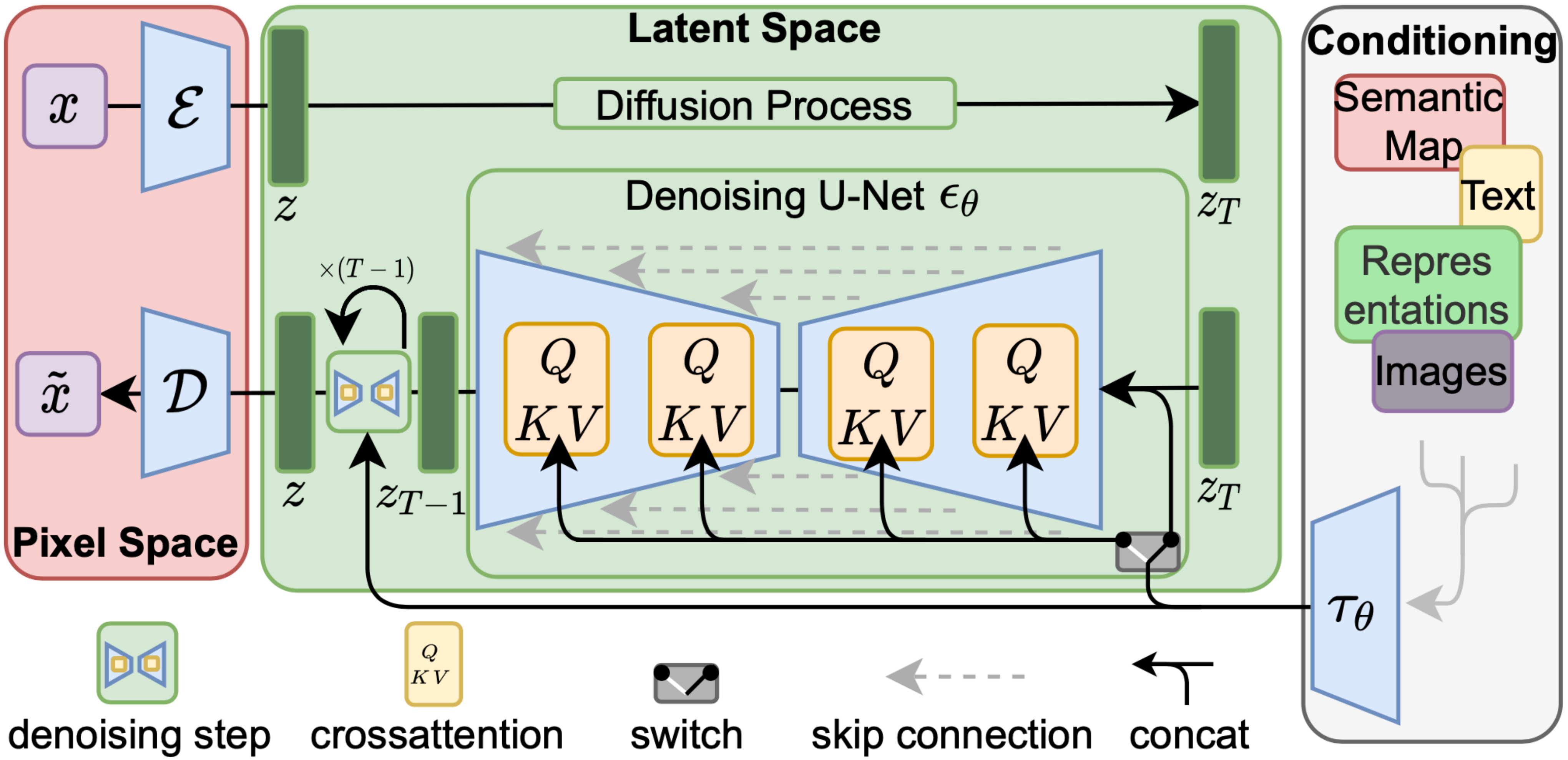
(2) Latent space → *More expressivity and flexibility in design!*

(3) Tailored Autoencoders → *More expressivity, Application to any data type (graphs, text, 3D data, etc.) !*

Vahdat et al., "Score-based generative modeling in latent space", NeurIPS 2021.

Latent Diffusion Model (CVPR'22): Important Jump toward High-Resolution!

DDIM sampler + classifier-free guidance + many other tweaks …

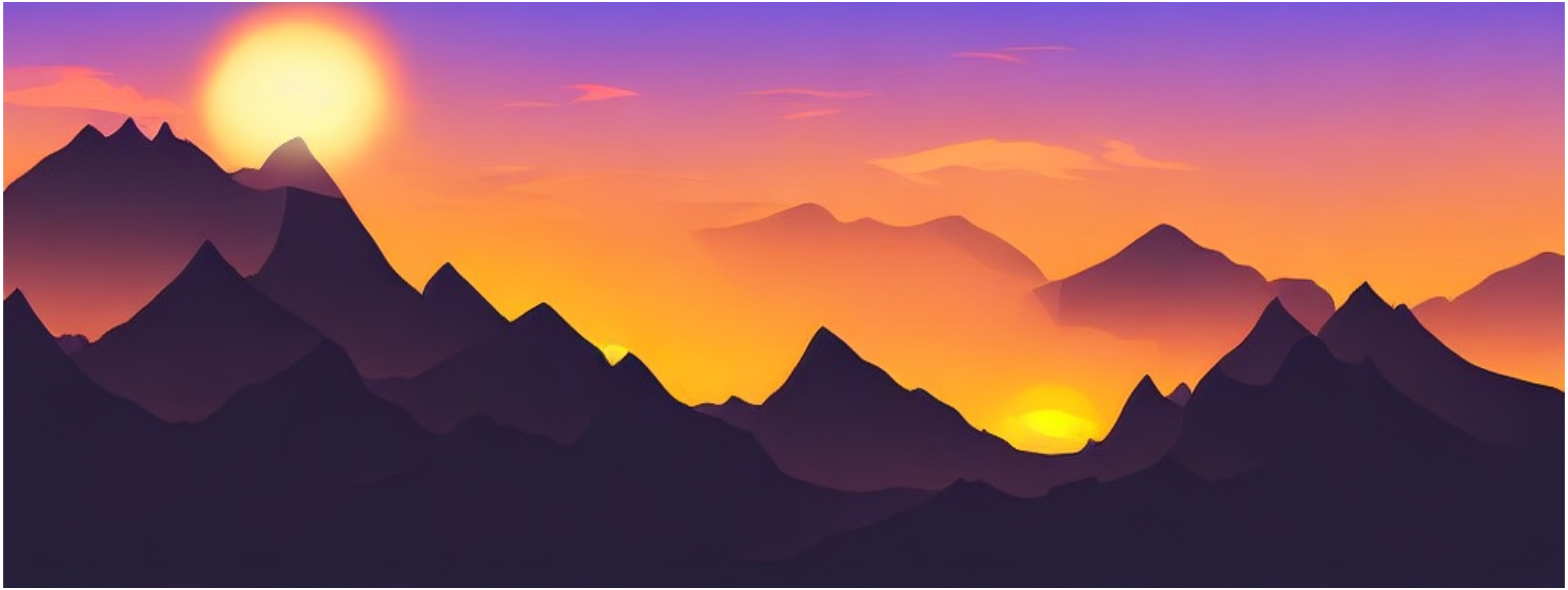


Latent Diffusion Model (CVPR'22): Important Jump toward High-Resolution!

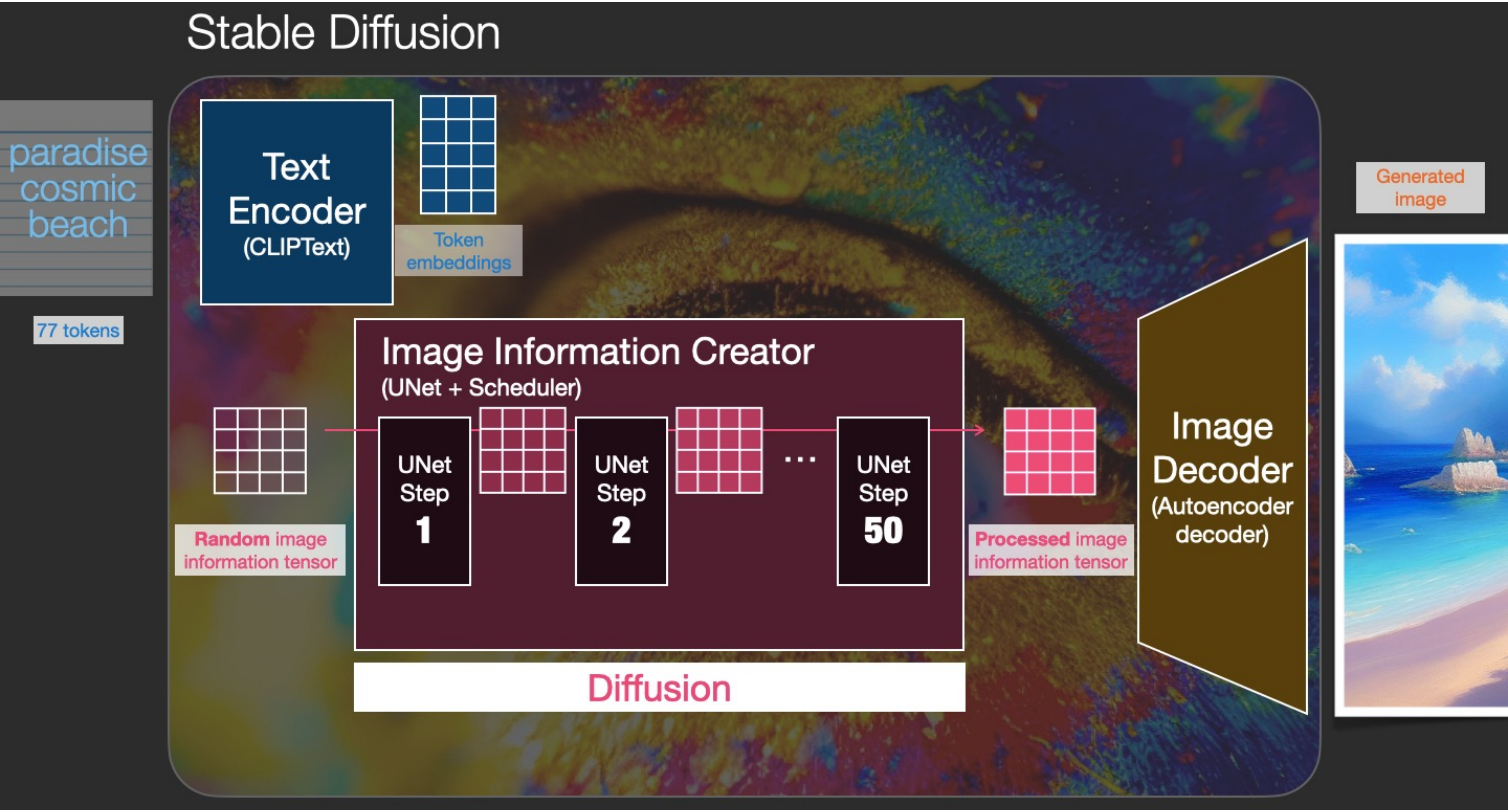
- *The seminal work from Rombach et al. CVPR 2022:*
  - *Two stage training: train autoencoder first, then train the diffusion prior*
  - *Focus on compression without of any loss in reconstruction quality*
  - *Demonstrated the expressivity of latent diffusion models on many conditional problems*

- *The efficiency and expressivity of latent diffusion models + open-source access fueled a large body of work in the community (e.g.* ***Stable Diffusion****!)*

Latent Diffusion Model (CVPR'22): Important Jump toward High-Resolution!

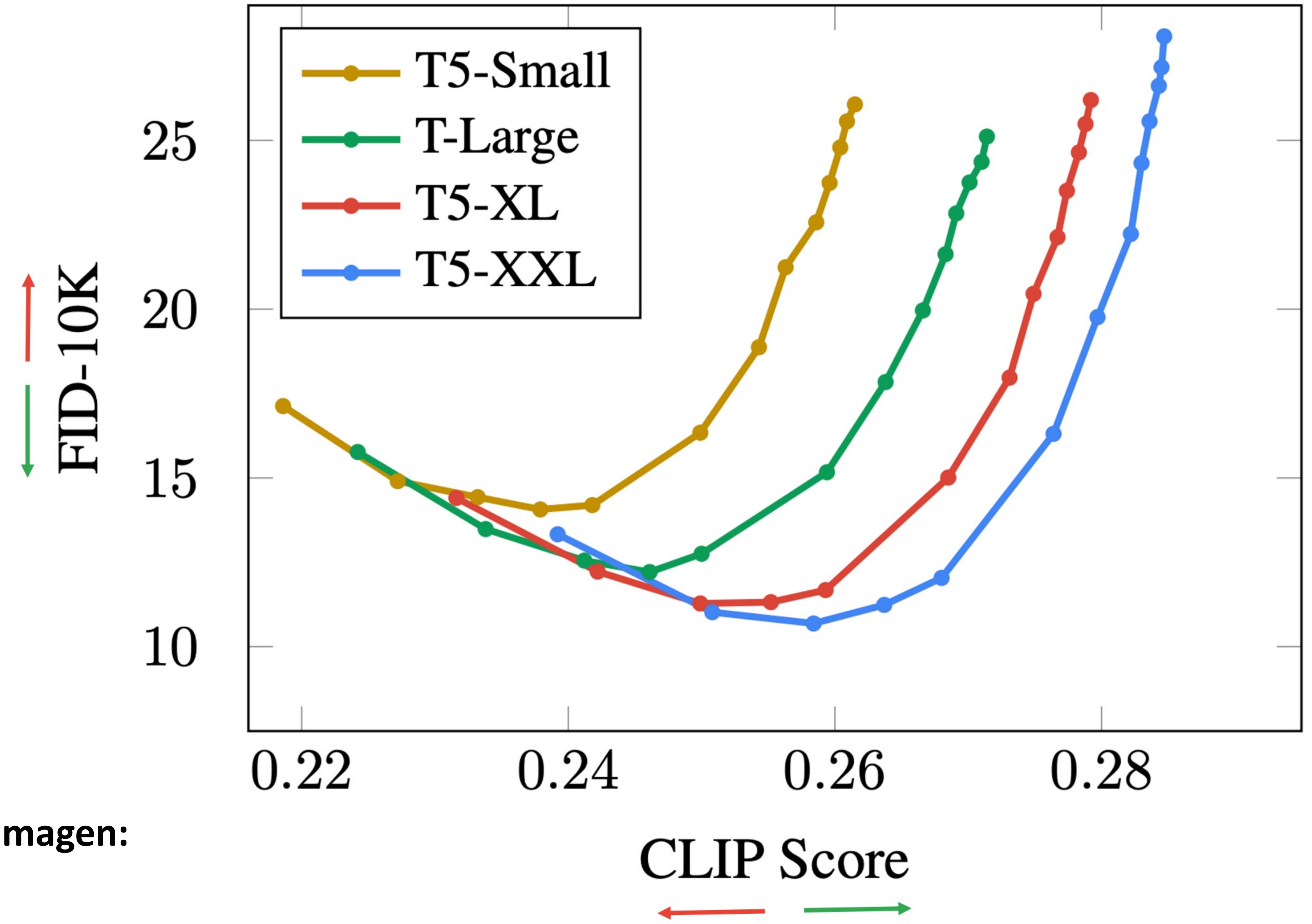


python scripts/txt2img.py --prompt "a sunset behind a mountain range, vector image" --ddim_eta 1.0 --n_samples 1 --n_iter 1 --H 384 --W 1024 --scale 5.0


Stable Diffusion
paradise cosmic beach
77 tokens
Text Encoder (CLIPText)
Token embeddings
Image Information Creator
(UNet + Scheduler)
Random image information tensor
UNet Step 1
UNet Step 2
UNet Step 50
Processed image information tensor
Diffusion
Image Decoder (Autoencoder decoder)
Generated image

Larger Text Encoders → Better Alignment, Better Fidelity

From Google Imagen:



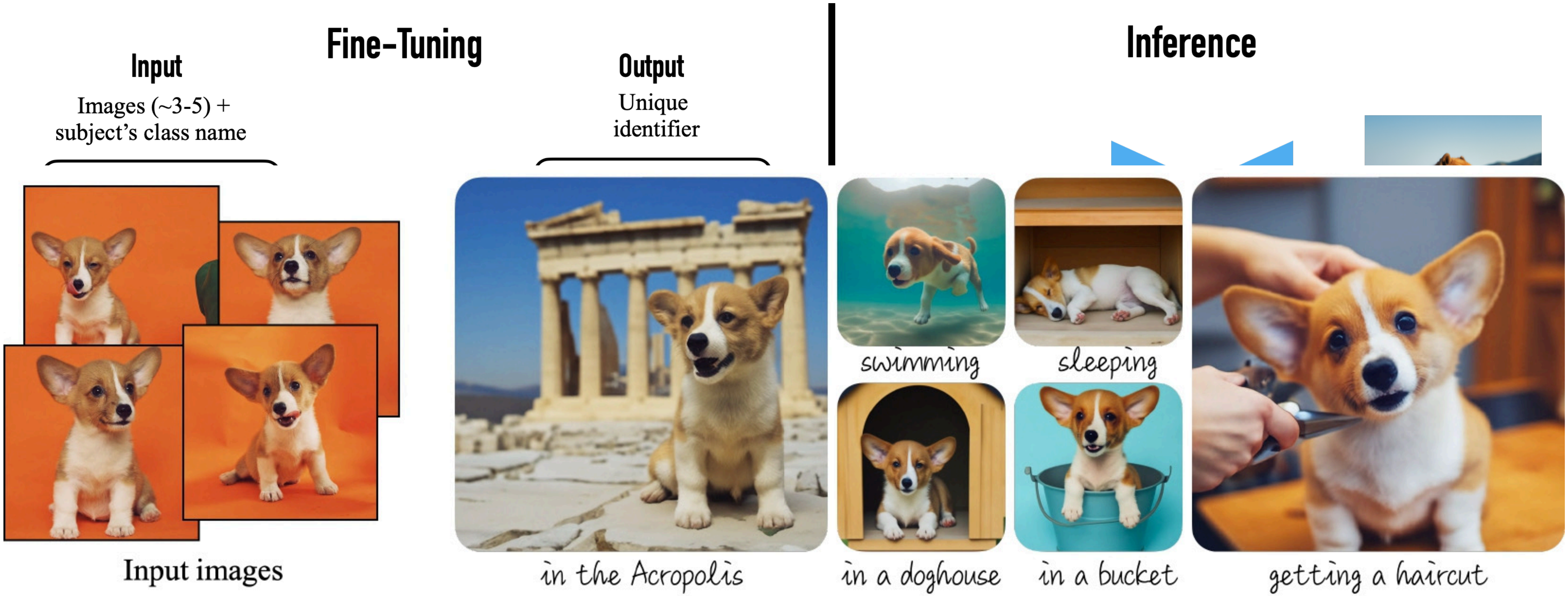
A Few More Essentials…

- How to “Personalize”

- How to “Control”

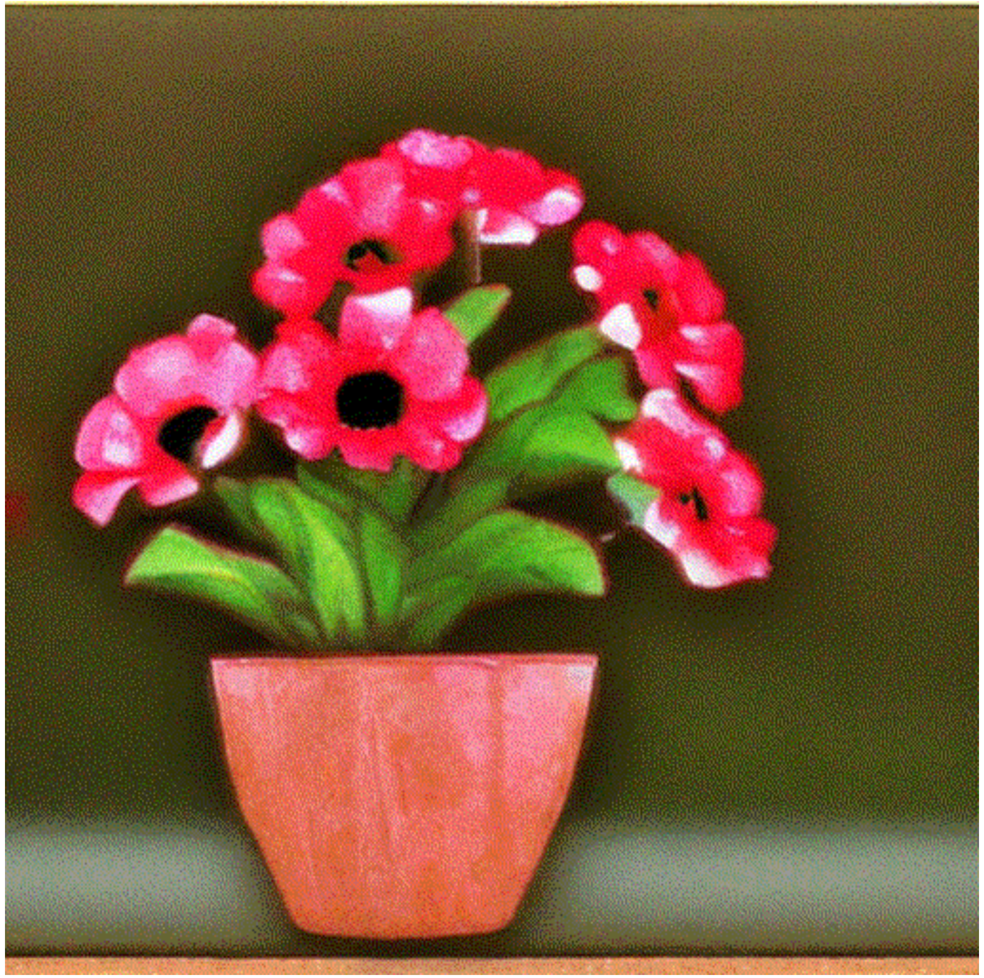
- How to “Erase”

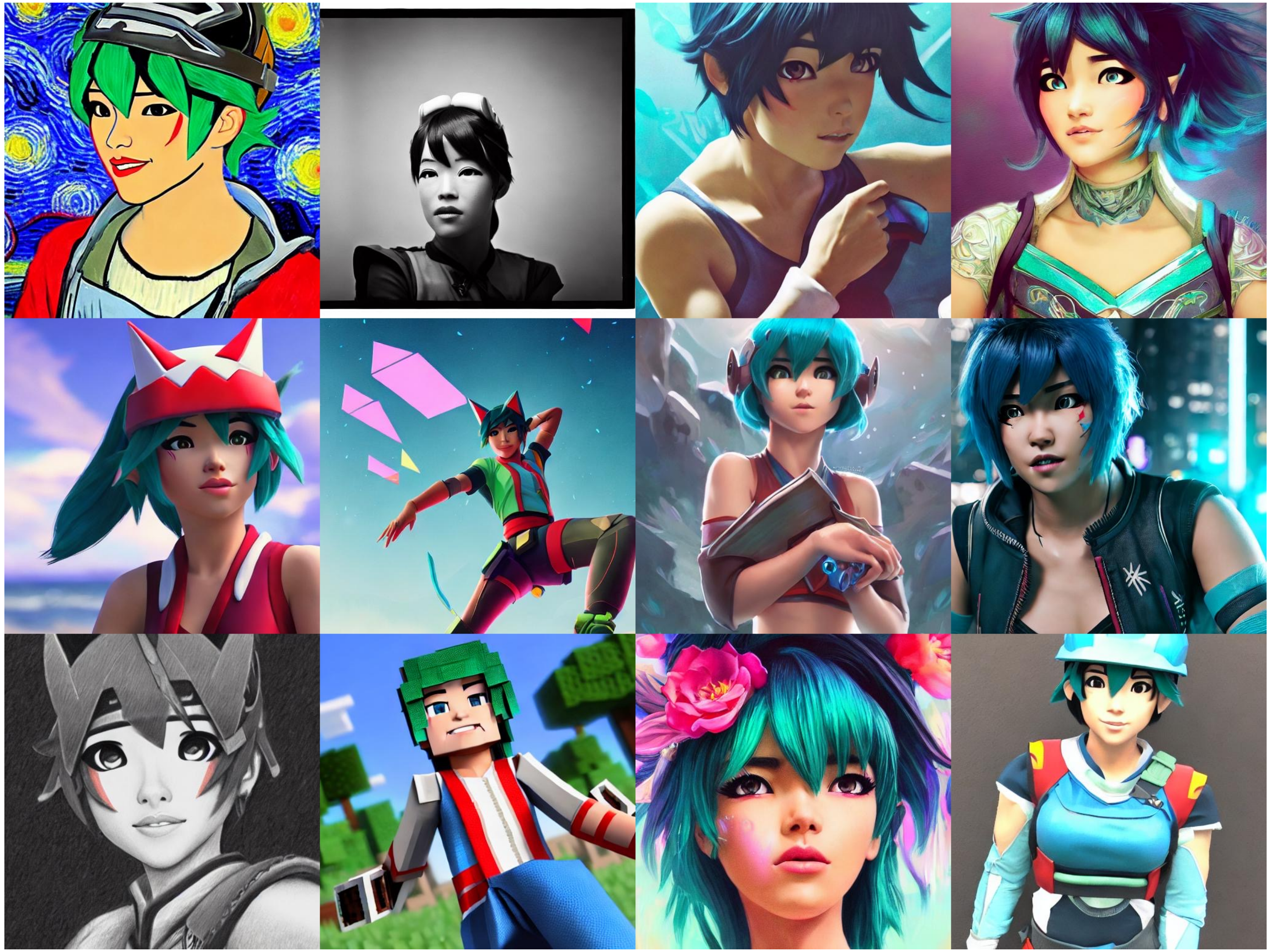
Personalizing Your Diffusion: DreamBooth



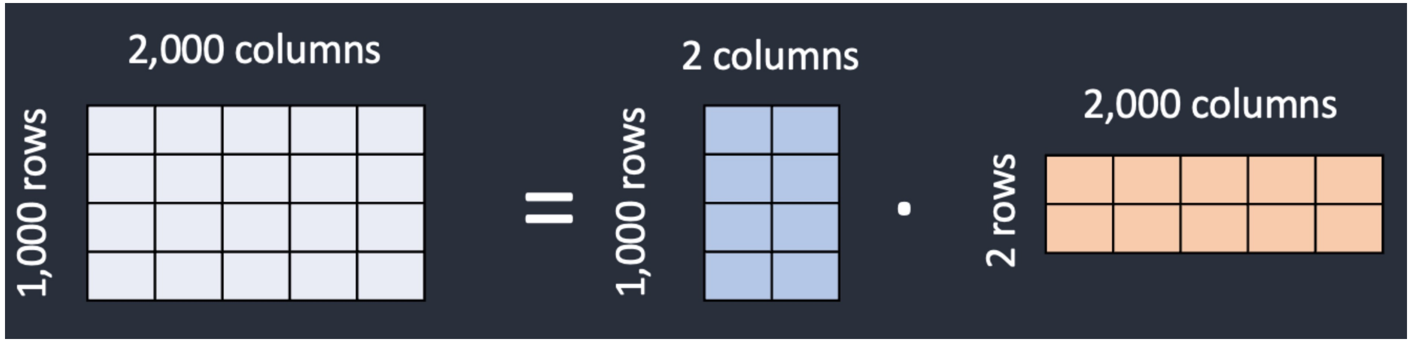
Personalizing Your Diffusion: DreamBooth

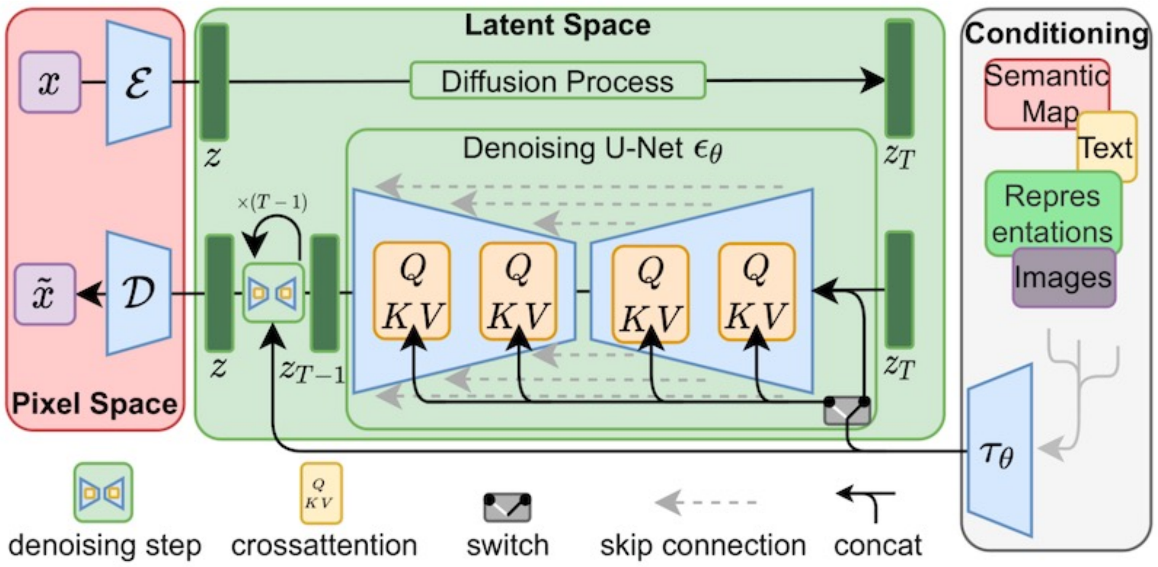
LoRA: Low-rank Adaptation for Fast Diffusion Fine-tuning





LoRA: Low-rank Adaptation for Fast Diffusion Fine-tuning





A LoRA model fine-tunes a model by adding its update weights to the pre-trained matrices, but using **low-rank compression**

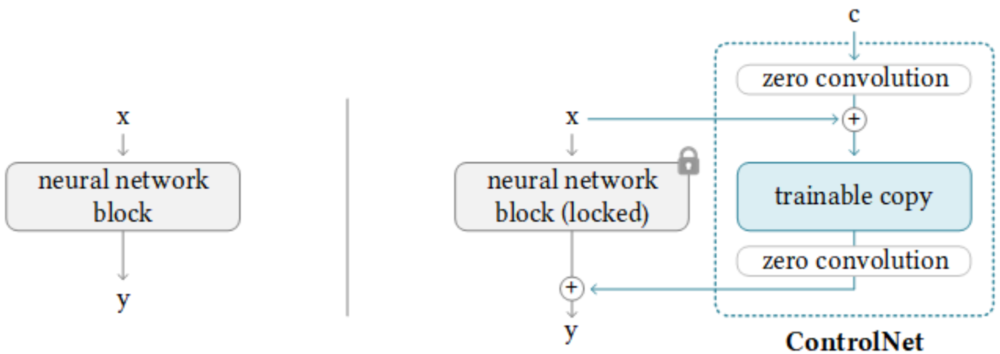
Original weights

$$W = W_0 + BA$$

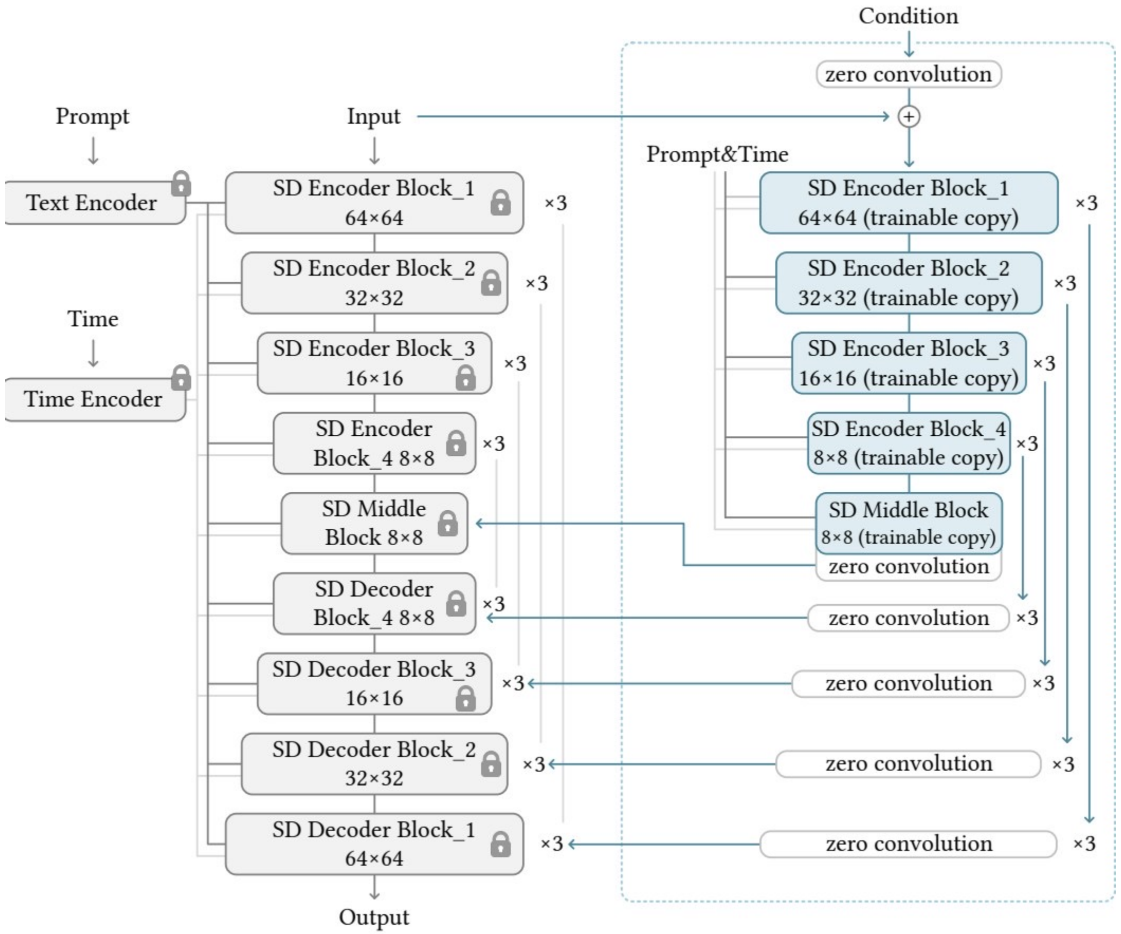
Low-rank difference

In Practice now LORA fine-tunes the **cross-attention layers** (the QKV parts of the U-Net noise predictor)

ControlNet



(a) Before (b) After



(a) Stable Diffusion (b) ControlNet

ControlNet

Q: If the weight of a conv layer is zero, the gradient will also be zero, and the network will not learn anything. Why "zero convolution" works?

A: This is wrong. Let us consider a very simple

$$y = wx + b$$

and we have

$$\partial y/\partial w = x, \partial y/\partial x = w, \partial y/\partial b = 1$$

and if $w = 0$ and $x \neq 0$, then

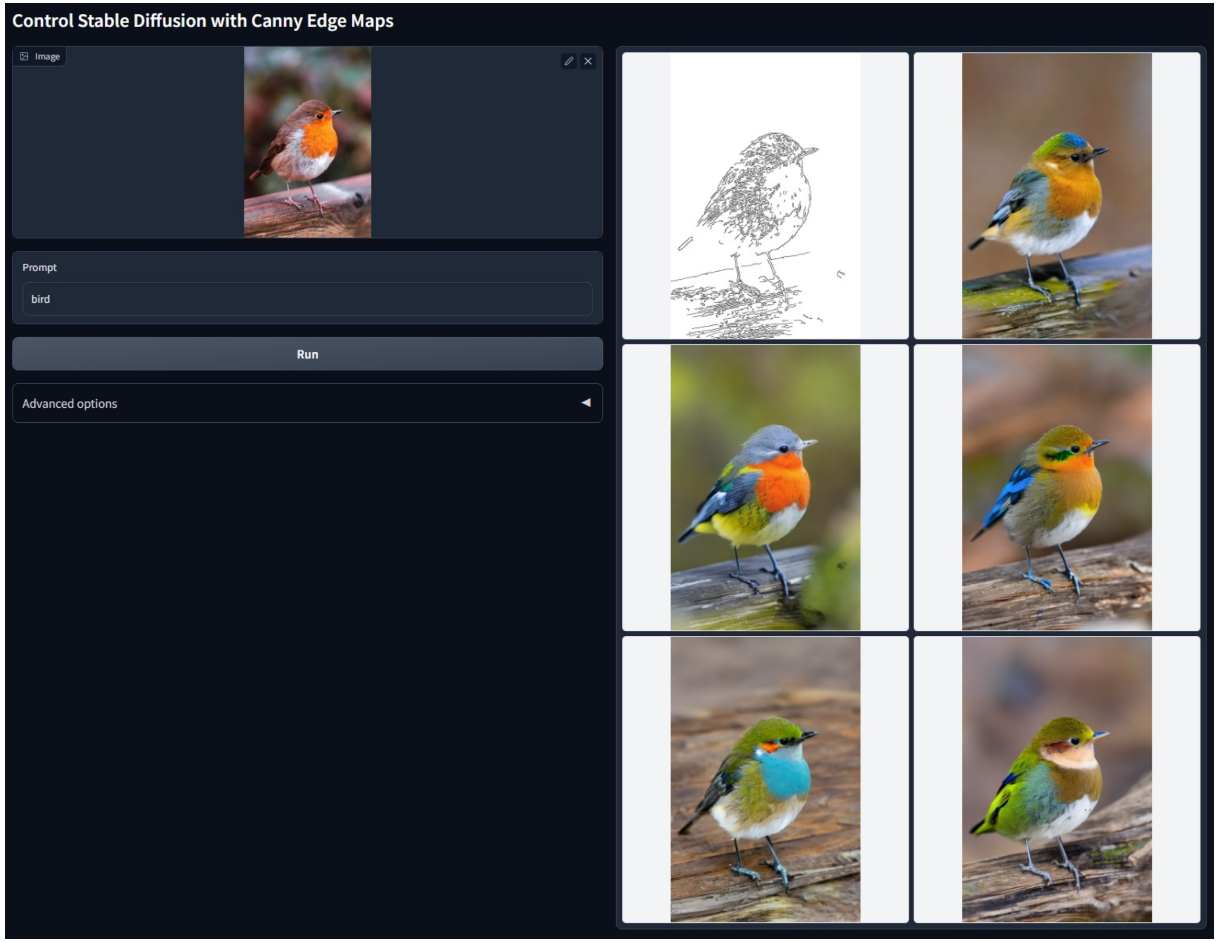
$$\partial y/\partial w \neq 0, \partial y/\partial x = 0, \partial y/\partial b \neq 0$$

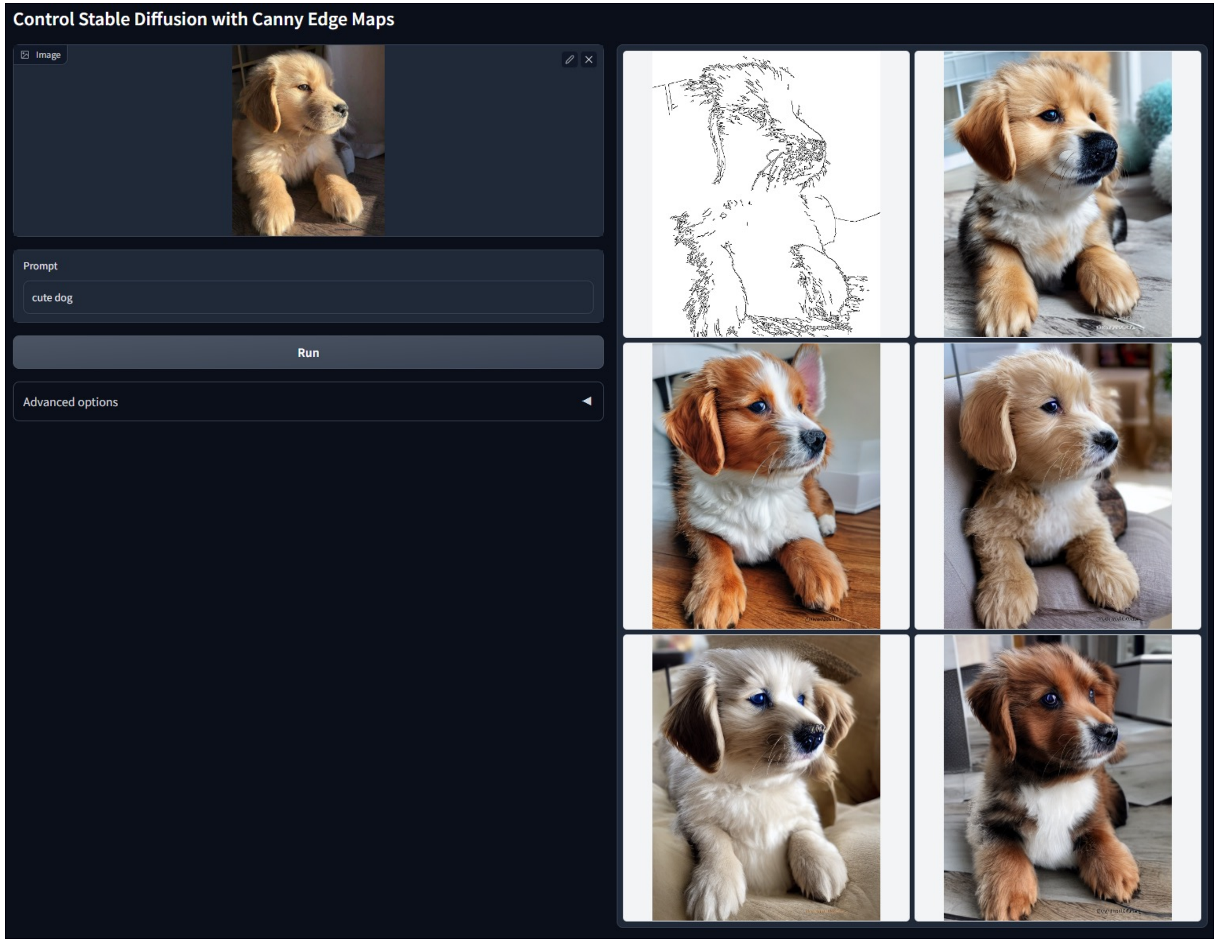
which means as long as $x \neq 0$, one gradient descent iteration will make w non-zero. Then

$$\partial y/\partial x \neq 0$$

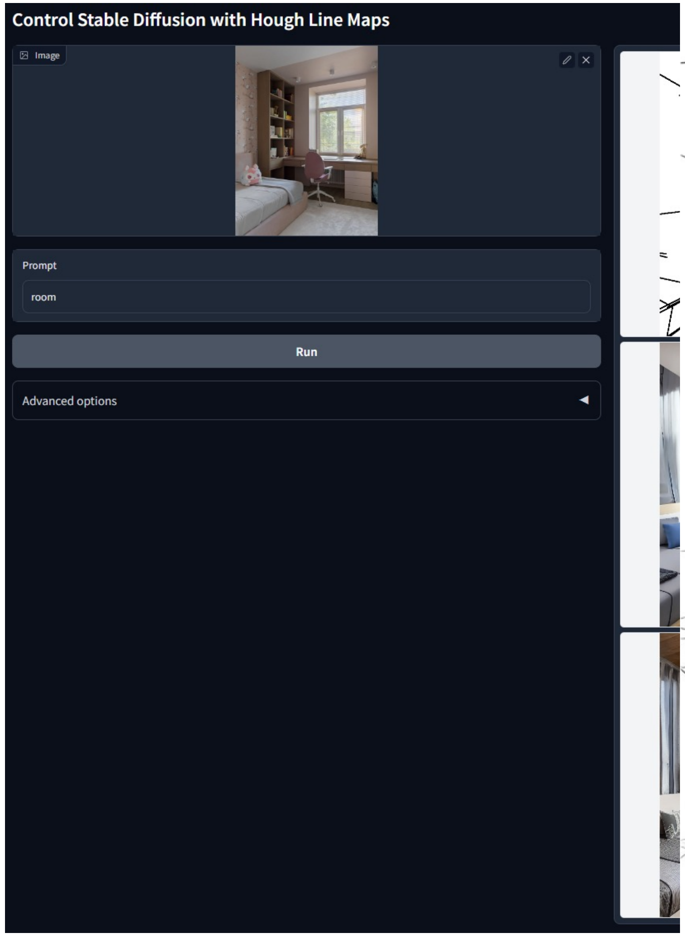
so that the zero convolutions will progressively become a common conv layer with non-zero weights.

ControlNet (Canny Edge)

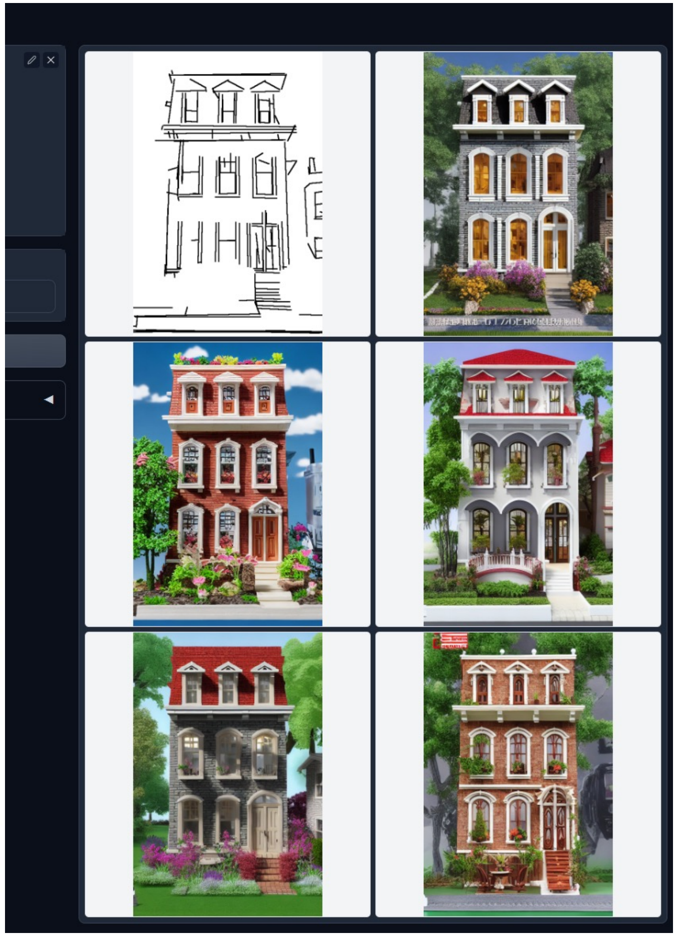




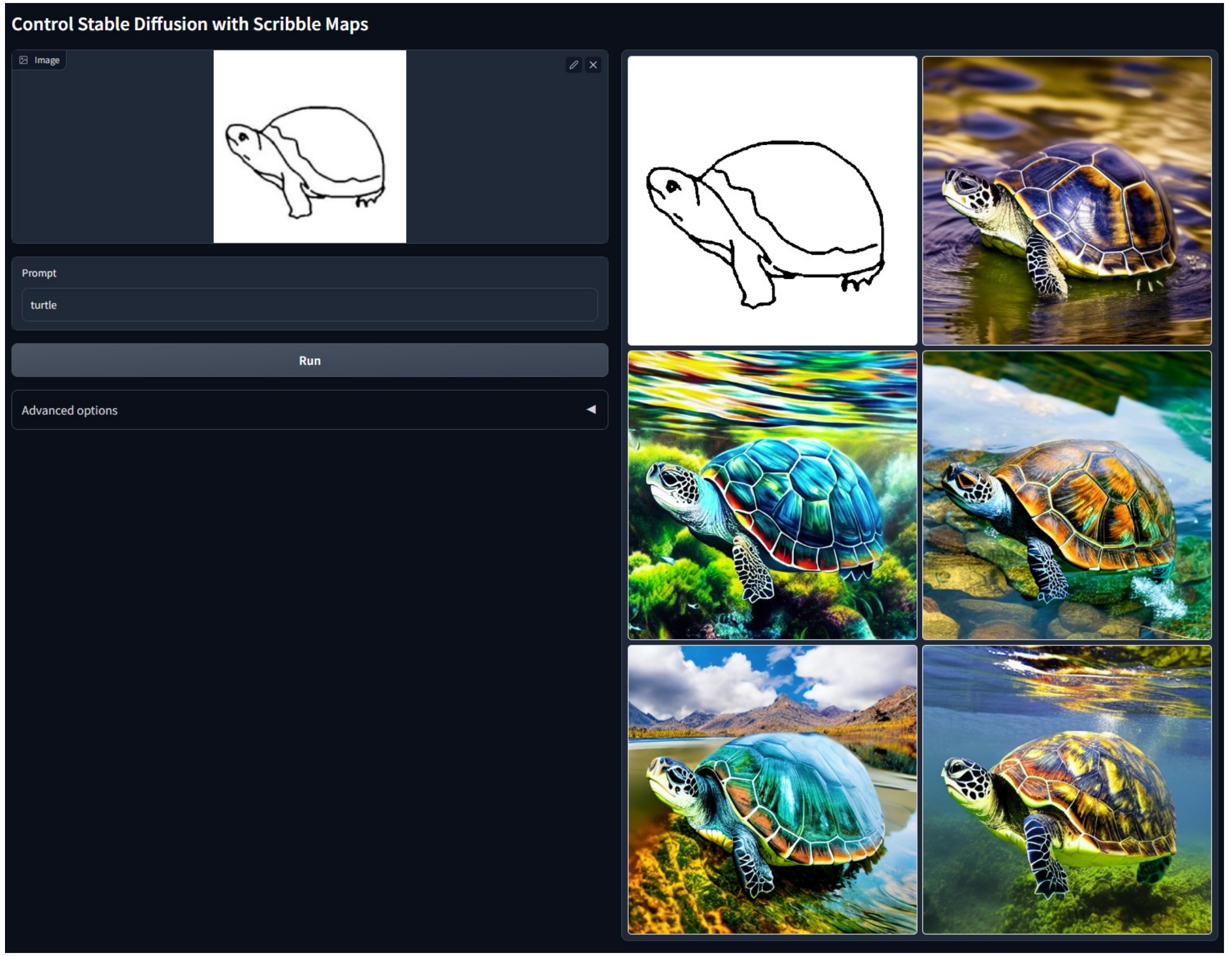
ControlNet (Sketch Lines)

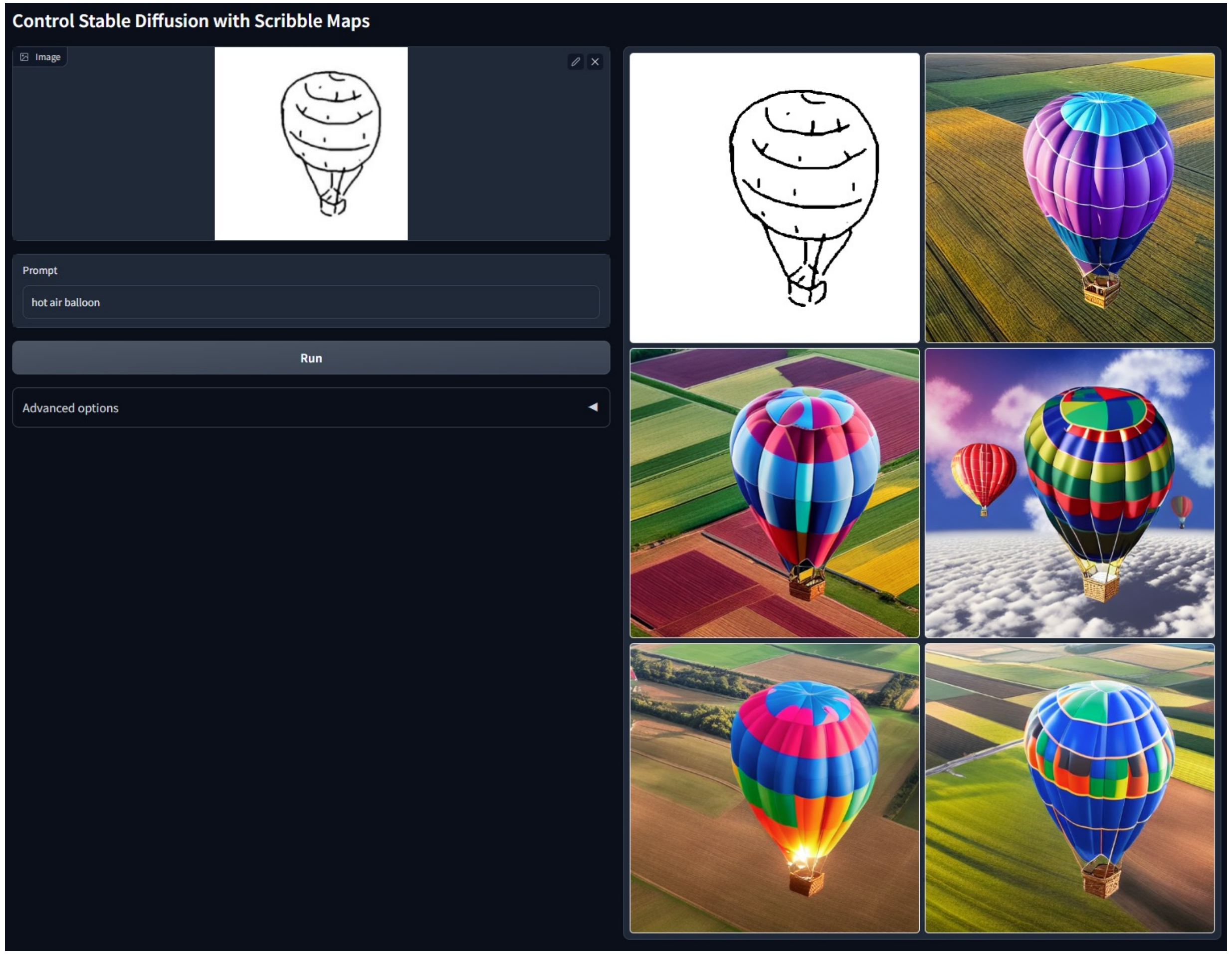


Cartoon line drawing “1girl, masterpiece, best quality, ultra-detailed, illustration”

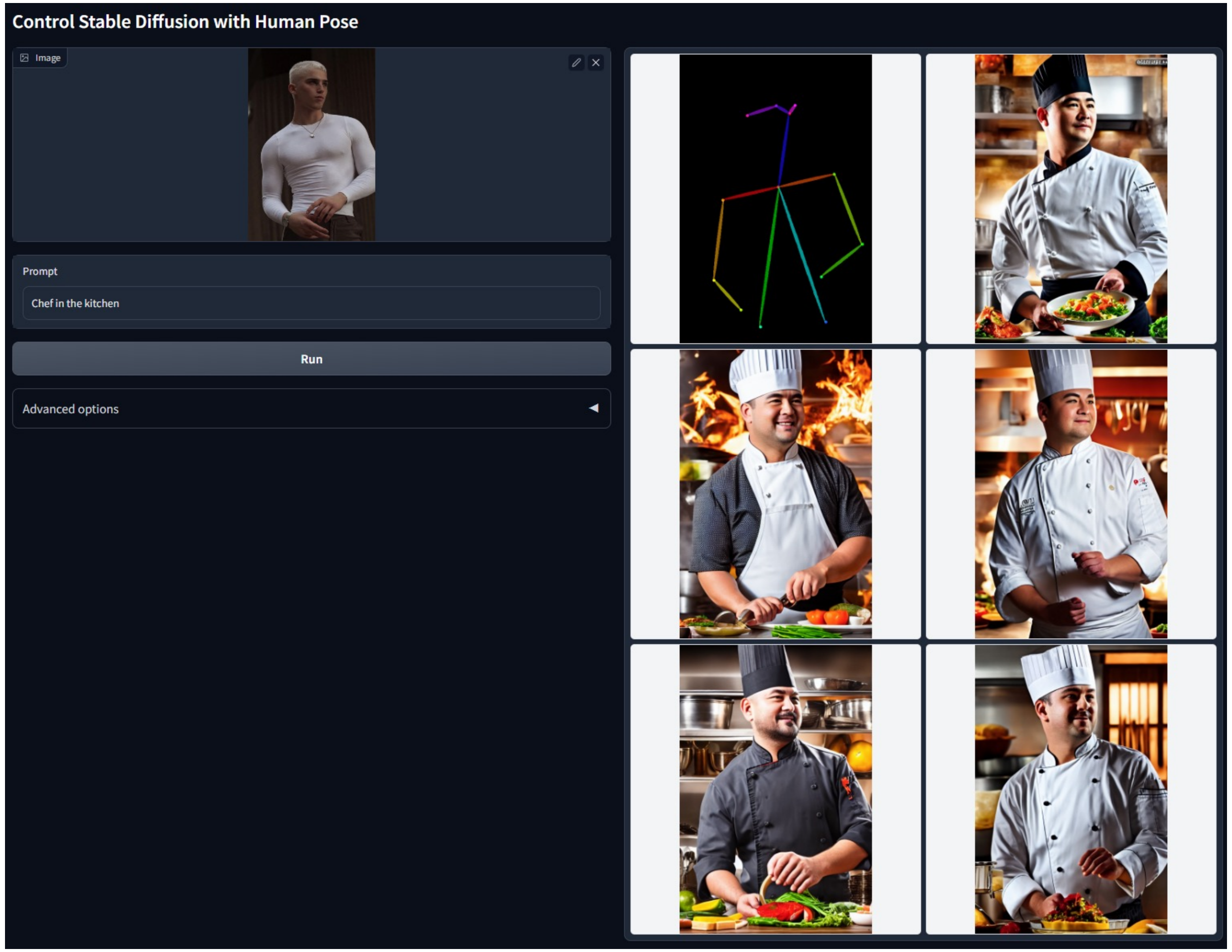


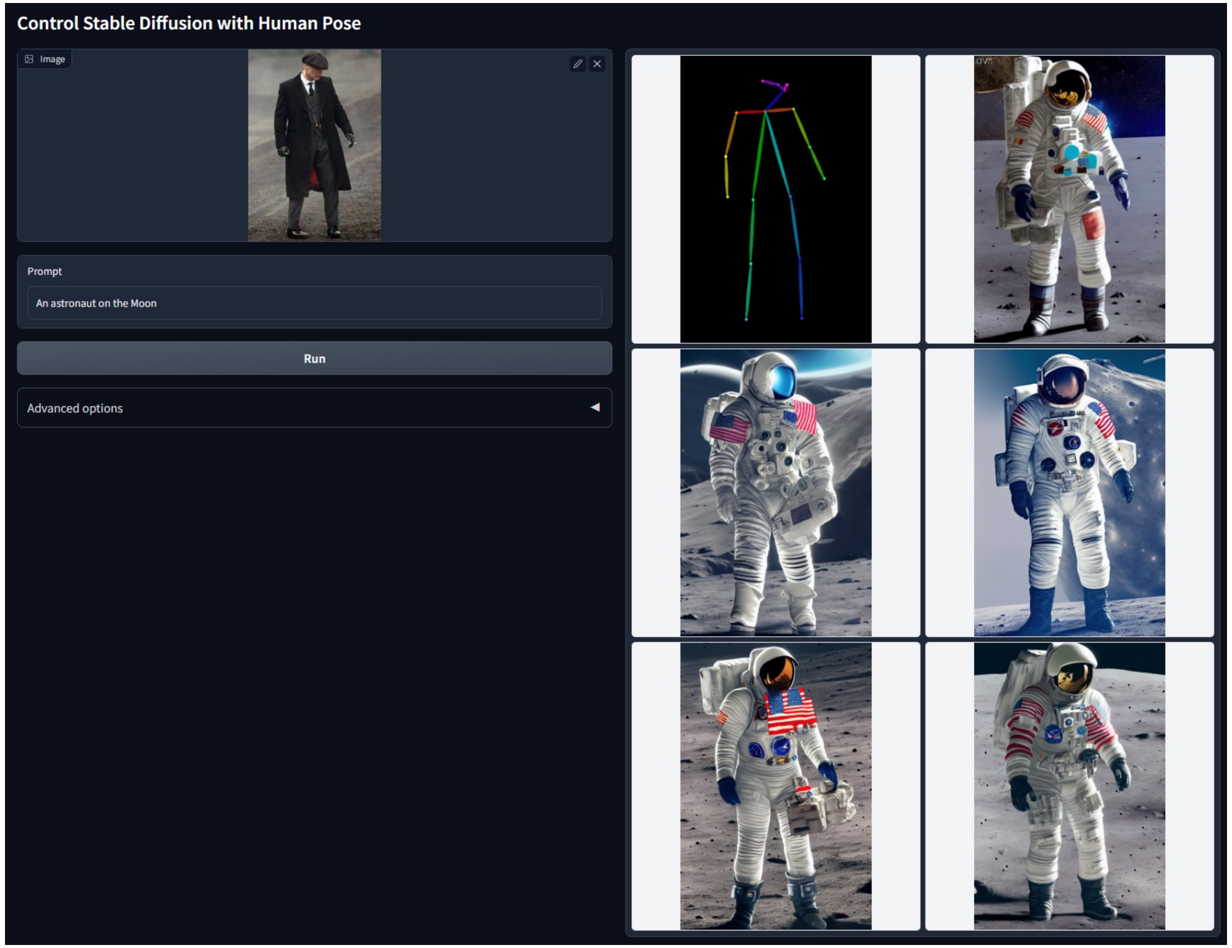
ControlNet (User Scribbles)



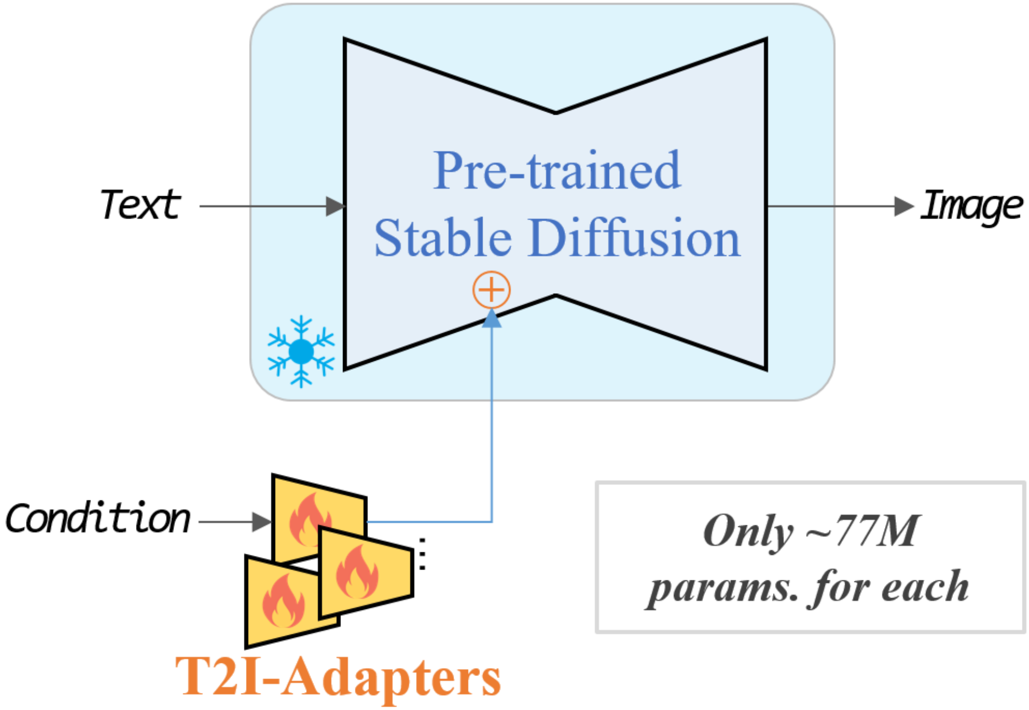


ControlNet (Human Pose)





T2I Adapter



✓ ***Plug-and-play.*** *Not affect original network topology and generation ability*

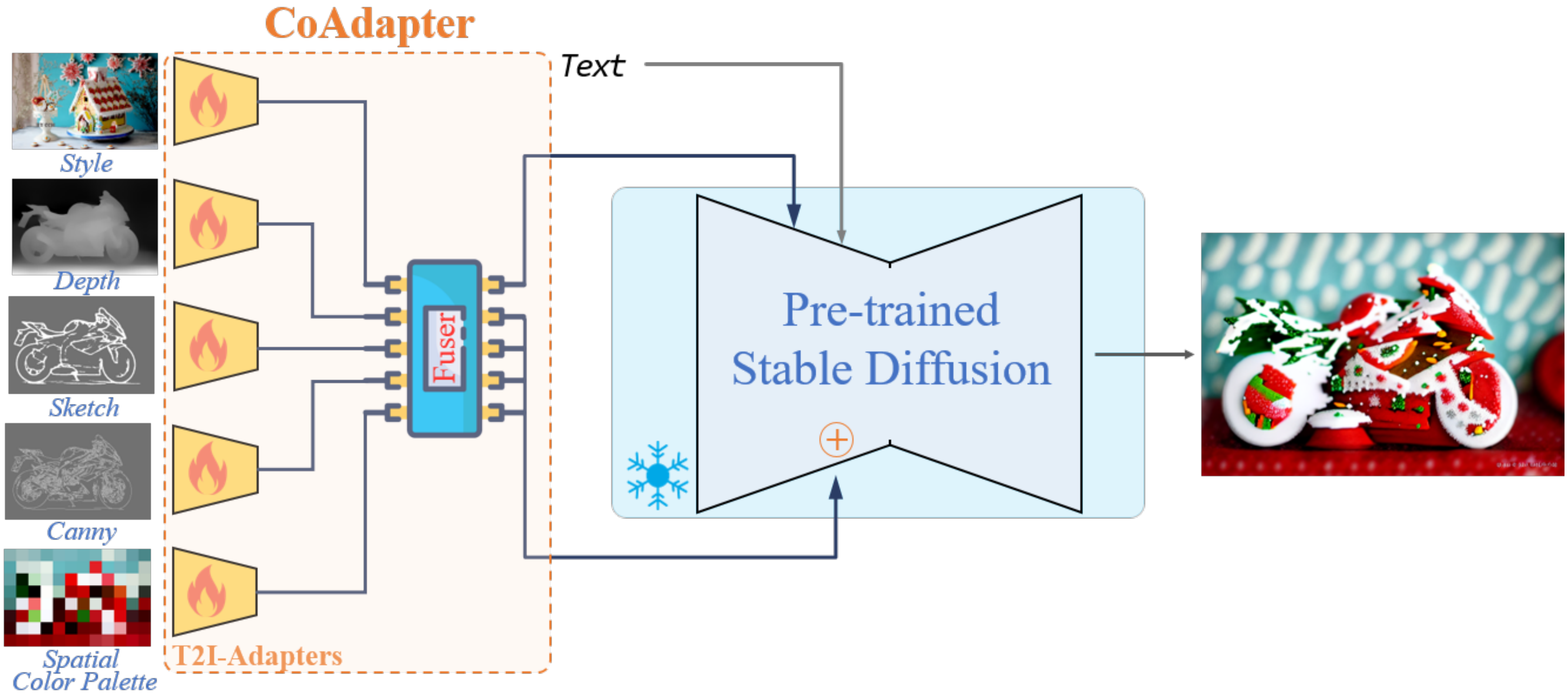
✓ ***Simple and small.*** *~77M parameters and ~300M storage*

✓ ***Flexible.*** *Various adapters for different control conditions*

✓ ***Composable.*** *More than one adapter can be easily composed to achieve multi-condition control*

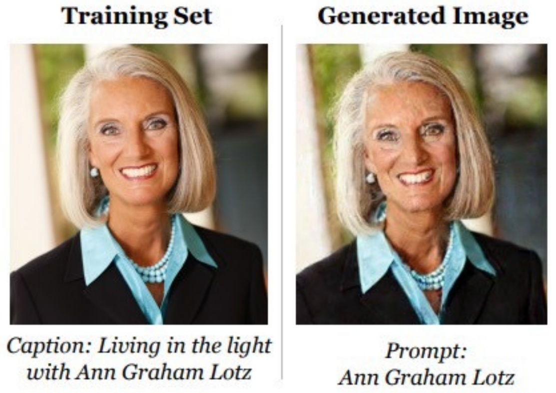
✓ ***Generalizable.*** *Can be directly used on customed models*

T2I Adapter

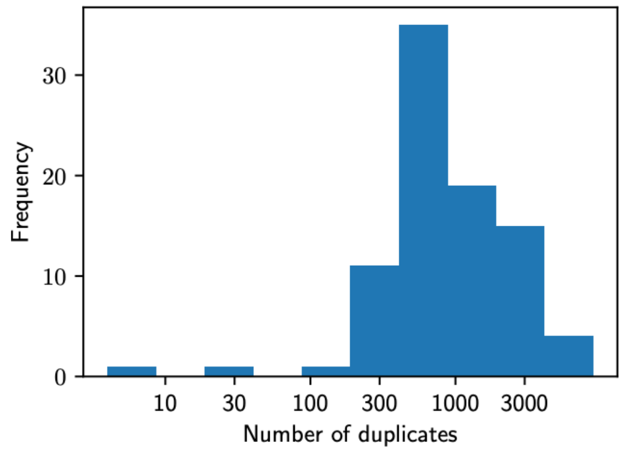

CoAdapter
Text
Style
Depth
Sketch
Canny
Spatial
Color Palette
T2I-Adapters
Fuser
Pre-trained
Stable Diffusion

Data Memorization in Diffusion Models

- Due to the likelihood-base objective function, diffusion models can ”memorize” data.
- And with a higher chance than GANs!
- Nevertheless, a lot of “memorized images” are highly-duplicated in the dataset.



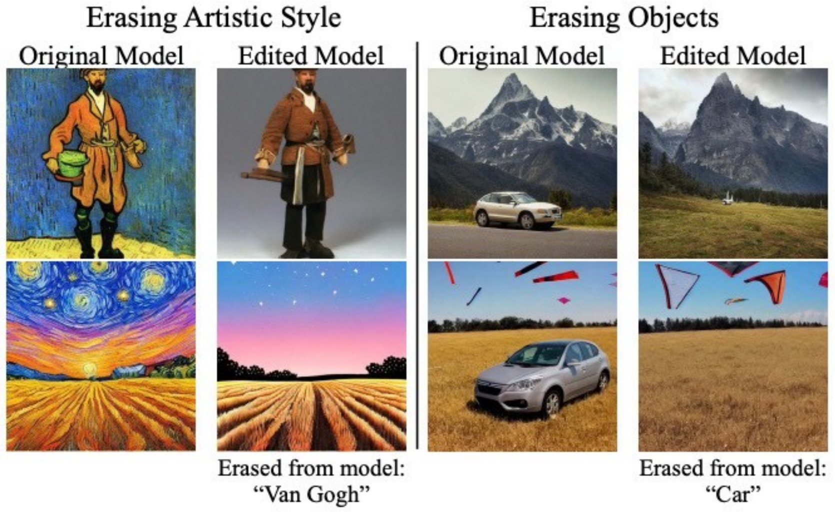
Architecture		Images Extracted	FID
GANs	StyleGAN-ADA [43]	**150**	**2.9**
	DiffBigGAN [82]	57	4.6
	E2GAN [69]	95	11.3
	NDA [63]	70	12.6
	WGAN-ALP [68]	49	13.0
DDPMs	OpenAI-DDPM [52]	**301**	**2.9**
	DDPM [33]	232	3.2

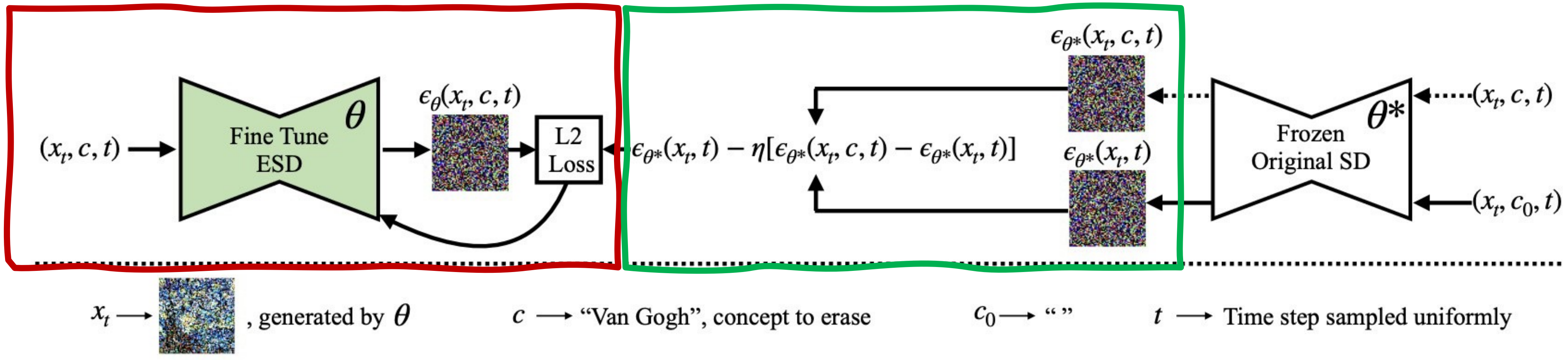


Carlini et al., "Extracting Training Data from Diffusion Models", arXiv 2023

Erasing Concepts in Diffusion Models

- Fine-tune a model to remove unwanted concepts.
- From original model, obtain score via negative CFG.
- A new model is fine-tuned from the new score function.





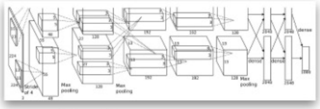
Gandikota et al., "Erasing Concepts from Diffusion Models", arXiv 2023

Is Diffusion Model Destined to be the Final Winner?

StyleGAN-T: Unlocking the Power of GANs for Fast Large-Scale Text-to-Image Synthesis

Axel Sauer Tero Karras Samuli Laine Andreas Geiger Timo Aila

Generative AI is revolutionizing the AI landscape EVERYDAY

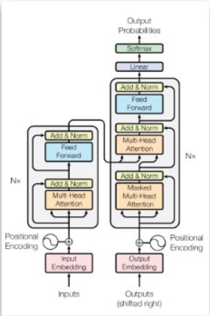


AlexNet

2012

2014

AlphaGo

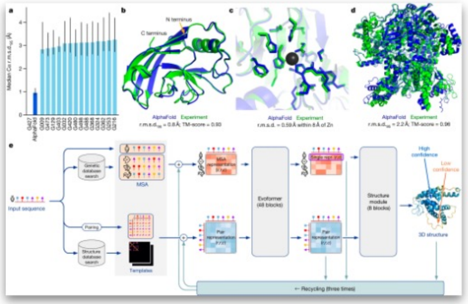


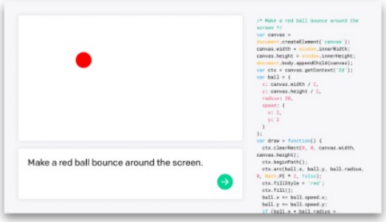
Transformers

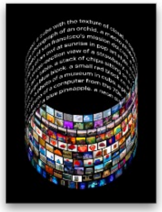
2017

2020

AlphaFold, GPT-3







Codex, DALL-E

2021

2022

DALLE-2, Imagen, Stable Diffusion, Versatile Diffusion, ChatGPT,...

Text-to-Video, Text-to-3D, Text-to-Vector...

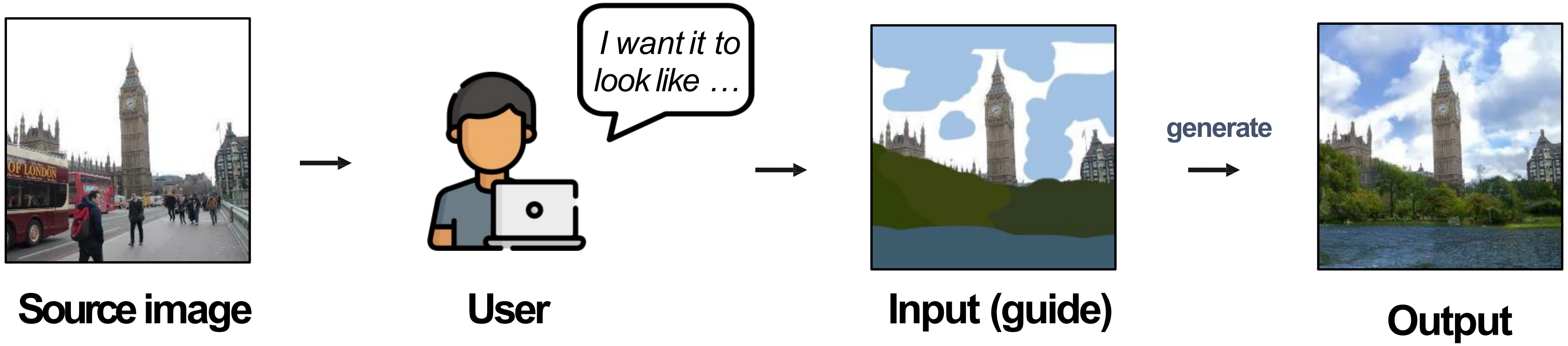
2023

What's next?

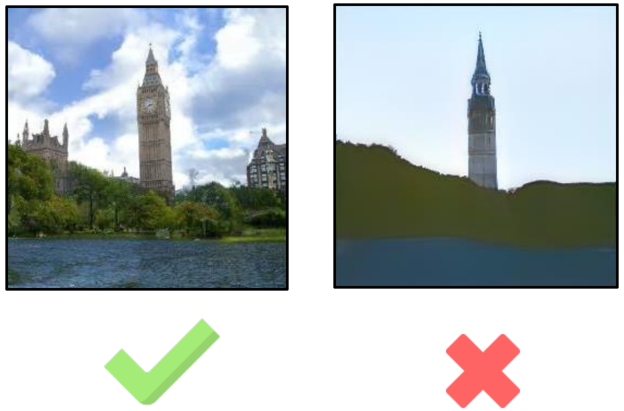
Application Aspects, Now!

- Image Editing
- Video Generation
- 3D Generation
- Ethic and Privacy Concerns

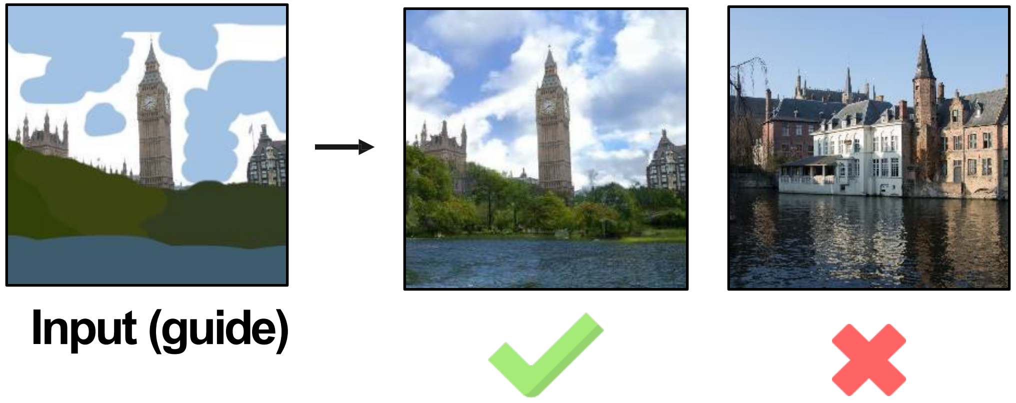
How to perform guided synthesis/editing?



Realistic

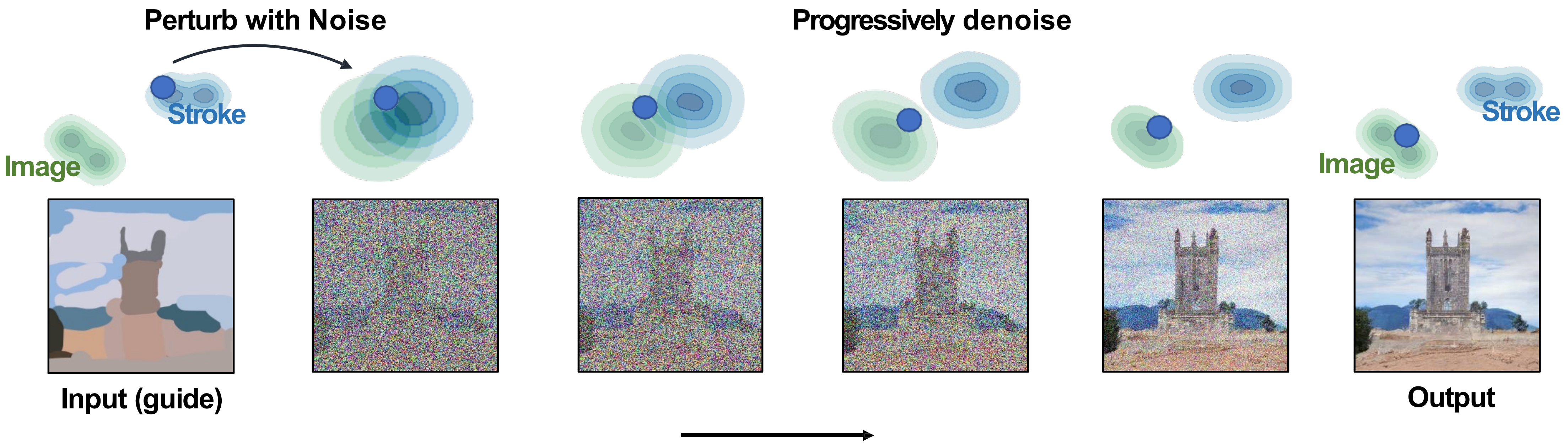


Faithful



SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations

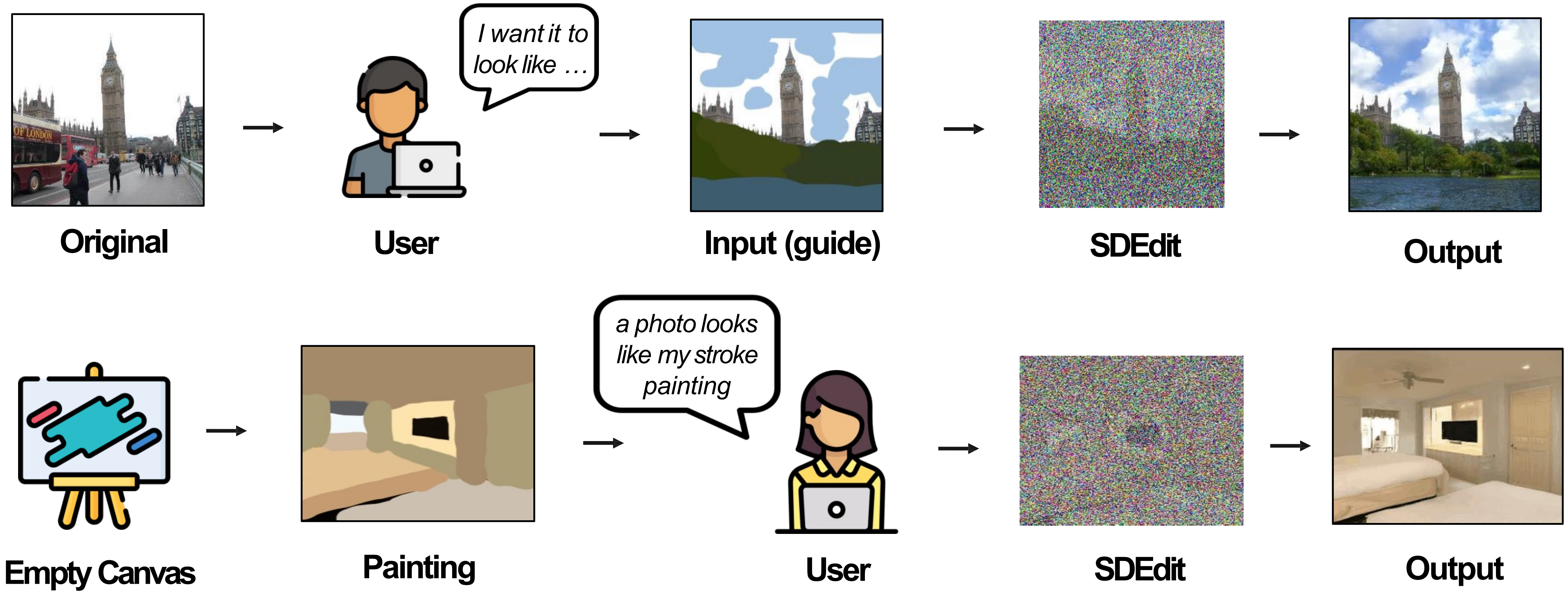
First perturb the input with **Gaussian noise** and then progressively remove the noise using a pretrained diffusion model.



Gradually projects the input to the manifold of natural images.

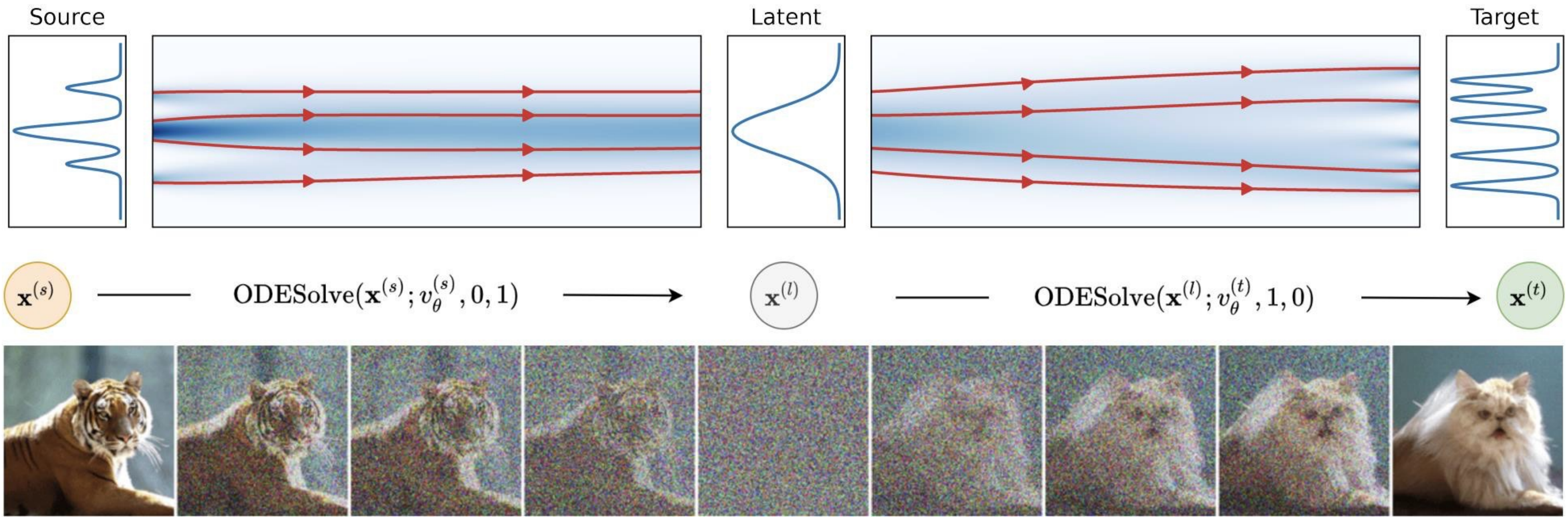
Meng et al., "SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations", ICLR2022

Fine-grained control using strokes



Meng et al., "SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations", ICLR2022

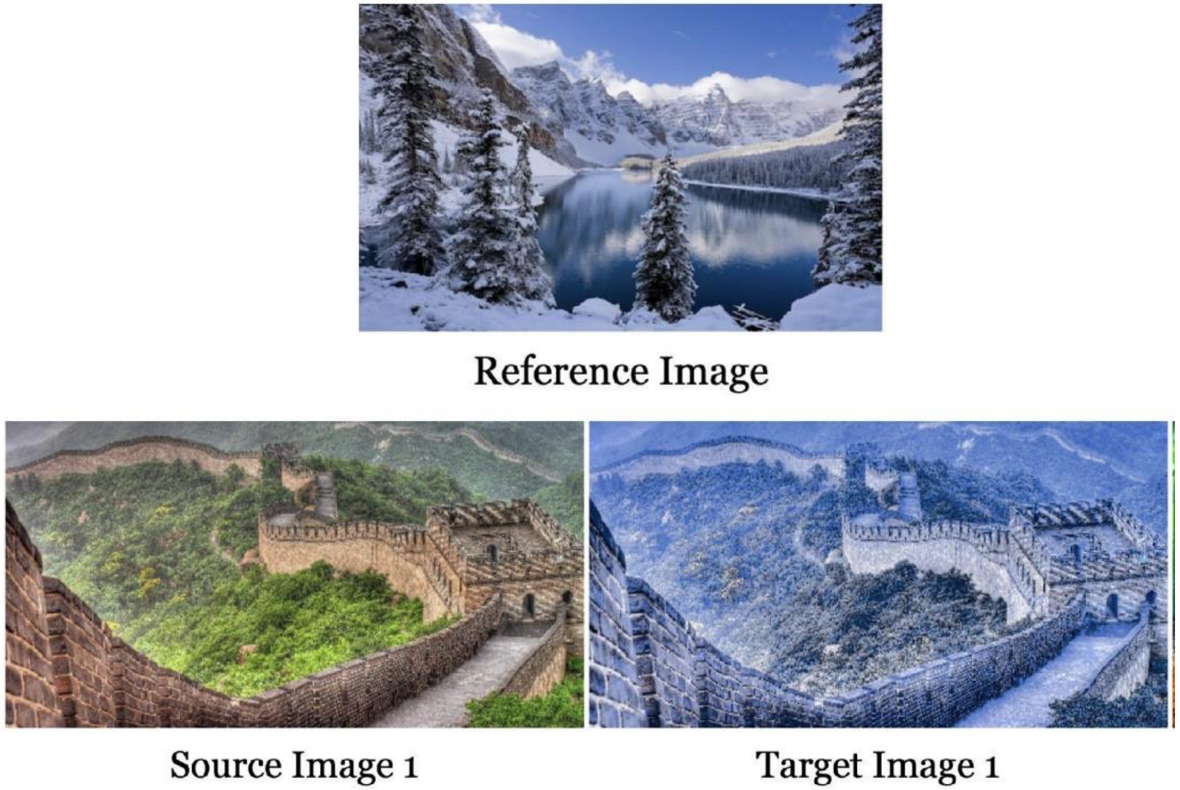
Style transfer with DDIM inversion



Su et al., "Dual diffusion implicit bridges for image-to-image translation", ICLR 2023

Style transfer with DDIM inversion

Multi-domain translation



Example-Guided Color Transfer

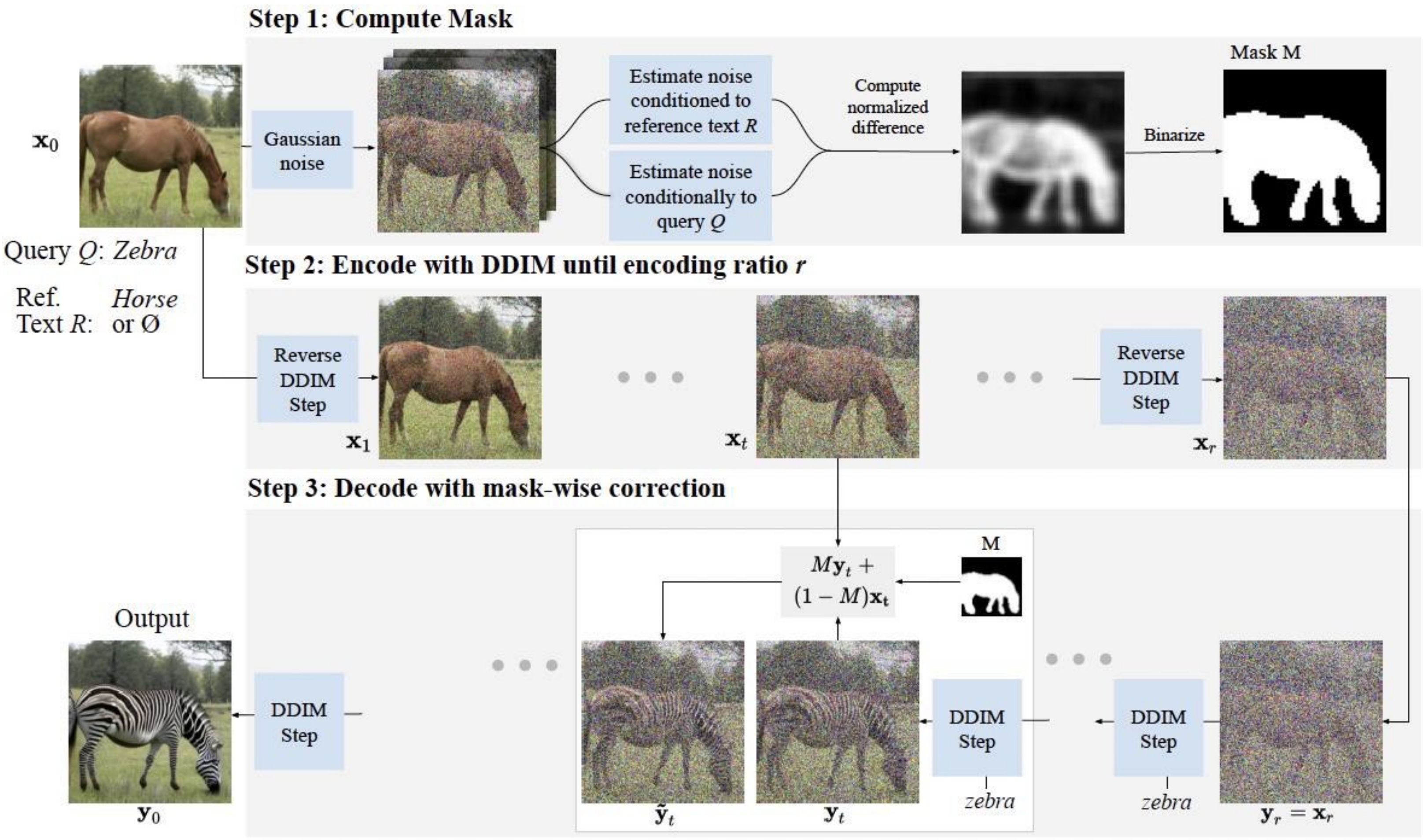
Su et al., ["Dual diffusion implicit bridges for image-to-image translation"](), ICLR 2023

DiffEdit: Diffusion-based semantic image editing with mask guidance

Instead of asking users to provide the mask, the model will generate the mask itself based on the caption and query.

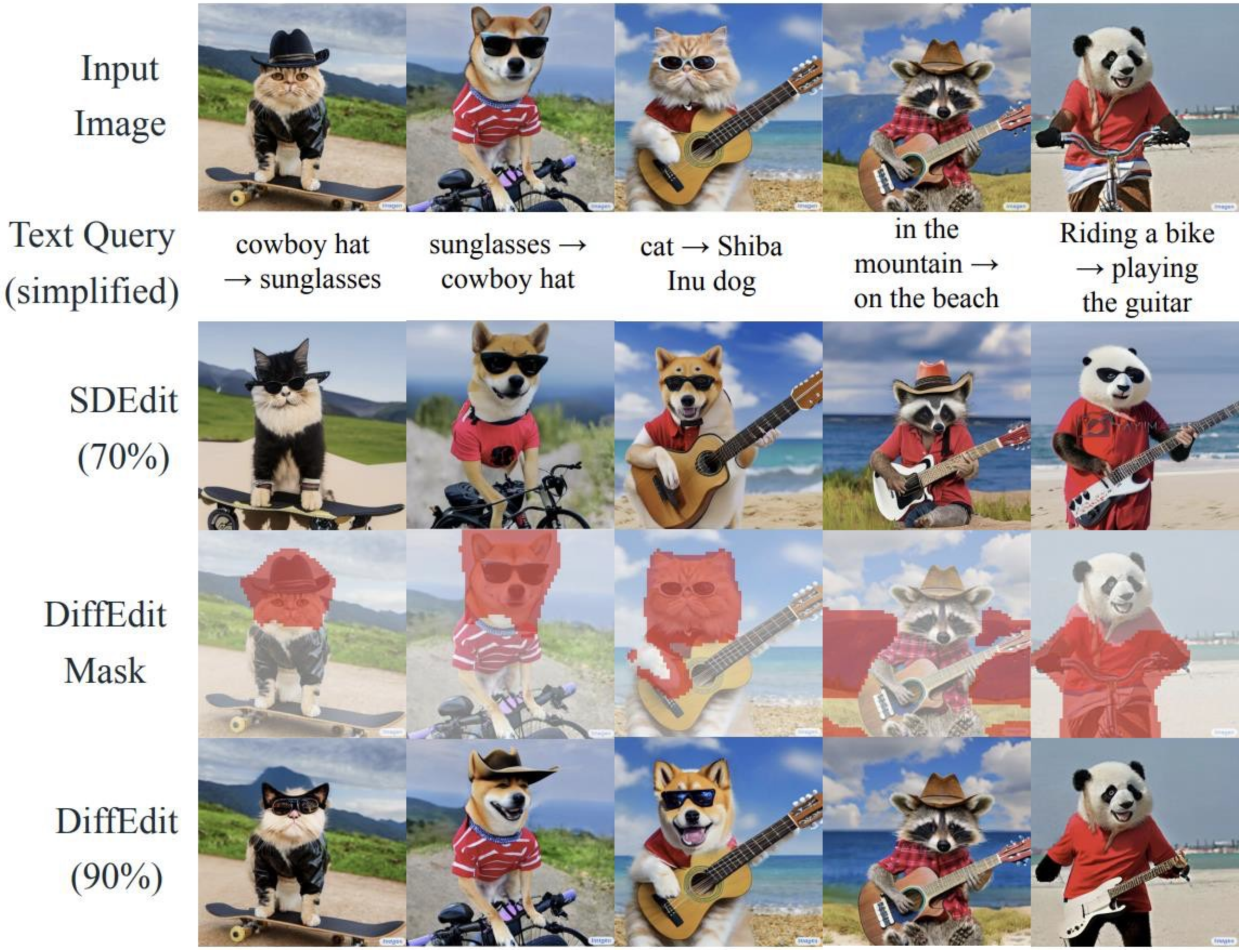
Couairon et al., ["DiffEdit: Diffusion-based semantic image editing with mask guidance"](), ICLR 2023

DiffEdit: Diffusion-based semantic image editing with mask guidance



Couairon et al., "DiffEdit: Diffusion-based semantic image editing with mask guidance", ICLR 2023

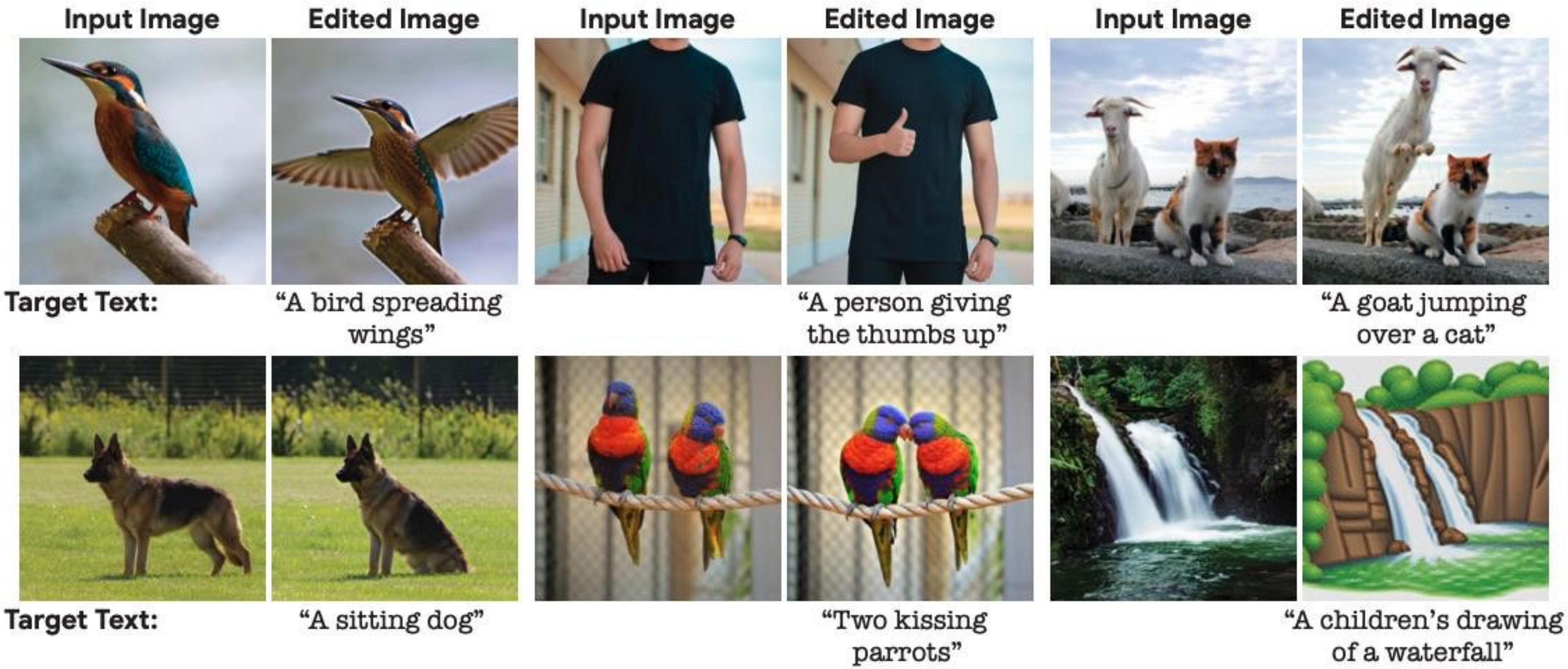
DiffEdit: Diffusion-based semantic image editing with mask guidance



Edits on Imagen dataset

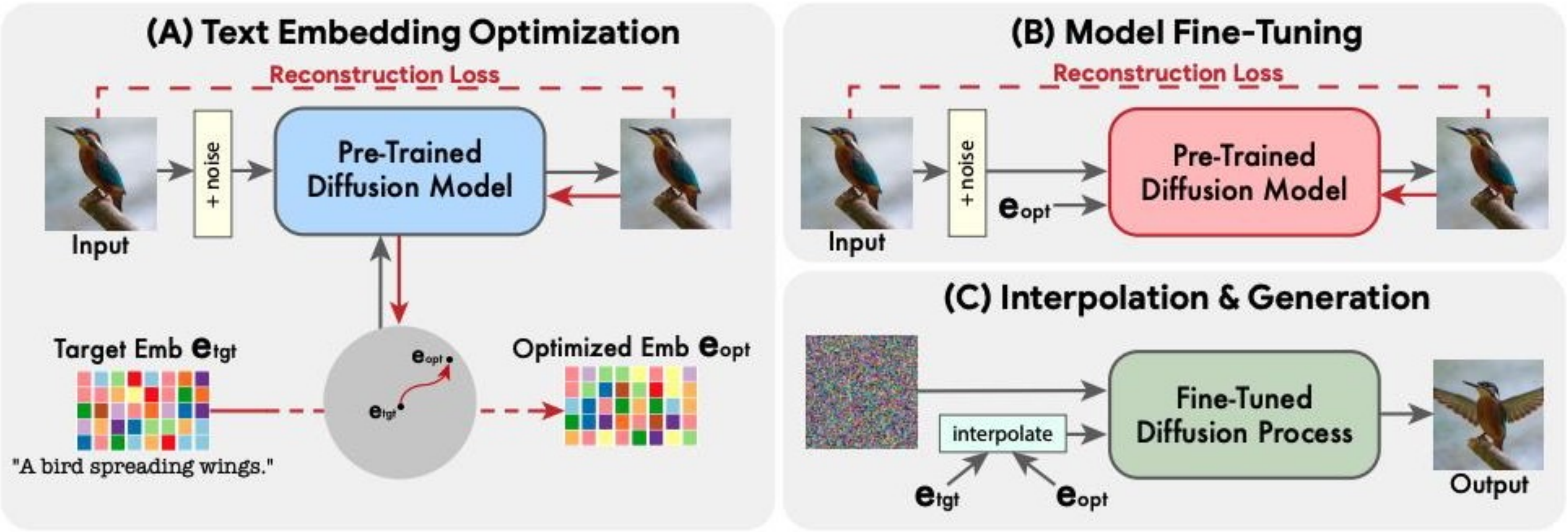
Couairon et al., "DiffEdit: Diffusion-based semantic image editing with mask guidance", ICLR 2023

Imagic: Text-Based Real Image Editing with Diffusion Models



Kawar et al., "Imagic: Text-Based Real Image Editing with Diffusion Models", CVPR 2023

Imagic: Text-Based Real Image Editing with Diffusion Models

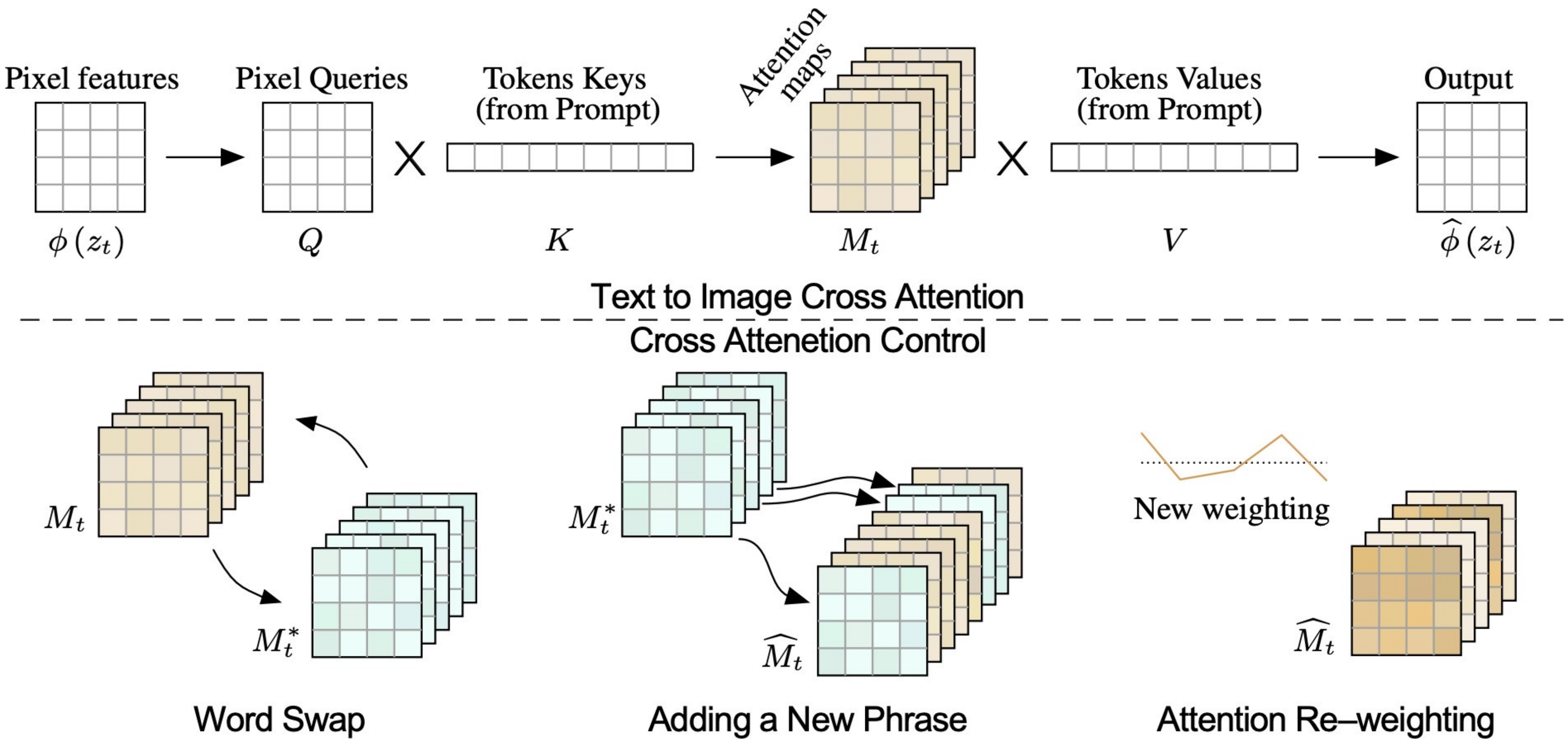


Kawar et al., "Imagic: Text-Based Real Image Editing with Diffusion Models", CVPR 2023

Prompt-to-Prompt Image Editing with Cross-Attention Control

Hertz et al., ["Prompt-to-Prompt Image Editing with Cross-Attention Control"](), ICLR 2023

Prompt-to-Prompt Image Editing with Cross-Attention Control



Hertz et al., ["Prompt-to-Prompt Image Editing with Cross-Attention Control"], ICLR 2023

InstructPix2Pix: Learning to Follow Image Editing Instructions

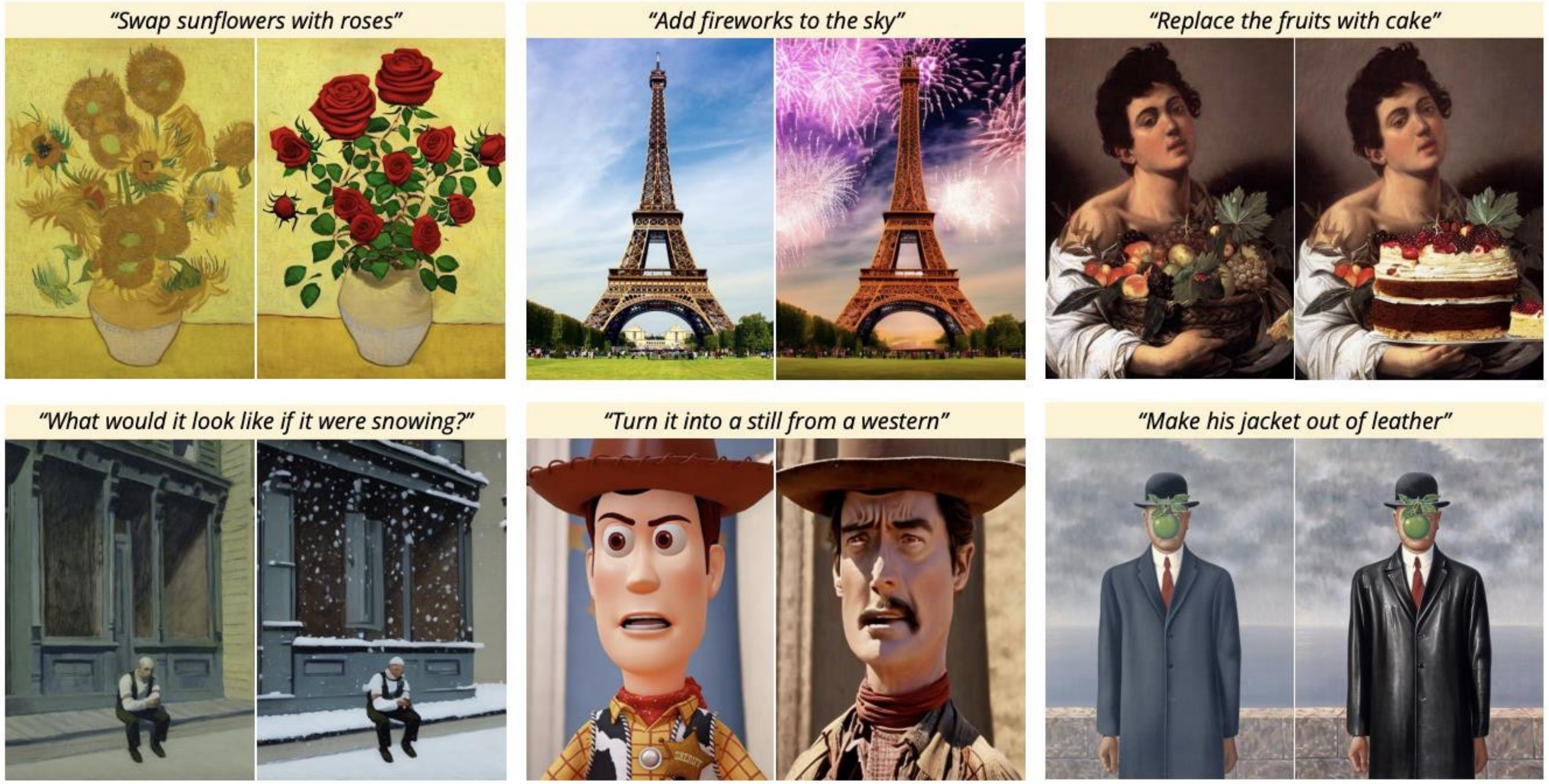
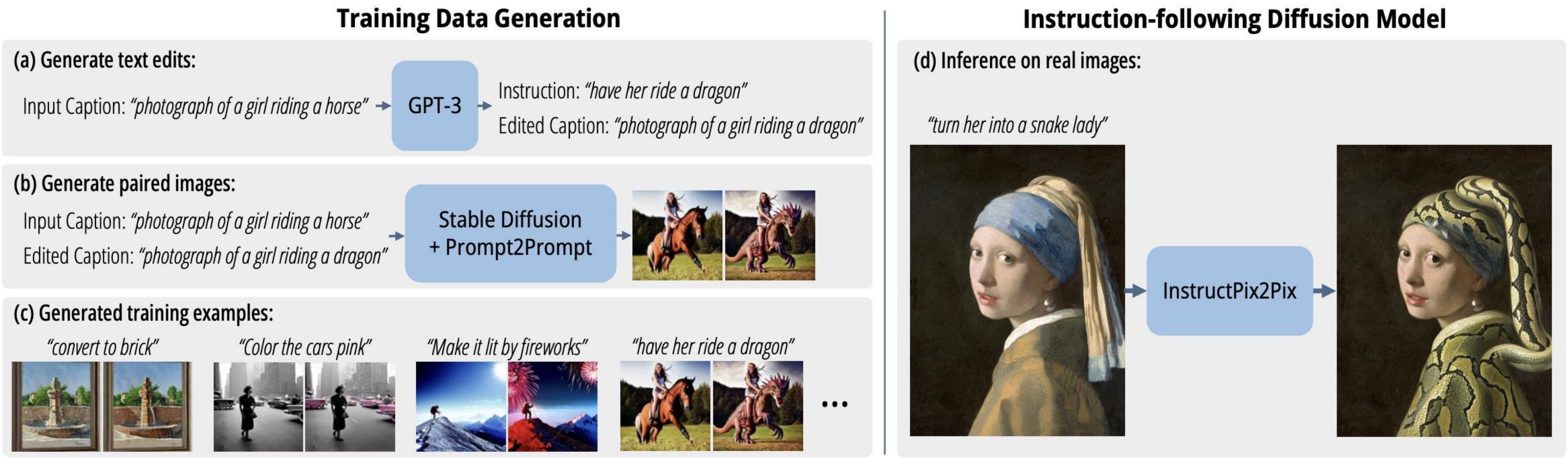


Figure 1. Given **an image** and **an instruction** for how to edit that image, our model performs the appropriate edit. Our model does not require full descriptions for the input or output image, and edits images in the forward pass without per-example inversion or fine-tuning.

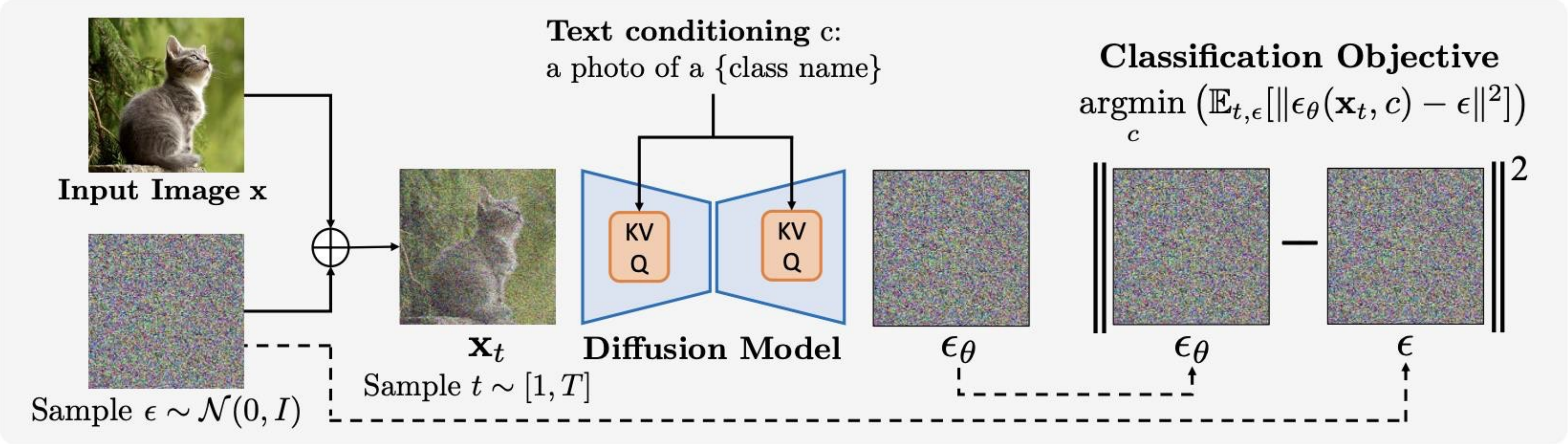
Brooks et al., "Instructpix2pix: Learning to follow image editing instructions", CVPR 2023

InstructPix2Pix: Learning to Follow Image Editing Instructions



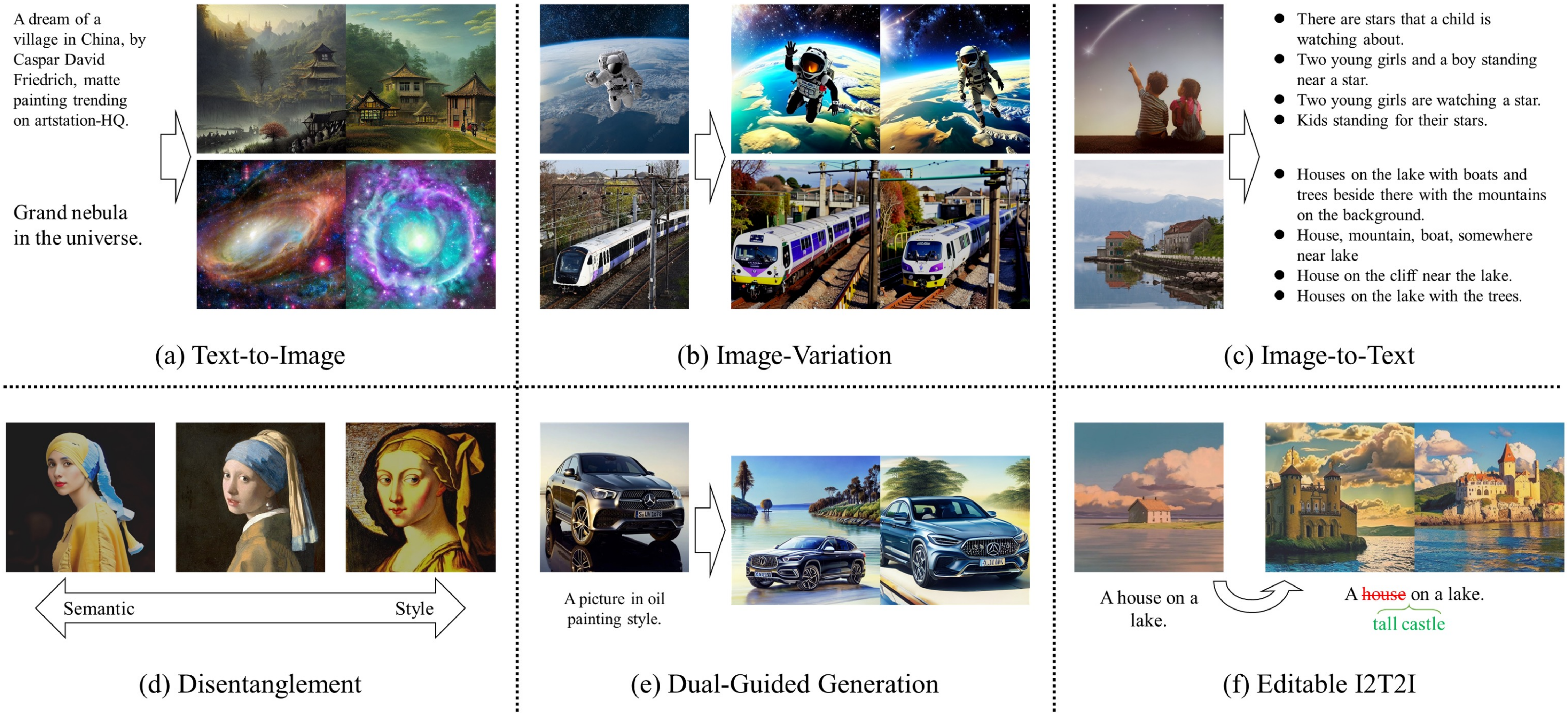
Brooks et al., "Instructpix2pix: Learning to follow image editing instructions", CVPR 2023

Your Diffusion Model is Secretly a Zero-Shot Classifier

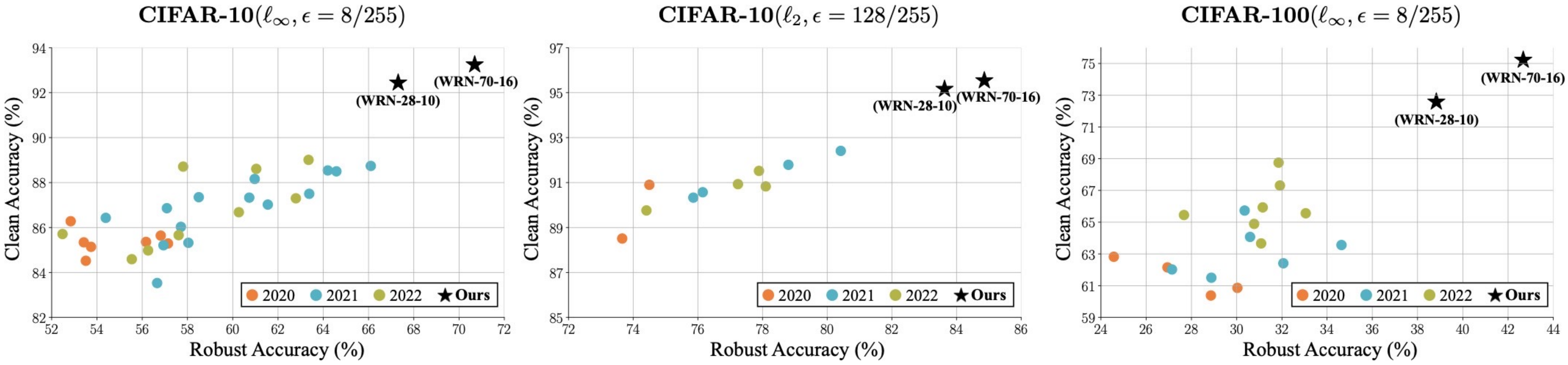


Li et al., "Your Diffusion Model is Secretly a Zero-Shot Classifier", arXiv 2023

Versatile Diffusion: All in One



Better Diffusion Models Improve Adversarial Training



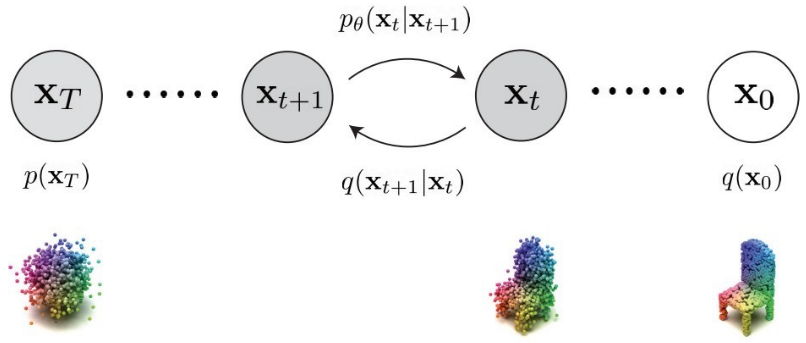
Wang et al., "Better Diffusion Models Further Improve Adversarial Training", ICML 2023

From 2D to 3D: A “natural” idea?

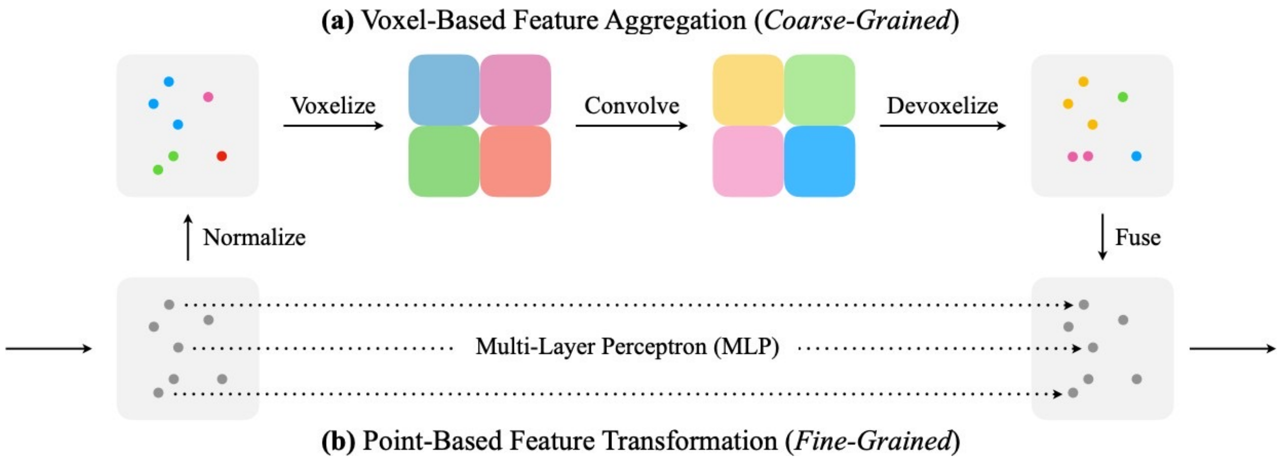
- Train a 3D diffusion model just like image diffusion model
  - Design proper diffusion architecture (still UNet?)
  - Choose proper 3D representation
  - Collect large 3D training corpus

Diffusion Models for Point Clouds

A set of points with location information.



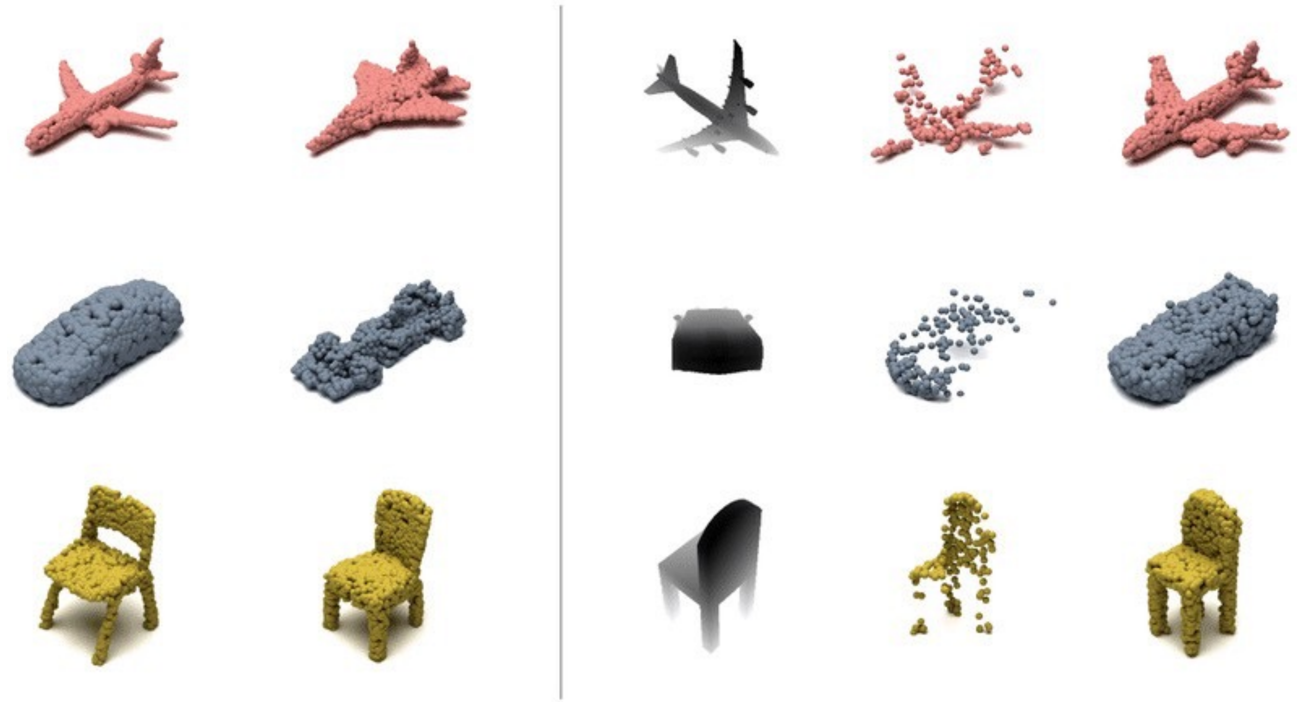
Procedure



Point-Voxel CNN architecture

Zhou et al., "3D Shape Generation and Completion through Point-Voxel Diffusion", ICCV 2021
Liu et al, "Point-Voxel CNN for Efficient 3D Deep Learning", NeurIPS 2019

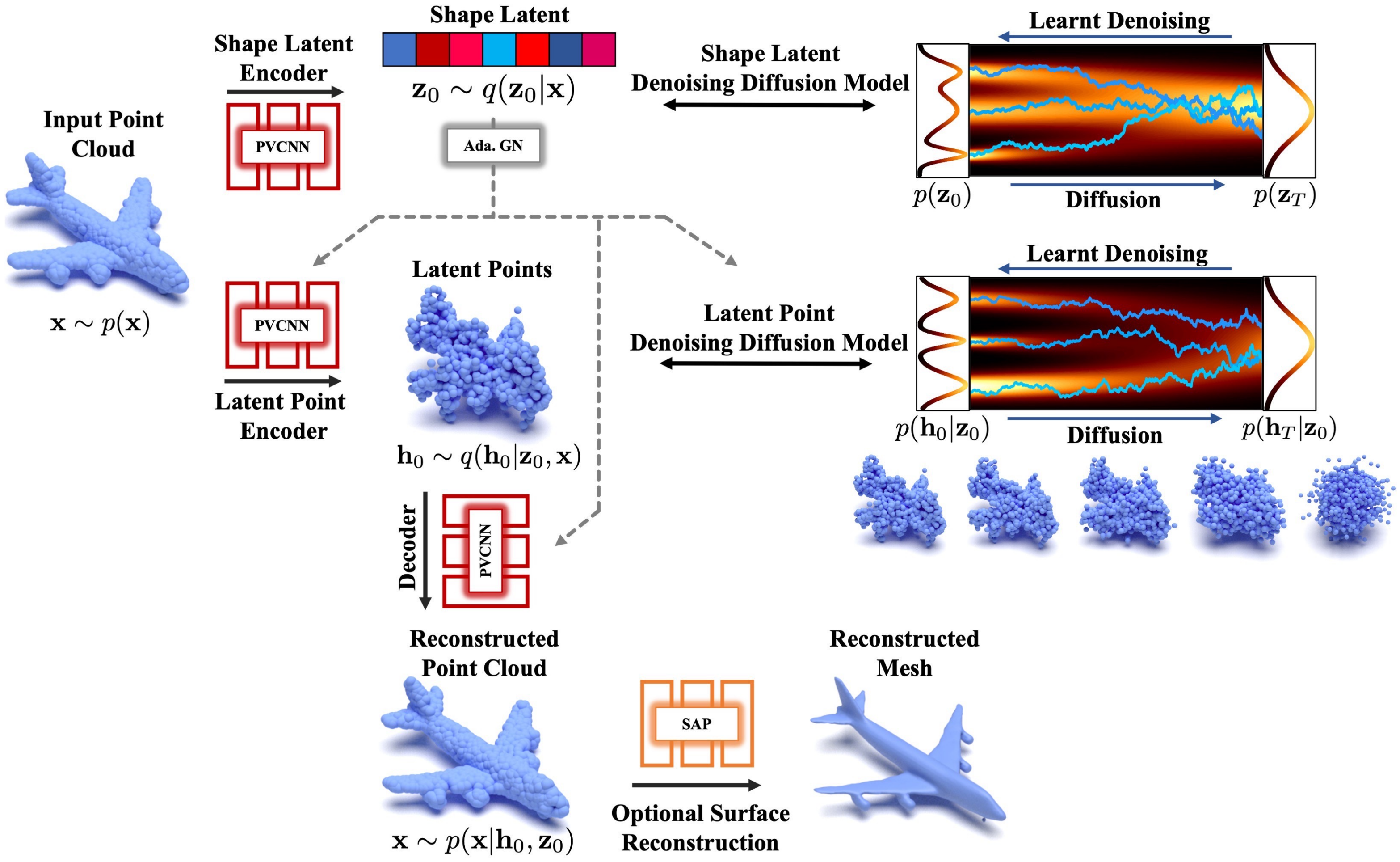
Diffusion Models for Point Clouds



Generation Completion

Zhou et al., "3D Shape Generation and Completion through Point-Voxel Diffusion", ICCV 2021

Diffusion Models for Point Clouds

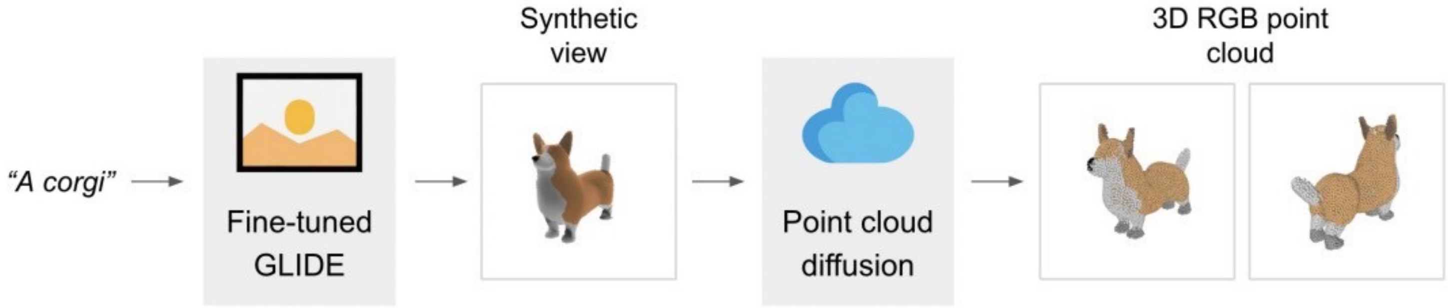


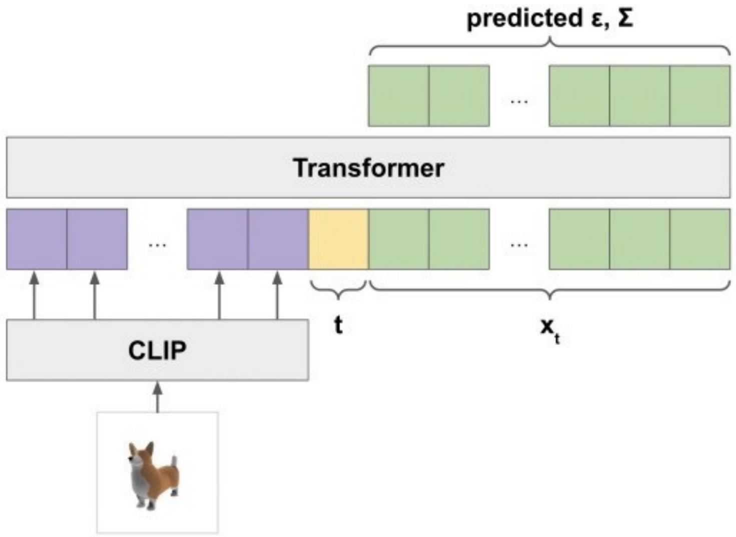
Point cloud diffusion in the latent space

Zeng et al., ["LION: Latent Point Diffusion Models for 3D Shape Generation"](), NeurIPS 2022

Diffusion Models for Point Clouds

Point-E uses a synthetic view from fine-tuned GLIDE, and then ”lifts” the image to a 3d point cloud.



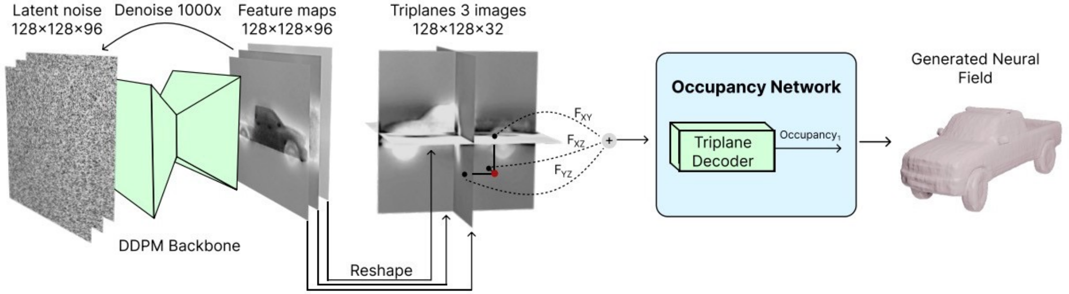


A transformer-based architecture

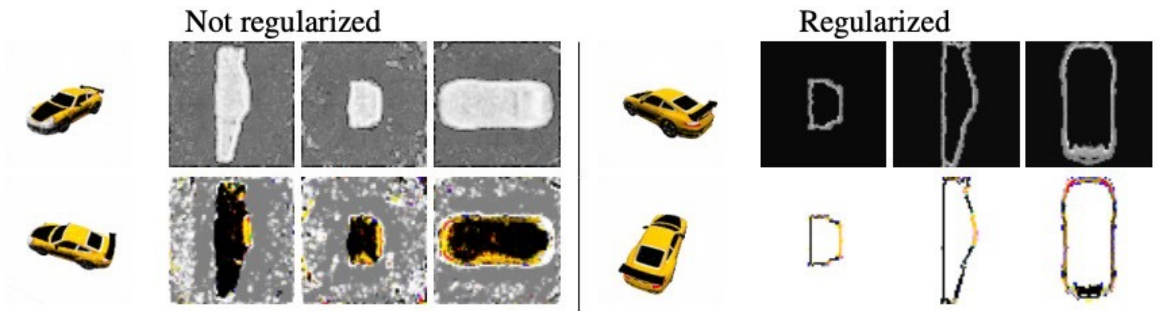
Nichol et al., "Point-E: A System for Generating 3D Point Clouds from Complex Prompts", arXiv 2022

Diffusion Models for Other 3D Representations

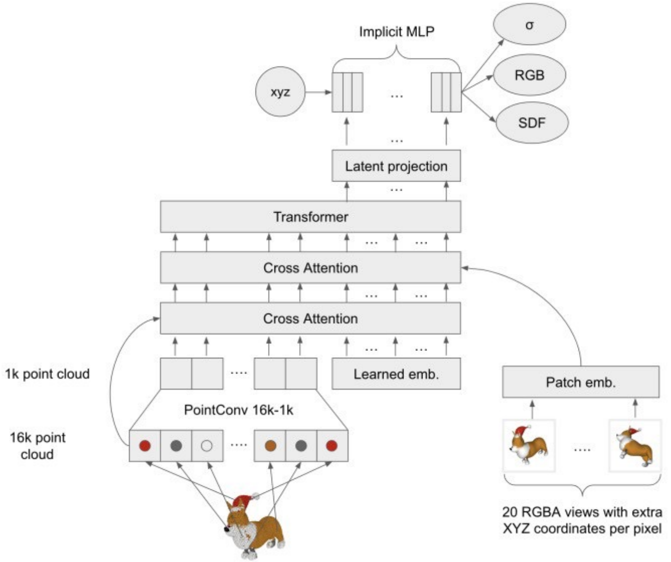
- Triplanes, regularized ReLU Fields, the MLP of NeRFs…
- A good representation is important!



Triplane diffusion



Regularized ReLU Fields



Implicit MLP of NeRFs

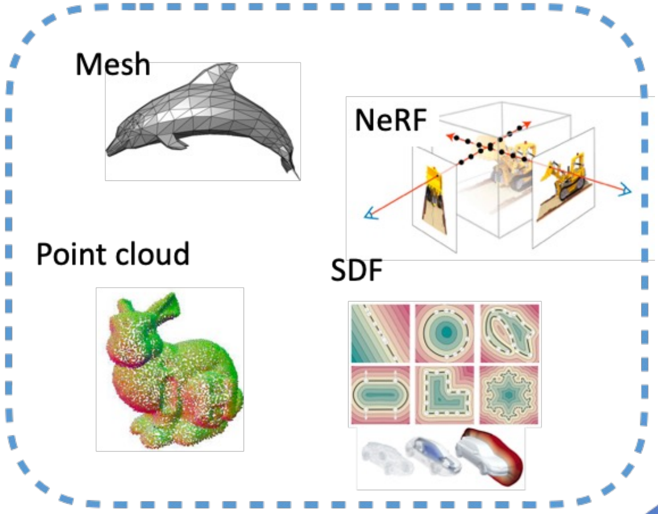
Shue et al., "3D Neural Field Generation using Triplane Diffusion", arXiv 2022
Yang et al., "Learning a Diffusion Prior for NeRFs", ICLR Workshop 2023
Jun and Nichol, "Shap-E: Generating Conditional 3D Implicit Functions", arXiv 2023

2D Diffusion Models for 3D Generation

- We just discussed diffusion models directly on 3d

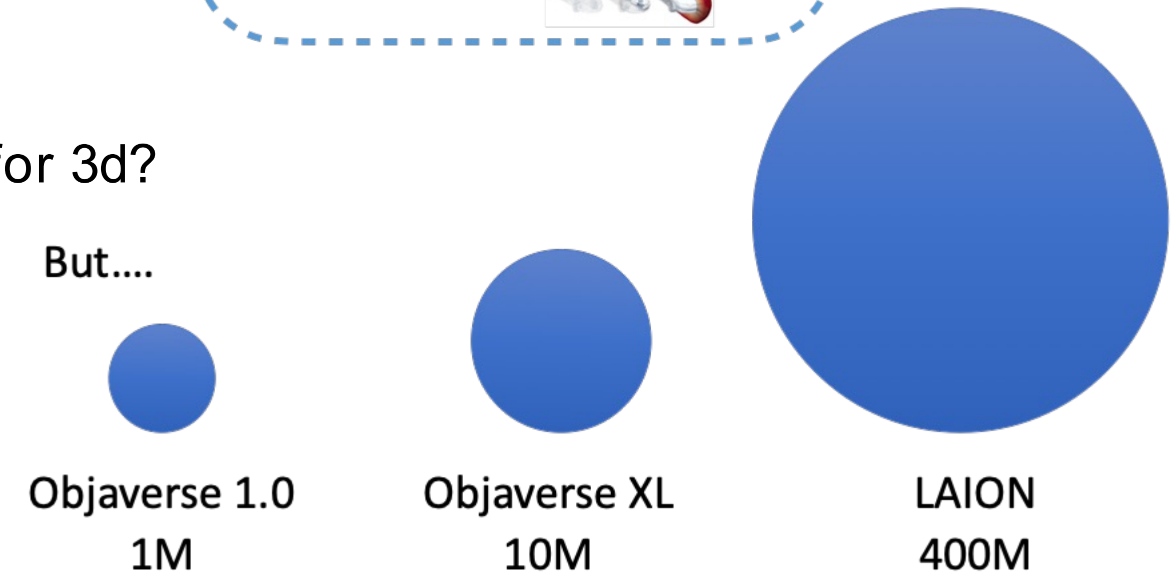
However:

- Design neural architecture for 3D domain is harder
- 3D data are way more flexible in representation and data preprocessing is heavily demanded
- A sufficiently large 3D dataset is less realistic at present (too many experiments on ShapeNet!)

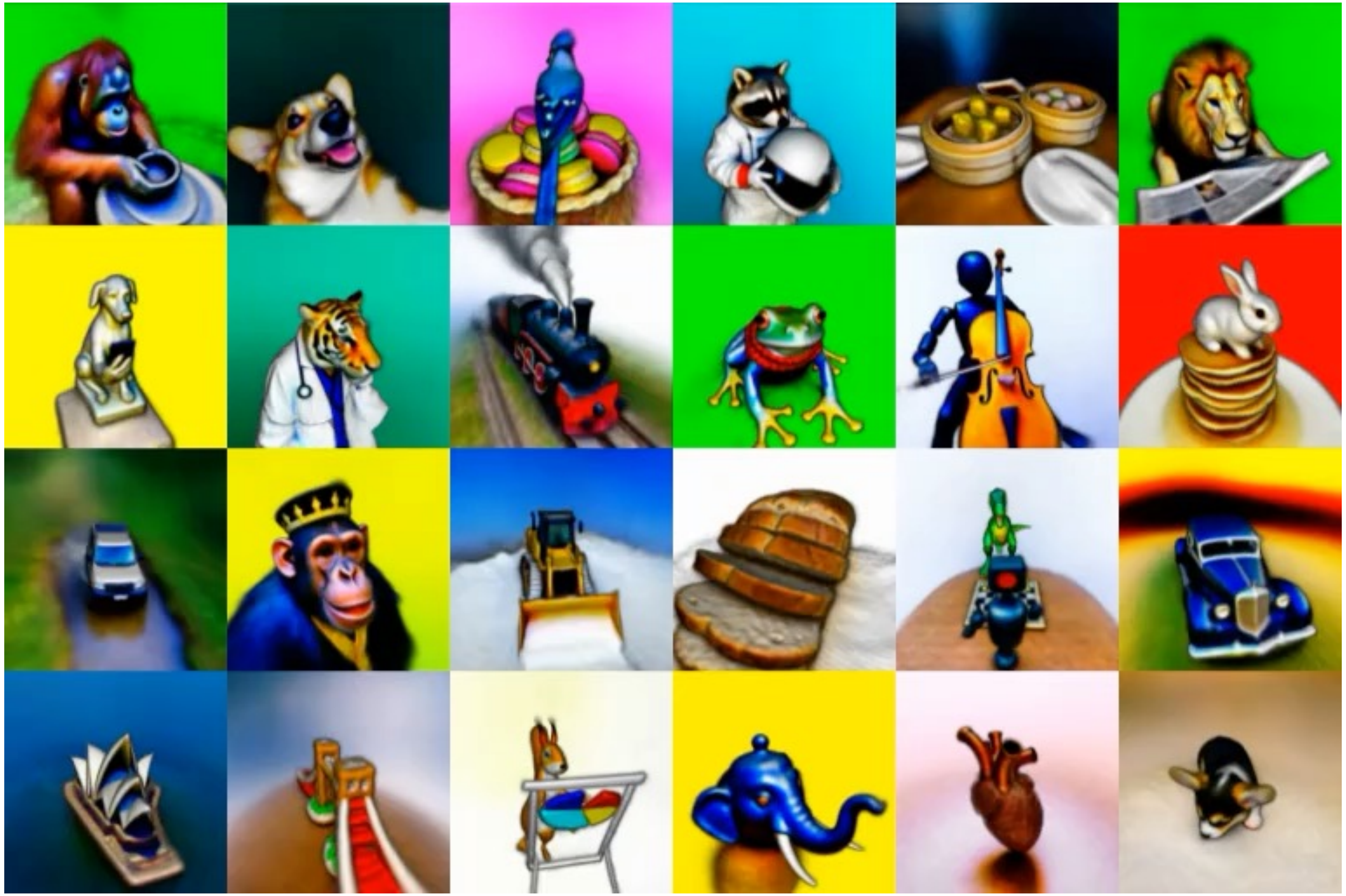


- Can we use 2d diffusion models as a “prior” for 3d?

But....



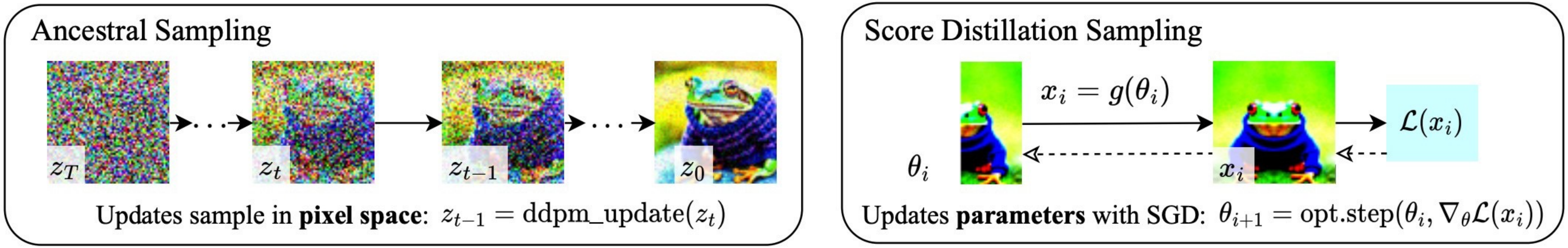
DreamFusion: where it all started



Poole et al., "DreamFusion: Text-to-3D using 2D Diffusion", ICLR 2023

DreamFusion: Setup

- Suppose there is a text-to-image diffusion model.
- Goal: optimize NeRF parameter such that each angle “looks good” from the text-to-image model.
- Unlike ancestral sampling (e.g., DDIM), the underlying parameters are being optimized over some loss function.



Poole et al., "DreamFusion: Text-to-3D using 2D Diffusion", ICLR 2023

DreamFusion: Score Distillation Sampling

- Consider the diffusion model objective for a sample x:

$$\mathcal{L}_{\text{Diff}}(\phi, \mathbf{x}) = \mathbb{E}_{t\sim\mathcal{U}(0,1),\epsilon\sim\mathcal{N}(\mathbf{0},\mathbf{I})}\left[w(t)\|\epsilon_\phi(\alpha_t\mathbf{x}+\sigma_t\epsilon;t)-\epsilon\|_2^2\right] ,$$

- Directly computing the gradient leads to a Jacobian term over the U-Net:

$z_t = \alpha_t x + \sigma_t c$

$$\nabla_\theta\mathcal{L}_{\text{Diff}}(\phi, \mathbf{x}=g(\theta)) = \mathbb{E}_{t,\epsilon}\left[w(t)\underbrace{\left(\hat{\epsilon}_\phi(\mathbf{z}_t;y,t)-\epsilon\right)}_{\text{Noise Residual}}\underbrace{\frac{\partial\hat{\epsilon}_\phi(\mathbf{z}_t;y,t)}{\mathbf{z}_t}}_{\text{U-Net Jacobian}}\underbrace{\frac{\partial\mathbf{x}}{\partial\theta}}_{\text{Generator Jacobian}}\right]$$

- However, it turns out we can consider removing the U-Net Jacobian!

$$\nabla_\theta\mathcal{L}_{\text{SDS}}(\phi, \mathbf{x}=g(\theta)) \triangleq \mathbb{E}_{t,\epsilon}\left[w(t)\left(\hat{\epsilon}_\phi(\mathbf{z}_t;y,t)-\epsilon\right)\frac{\partial\mathbf{x}}{\partial\theta}\right]$$

Poole et al., "DreamFusion: Text-to-3D using 2D Diffusion", ICLR 2023

DreamFusion: Score Distillation Sampling

- Given image distribution as diffusion model: $\epsilon_t(x \mid y) \approx \nabla \log p_t(x \mid y)$
- Maximal log-likelihood estimation: $\min_{\theta} \mathbb{E}_{t,c}[-\log p_t(g(\theta, c) \mid y)]$

$$L_{MLE} = -\log p(x \mid y) \leq \mathbb{E}_{t,\varepsilon}\left[w(t)\|\epsilon_t(\alpha_t x + \sigma_t \varepsilon \mid y) - \varepsilon\|_2^2\right] = L_{DSM}(x) \qquad \text{(ELBO)}$$

$$\nabla_\theta L_{DSM}(x = g(\theta, c)) = \mathbb{E}_{t,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x} \mid y) - \varepsilon)\cancel{\frac{\partial \epsilon_t(\tilde{x} \mid y)}{\partial \tilde{x}}}\frac{\partial g(\theta, c)}{\partial \theta}\right] \qquad \text{(Grad.)}$$

$$\nabla_\theta L_{SDS}(x = g(\theta, c)) = \mathbb{E}_{t,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x} \mid y) - \varepsilon)\frac{\partial g(\theta, c)}{\partial \theta}\right] \qquad \text{(Drop UNet Jacobian)}$$

DreamFusion in Text-to-3D

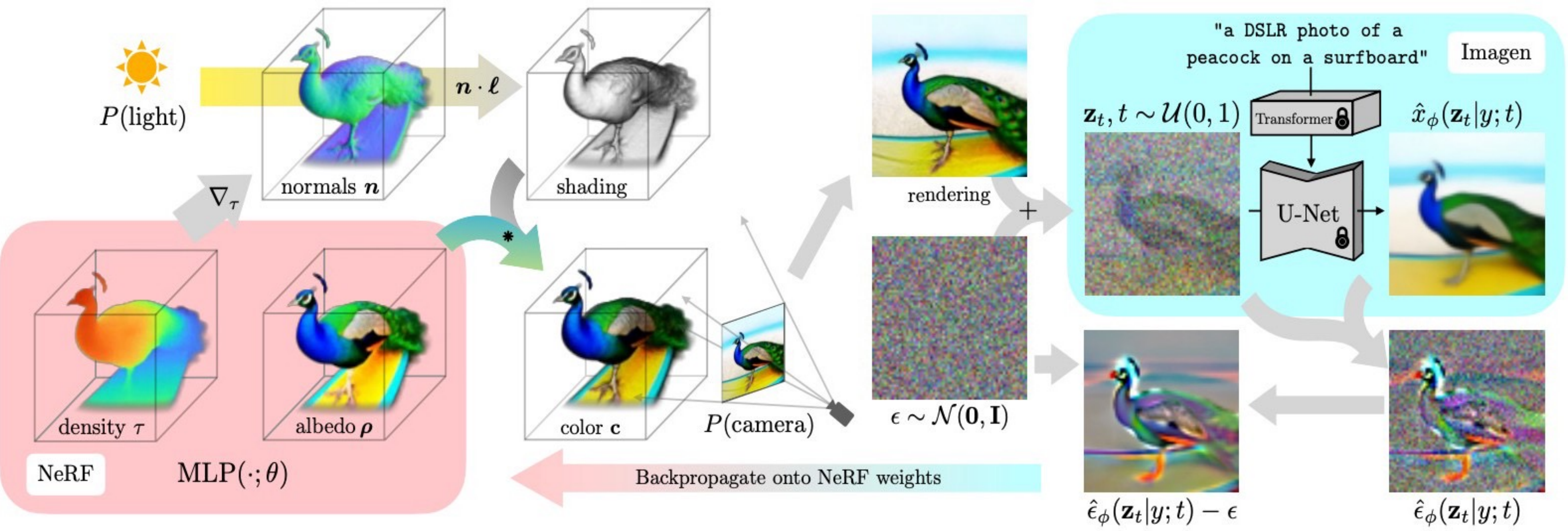
- Random sample a camera pose and render an image: $x = g(\theta, c)$
- Sample t and $\varepsilon \sim \mathcal{N}(0, I)$.
- Let $\tilde{x} = \alpha_t x + \sigma_t \varepsilon$.
- Update θ via SDS gradient:

$$\nabla_\theta L_{SDS} = \mathbb{E}_{t,c,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x} \mid y) - \varepsilon)\frac{\partial \epsilon(\tilde{x} \mid y)}{\partial \theta}\right]$$

- Stop gradient trick:

$$\nabla_\theta L_{SDS} = \nabla_\theta \mathbb{E}_{t,c,\varepsilon}\left[\text{stopgrad}[\epsilon_t(\tilde{x} \mid y) - \epsilon]^\top g(\theta, c)\right]$$

- SDS can be used to optimize a 3D representation, like NeRF.

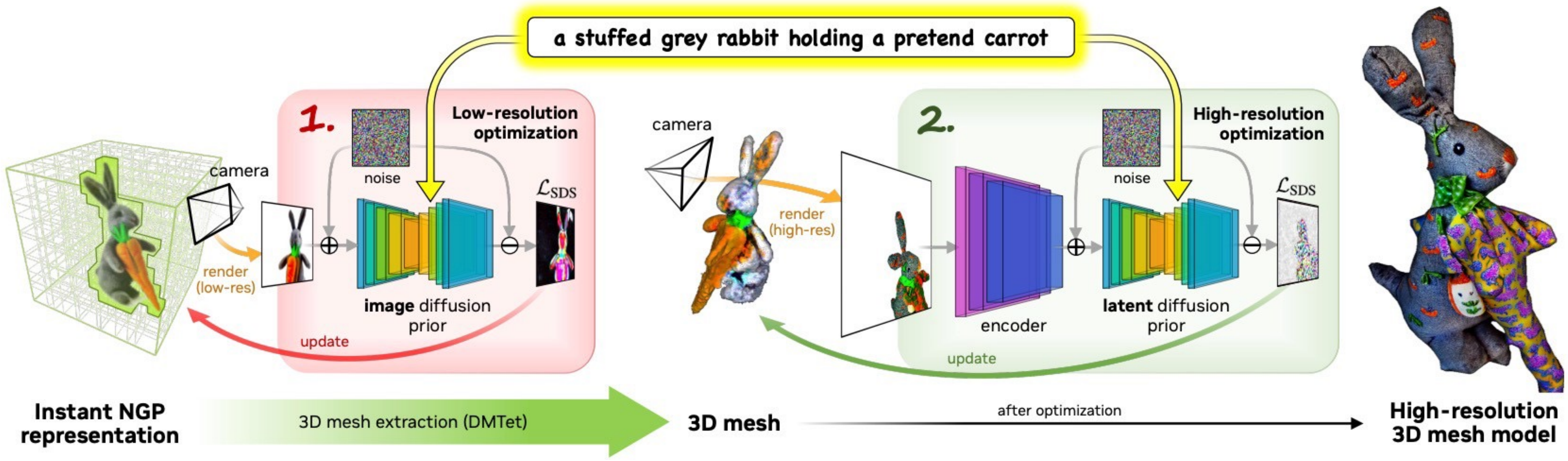


Poole et al., "DreamFusion: Text-to-3D using 2D Diffusion", ICLR 2023

Extensions to SDS: Magic3D

2x speed and higher resolution

- Accelerate NeRF with Instant-NGP, for coarse representations.
- Optimize a fine mesh model with differentiable renderer.



Lin et al., "Magic3D: High-Resolution Text-to-3D Content Creation", CVPR 2023

Alternative to SDS: Score Jacobian Chaining

A different formulation, motivated from approximating 3D score.

$$\nabla_{\boldsymbol{\theta}} \log \tilde{p}_\sigma(\boldsymbol{\theta}) = \mathbb{E}_\pi \left[\nabla_{\boldsymbol{\theta}} \log p_\sigma(\boldsymbol{x}_\pi)\right]$$

$$\frac{\partial \log \tilde{p}_\sigma(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \mathbb{E}_\pi \left[\frac{\partial \log p_\sigma(\boldsymbol{x}_\pi)}{\partial \boldsymbol{x}_\pi} \cdot \frac{\partial \boldsymbol{x}_\pi}{\partial \boldsymbol{\theta}}\right]$$

$$\underbrace{\nabla_{\boldsymbol{\theta}} \log \tilde{p}_\sigma(\boldsymbol{\theta})}_{\text{3D score}} = \mathbb{E}_\pi [\underbrace{\nabla_{\boldsymbol{x}_\pi} \log p_\sigma(\boldsymbol{x}_\pi)}_{\text{2D score; pretrained}} \cdot \underbrace{\boldsymbol{J}_\pi}_{\text{renderer Jacobian}}].$$

In principle, the diffusion model is the noisy 2D score (over clean images),
but in practice, the diffusion model suffers from out-of-distribution (OOD) issues!

For diffusion model on noisy images, the non-noisy images are OOD!

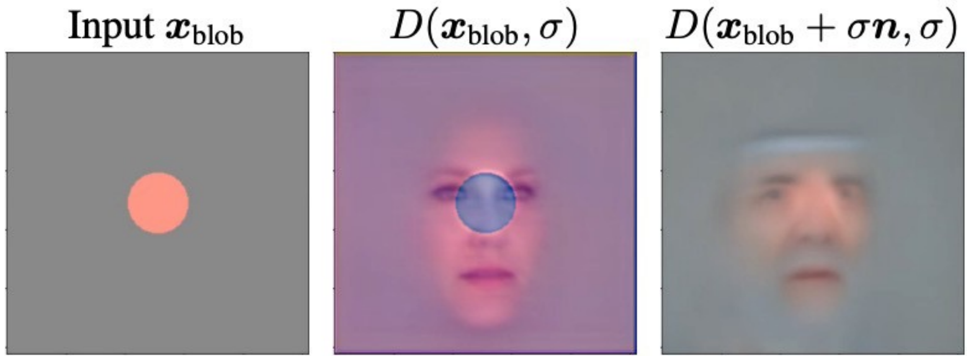
Wang et al., ["Score Jacobian Chaining: Lifting Pretrained 2D Diffusion Models for 3D Generation"](), CVPR 2023.

Score Jacobian Chaining

- SJC approximates noisy score with “Perturb-and-Average Scoring”, which is not present in SDS.
- Use score model on multiple noise-perturbed data, then average it.

$$
\begin{aligned}
&\text{PAAS}(\boldsymbol{x}_\pi, \sqrt{2}\sigma) \\
&\triangleq \mathbb{E}_{\boldsymbol{n}\sim\mathcal{N}(0,\mathbf{I})}\left[\text{score}(\boldsymbol{x}_\pi + \sigma\boldsymbol{n}, \sigma)\right] \\
&= \mathbb{E}_{\boldsymbol{n}}\left[\frac{D(\boldsymbol{x}_\pi + \sigma\boldsymbol{n}, \sigma) - (\boldsymbol{x}_\pi + \sigma\boldsymbol{n})}{\sigma^2}\right] \\
&= \mathbb{E}_{\boldsymbol{n}}\left[\frac{D(\boldsymbol{x}_\pi + \sigma\boldsymbol{n}, \sigma) - \boldsymbol{x}_\pi}{\sigma^2}\right] \cancel{- \underbrace{\mathbb{E}_{\boldsymbol{n}}\left[\frac{\boldsymbol{n}}{\sigma}\right]}_{=0}}.
\end{aligned}
$$

$$
\text{PAAS}(\boldsymbol{x}_\pi, \sqrt{2}\sigma) \approx \boldsymbol{\nabla}_{\boldsymbol{x}_\pi} \log p_{\sqrt{2}\sigma}(\boldsymbol{x}_\pi).
$$



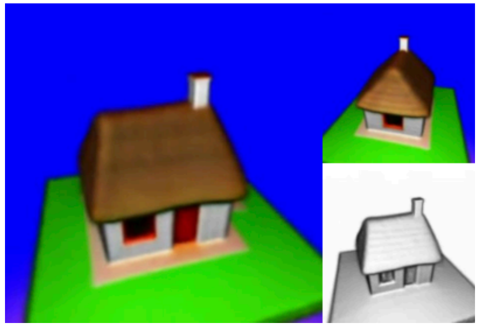
PAAS helps guide updates with a better score.

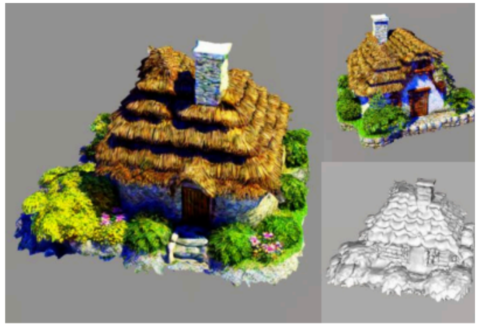
Wang et al., "Score Jacobian Chaining: Lifting Pretrained 2D Diffusion Models for 3D Generation", CVPR 2023.

Advancements on score distillation

- ProlificDreamer - Variational Score Distillation (VSD):
  - $\nabla_\theta L_{VSD} = \mathbb{E}_{t,c,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x}\ \ y) - \epsilon_t^{Lora}(\tilde{x}\ \ c, y))\frac{\partial g(\theta, c)}{\partial \theta}\right]$
  - where $\epsilon_t^{LoRA}(\tilde{x}\ \ c, y)$ is camera pose conditioned and fine-tuned from pre-trained SD using LoRA.
  - Wasserstein gradient flow to minimize KL divergence between noisy rendered image distribution and perturbed 2D image distribution.

DreamFusion





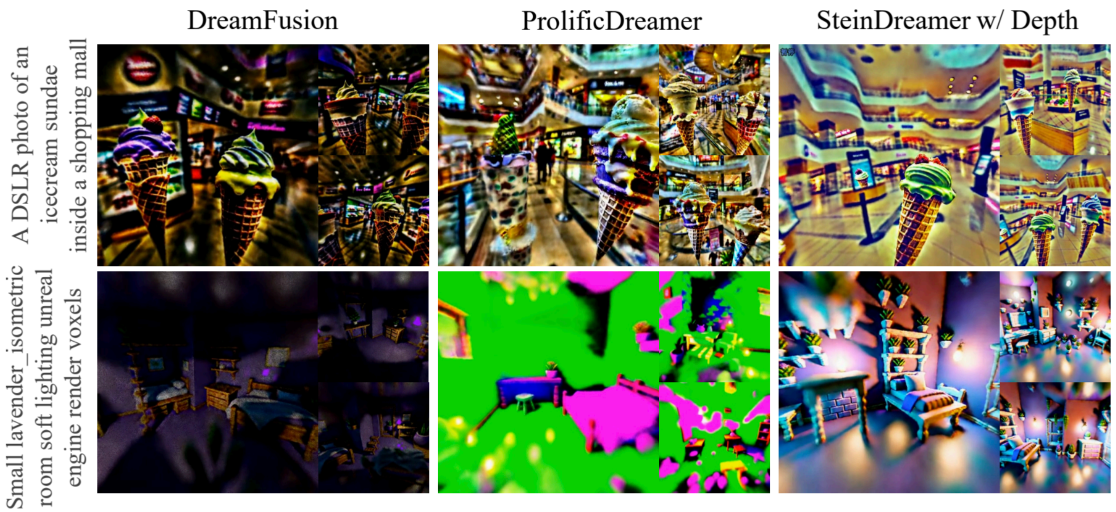
ProlificDreamer

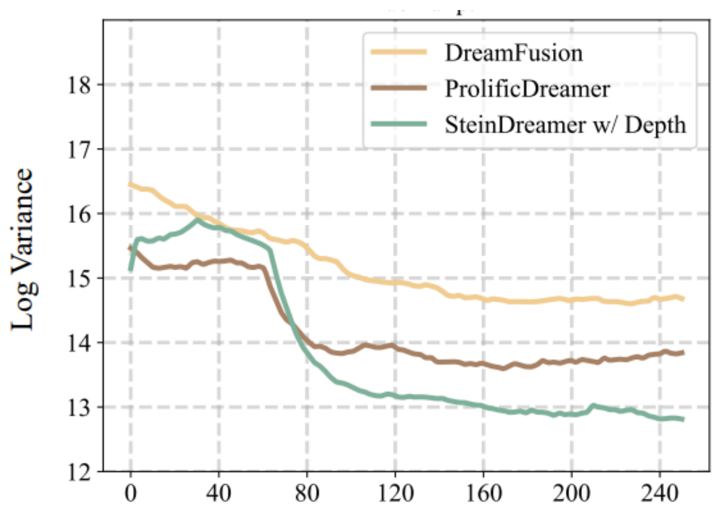
ProlificDreamer produces sharper and more photorealistic textures.

Wang et al., ProlificDreamer: High-Fidelity and Diverse Text-to-3D Generation with Variational Score Distillation

Advancements on score distillation

- SteinDreamer - Stein Score Distillation (SSD)
  - $$\nabla_\theta L_{SSD} = \mathbb{E}_{t,c,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x}\ \ y) + \varepsilon\phi(\tilde{x},\theta,c) + \nabla\phi(\tilde{x},\theta,c))\frac{\partial g(\theta,c)}{\partial\theta}\right]$$
  - Control variate method via Stein identity for variance reduction on gradient estimation.

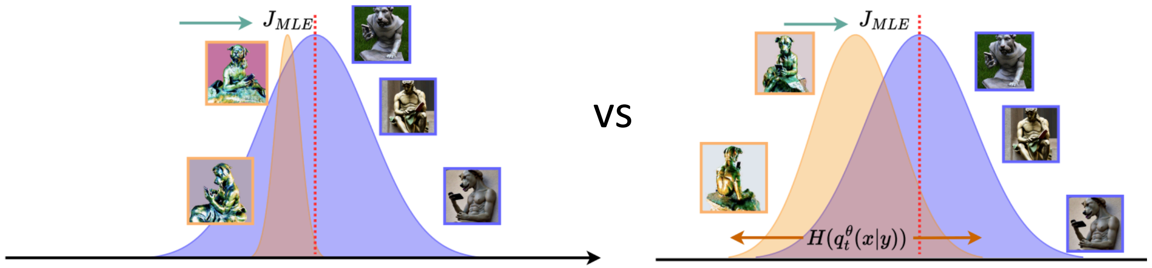


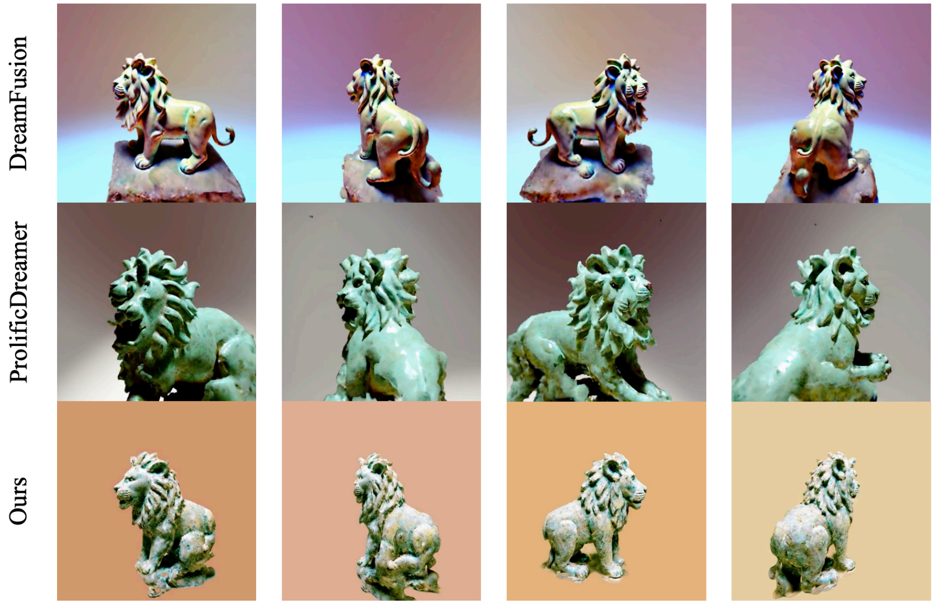


Wang et al., SteinDreamer: Variance Reduction for Text-to-3D Score Distillation via Stein Identity

Advancements on score distillation

- Entropic Score Distillation (ESD)
  - $\nabla_\theta L_{ESD} = \mathbb{E}_{t,c,\varepsilon}\left[w(t)(\epsilon_t(\tilde{x}\ \ y) - \lambda\epsilon_t^{Lora}(\tilde{x}\ \ c, y) - (1-\lambda)\epsilon_t^{Lora}(\tilde{x}\ \ y))\frac{\partial g(\theta, c)}{\partial \theta}\right]$
  - Recover the entropy maximization term for VSD when minimizing the KL divergence to alleviate Janus problem.





Wang et al., Taming Mode Collapse in Score Distillation for Text-to-3D Generation

Novel-view Synthesis with Diffusion Models

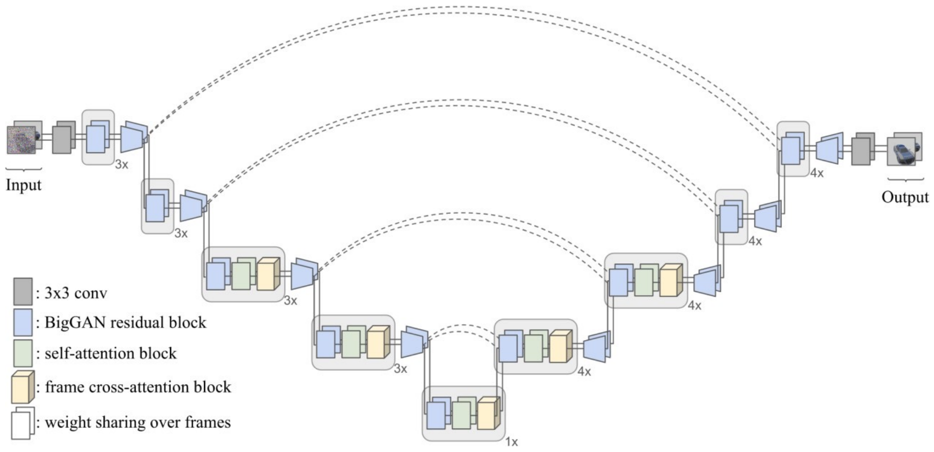
- These do not produce 3D as output, but synthesis the view at different angles.



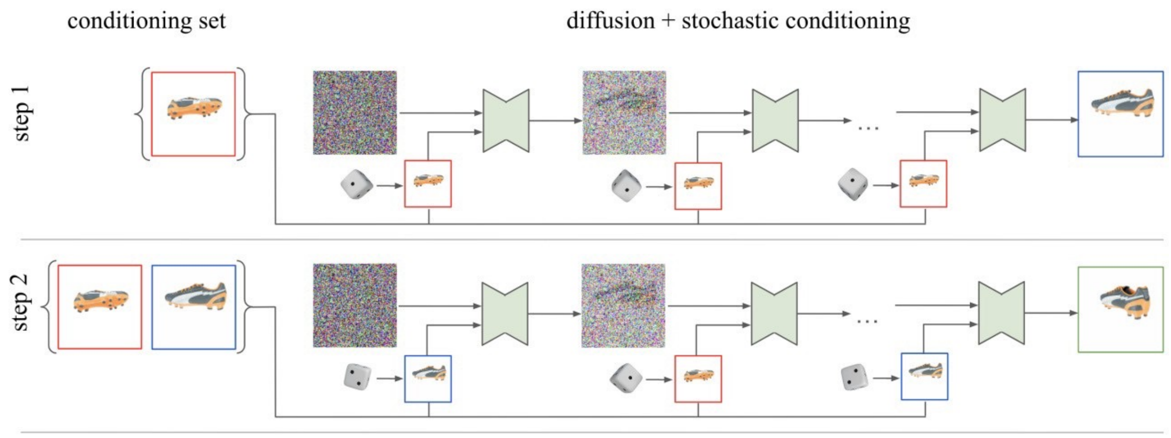

Watson et al., ["Novel View Synthesis with Diffusion Models"](), ICLR 2023

3DiM

- Condition on a frame and two poses, predict another frame.



UNet with frame cross-attention

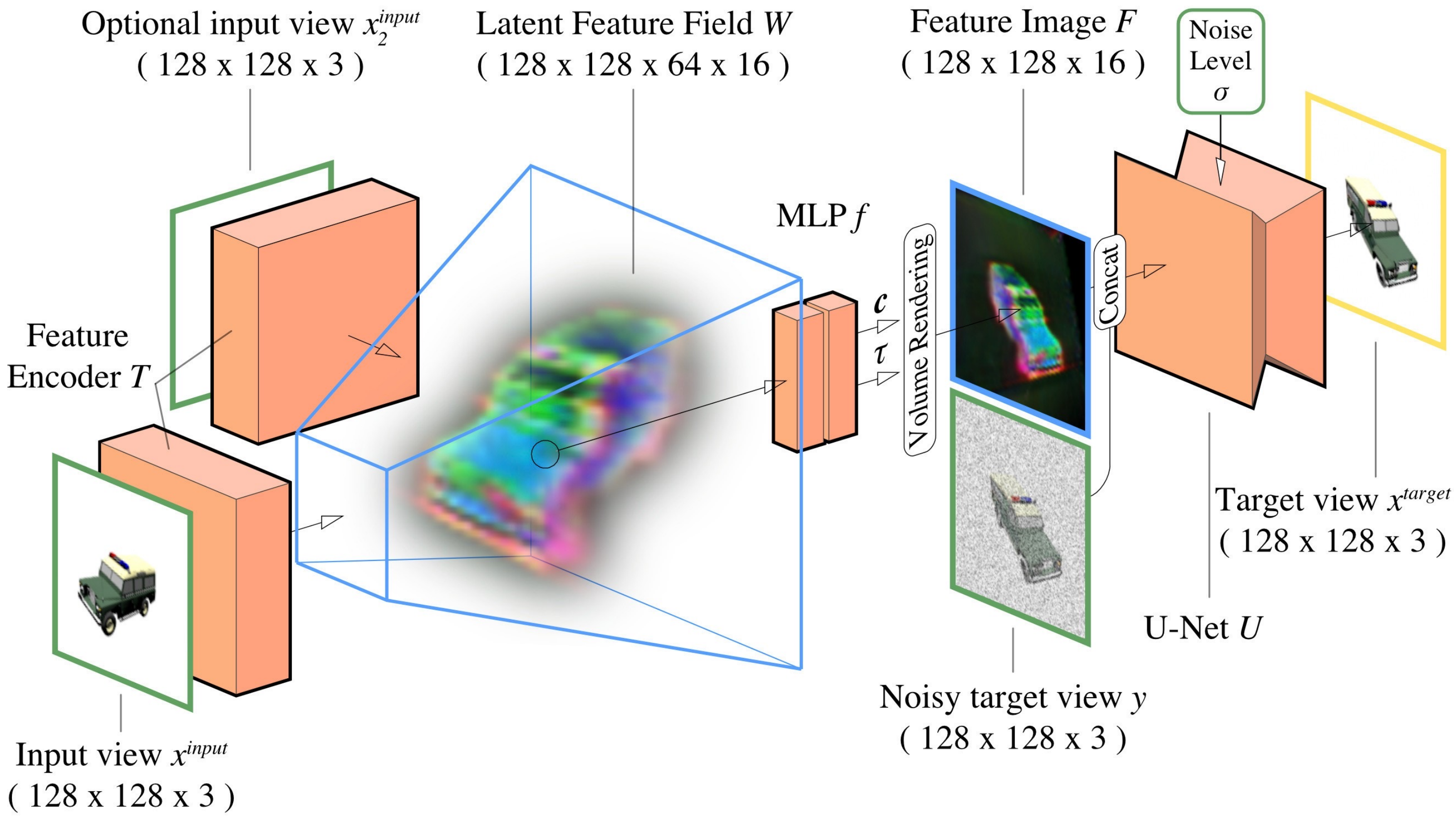


Sample based on stochastic conditions, allowing the use of multiple conditional frames.

Watson et al., ["Novel View Synthesis with Diffusion Models"](), ICLR 2023

GenVS

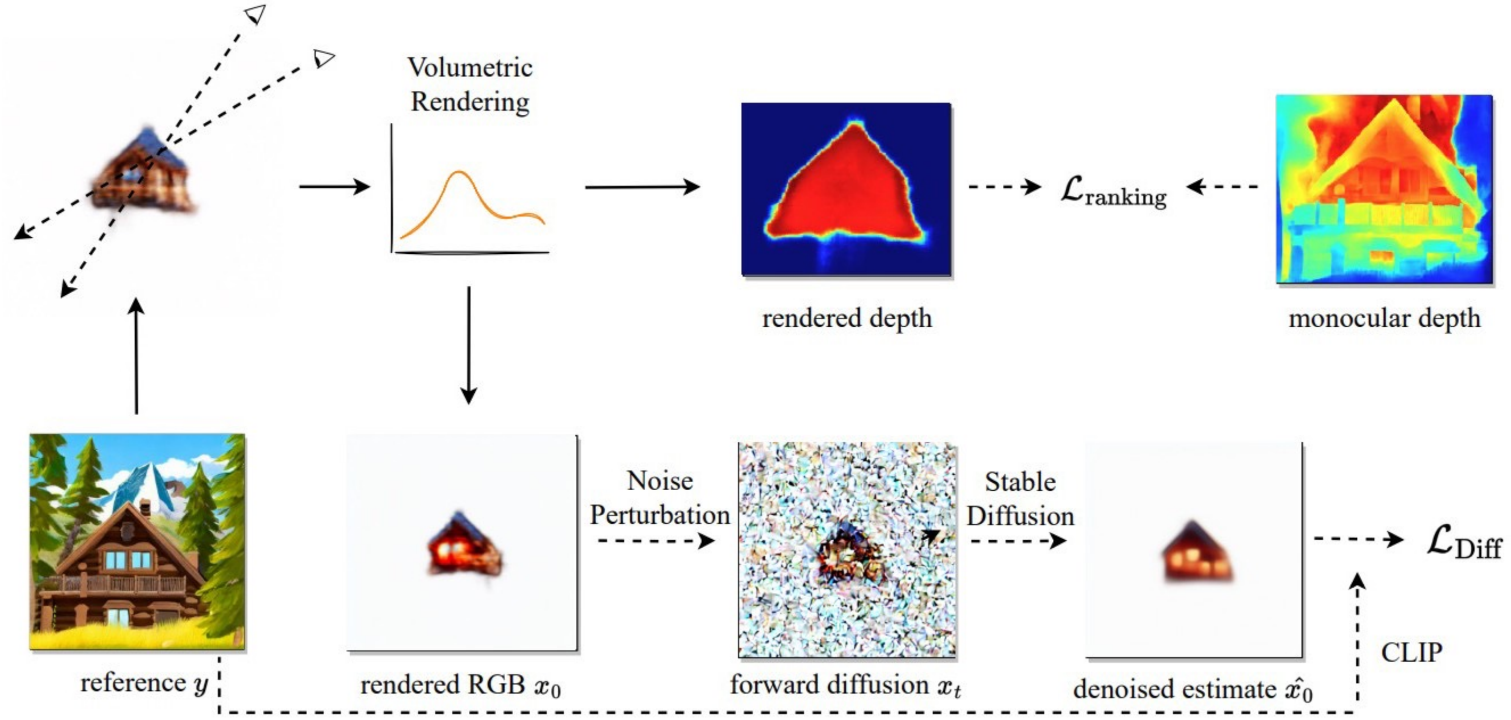
- 3D-aware architecture with latent feature field.
- Use diffusion model to improve render quality based on structure.



Chan et al., ["Generative Novel View Synthesis with 3D-Aware Diffusion Models"](), arXiv 2023

NeuralLift-360 for 3D reconstruction

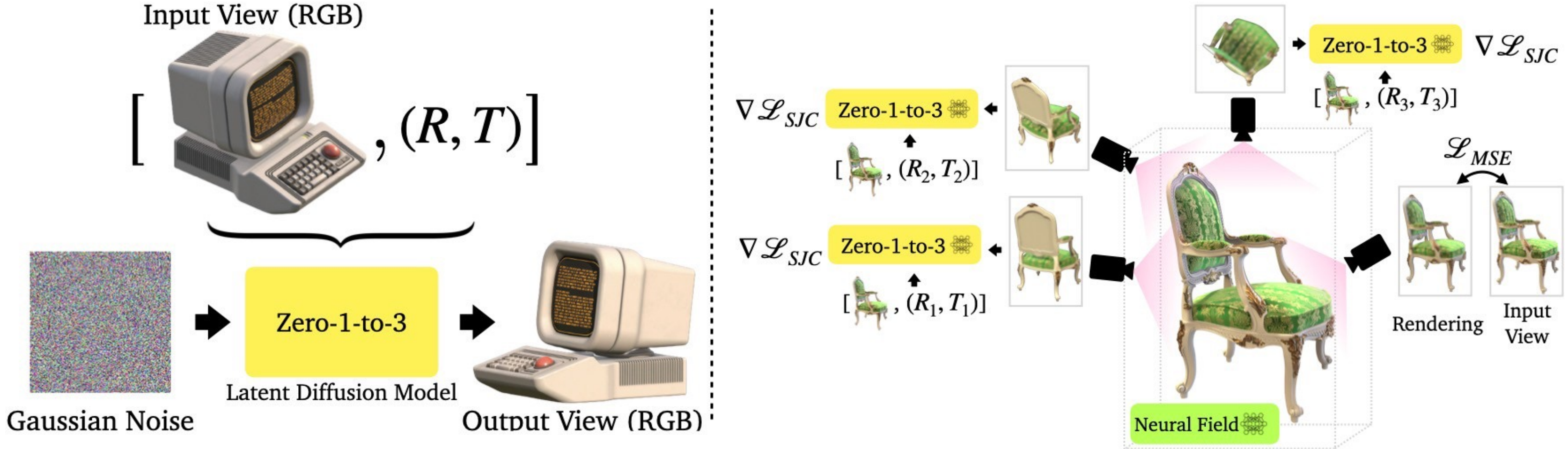
- SDS + Fine-tuned CLIP text embedding + Depth supervision



Xu et al., "NeuralLift-360: Lifting An In-the-wild 2D Photo to A 3D Object with 360° Views", CVPR 2023

Zero 1-to-3

- Generate novel view from 1 view and pose, with 2d model.
- Then, run SJC / SDS-like optimizations with camera view-conditioned model
- Training using Objaverse dataset from pre-trained SD
- Follow-up: Zero123++, MVDreamer …



Novel View Synthesis

3D Reconstruction

[1] Liu et al., Zero-1-to-3: Zero-shot One Image to 3D Object
[2] Shi et al., Zero123++: a Single Image to Consistent Multi-view Diffusion Base Model
[3] Shi et al., MVDream: Multi-view Diffusion for 3D Generation

Instruct NeRF2NeRF

Edit a 3D scene with text instructions

Haque et al., ["Instruct-NeRF2NeRF: Editing 3D Scenes with Instructions"](), arXiv 2023

Instruct NeRF2NeRF

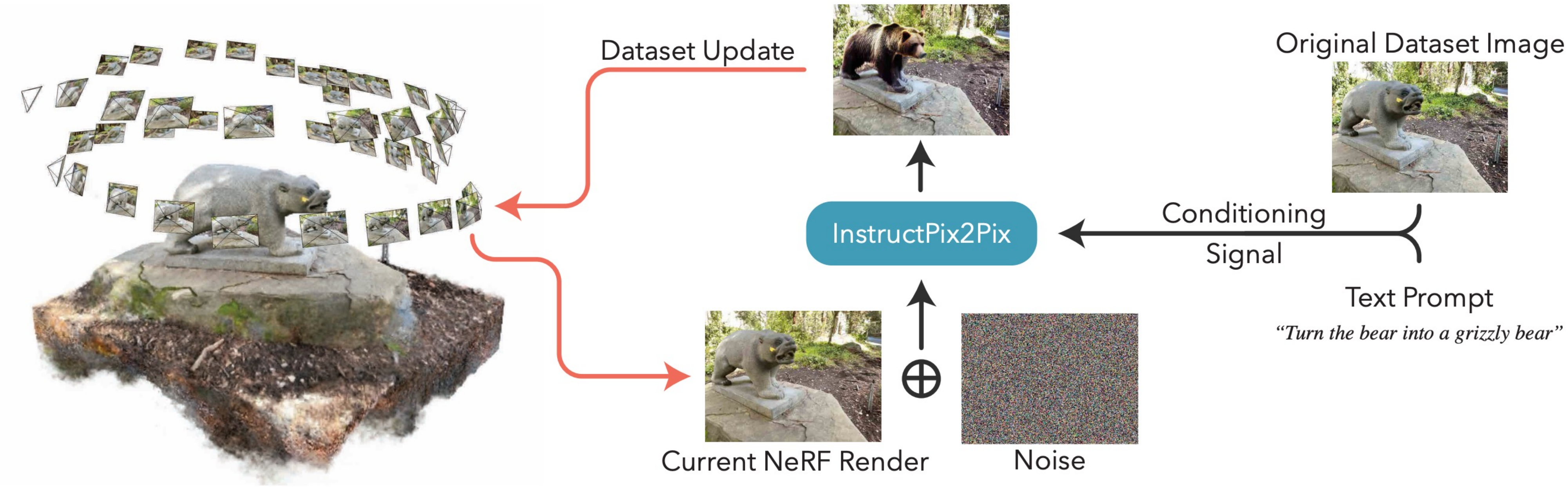
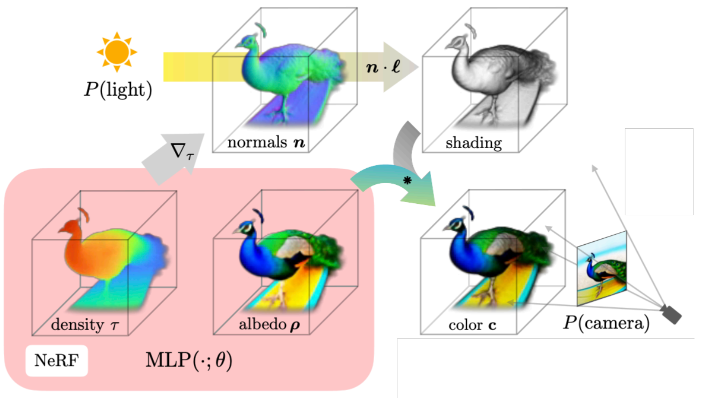


Figure 2: **Overview**: Our method gradually updates a reconstructed NeRF scene by iteratively updating the dataset images while training the NeRF: (1) an image is rendered from the scene at a training viewpoint, (2) it is edited by InstructPix2Pix given a global text instruction, (3) the training dataset image is replaced with the edited image, and (4) the NeRF continues training as usual.

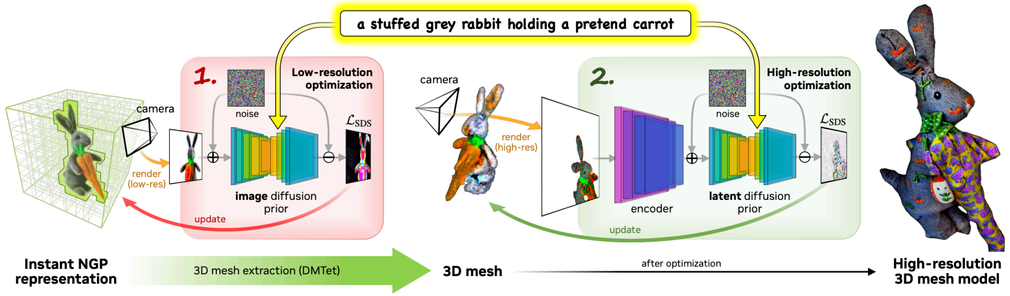
Haque et al., ["Instruct-NeRF2NeRF: Editing 3D Scenes with Instructions"](), arXiv 2023

Choosing 3D representation

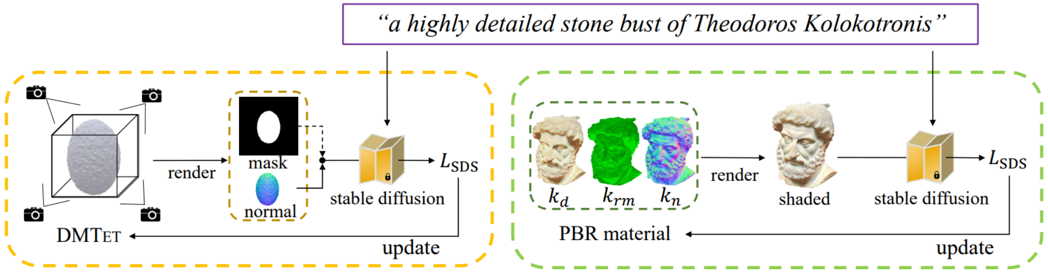
- DreamFusion: Ref-NeRF as base representation and apply lighting augmentation.
- Magic3D [1]: coarse generation via volumetric representation (NeRF) -> refinement with differentiable mesh representation (DMTet).
- Fantasia3D [2]: disentangle 3D representation to geometry and appearance (material) properties.



DreamFusion



Magic3D



Fantasia3D

[1] Lin et al., Magic3D: High-Resolution Text-to-3D Content Creation
[2] Chen et al., Fantasia3D: Disentangling Geometry and Appearance for High-quality Text-to-3D Content Creation




Text-to-Video Generation

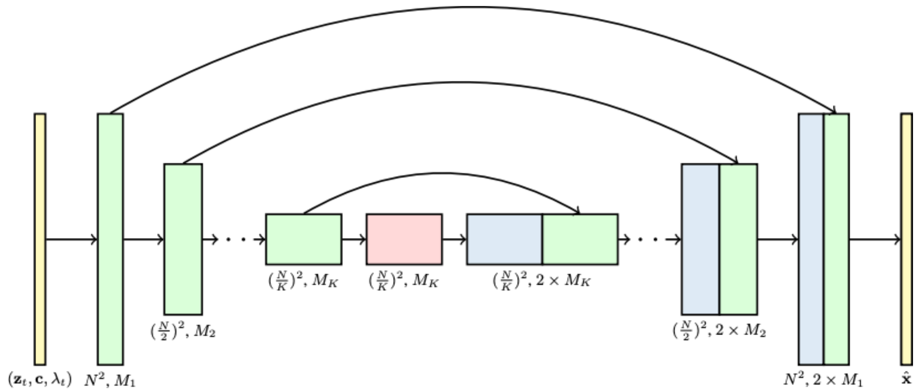
From Text-to-Image Diffusion Models to Text-to-Video Diffusion Models




Video Diffusion Models

3D UNet from a 2D UNet.

- 3x3 2d conv to 1x3x3 3d conv.
- Factorized spatial and temporal attentions.



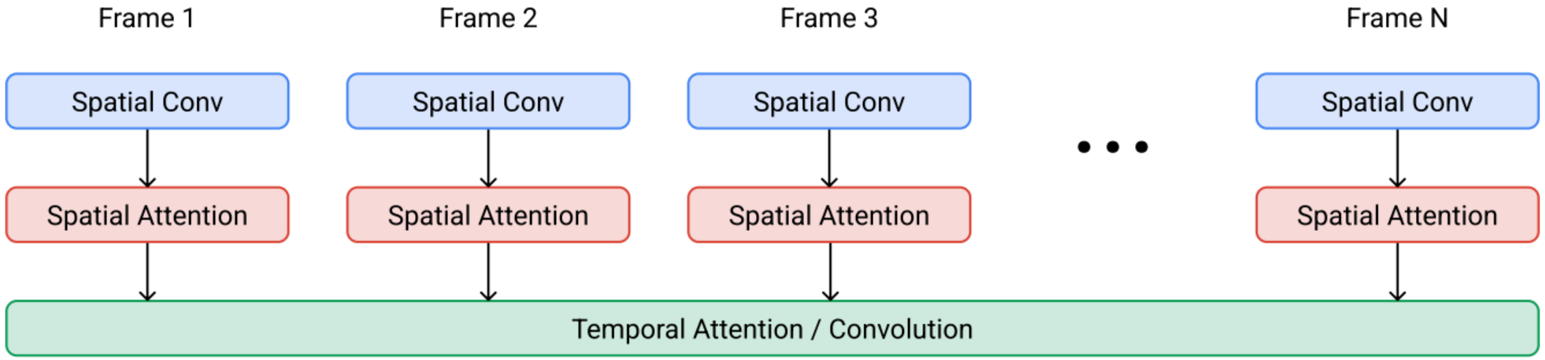
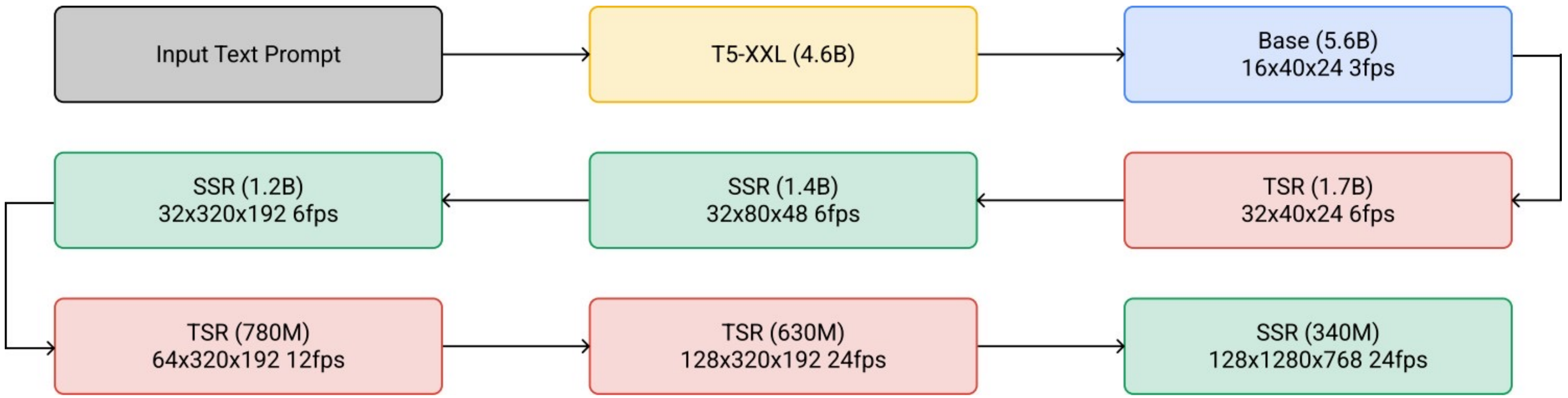


Illustration on how the 3d attention is factorized (from Imagen video)

Ho et al., ["Video Diffusion Models"](), NeurIPS 2022

Imagen Video: Large Scale Text-to-Video

- 7 cascade models in total.
- 1 Base model (16x40x24)
- 3 Temporal super-resolution models.
- 3 Spatial super-resolution models.



Ho et al., "Imagen Video: High Definition Video Generation with Diffusion Models", 2022

Make-A-Video: Text-to-Video Generation without Text-Video Data

Convert text into image embedding and train a video generator conditioned on image

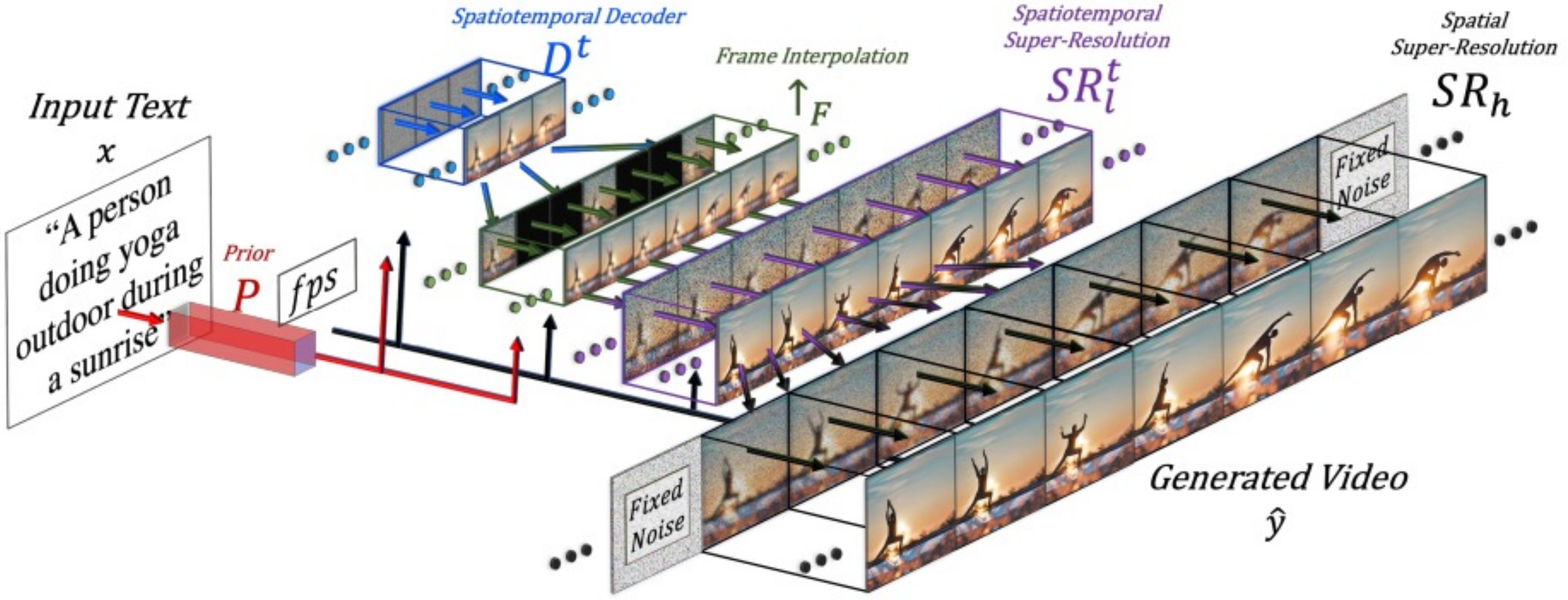


Figure 2: **Make-A-Video high-level architecture.** Given input text x translated by the prior P into an image embedding, and a desired frame rate fps, the decoder D^t generates 16 64×64 frames, which are then interpolated to a higher frame rate by $\uparrow_F$, and increased in resolution to 256×256 by SR_l^t and 768×768 by SR_h, resulting in a high-spatiotemporal-resolution generated video $\hat{y}$.

Make-A-Video: Text-to-Video Generation without Text-Video Data

Limited video data: 2.3B Text-image Pair + 20M Video Data

=> Adapt from Text-to-image Model

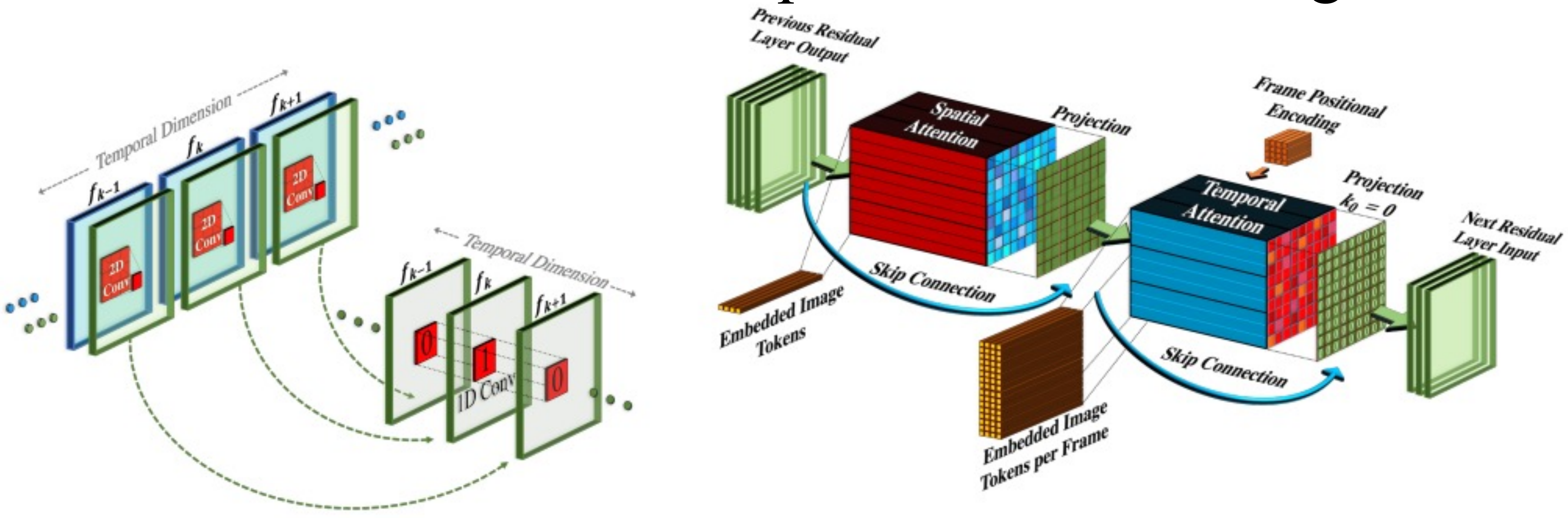
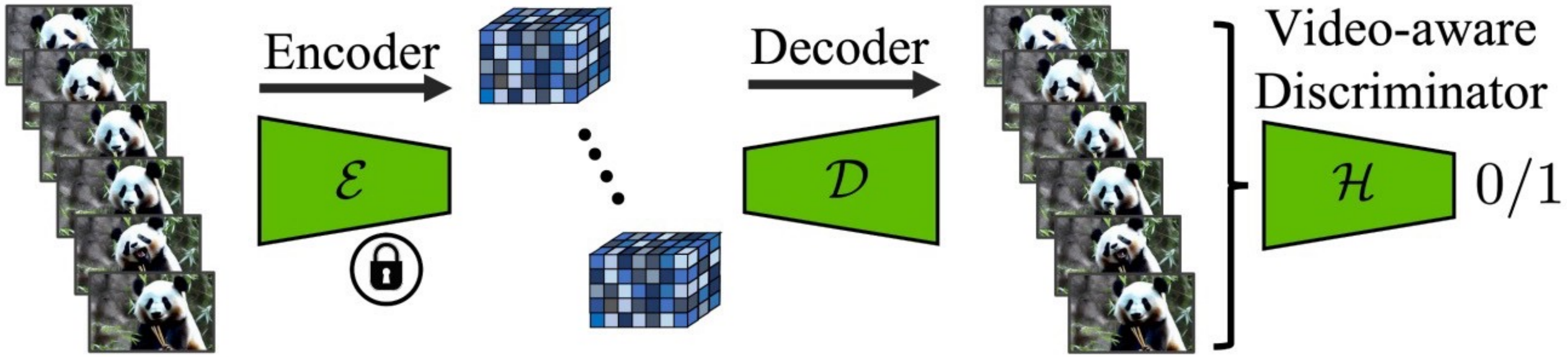
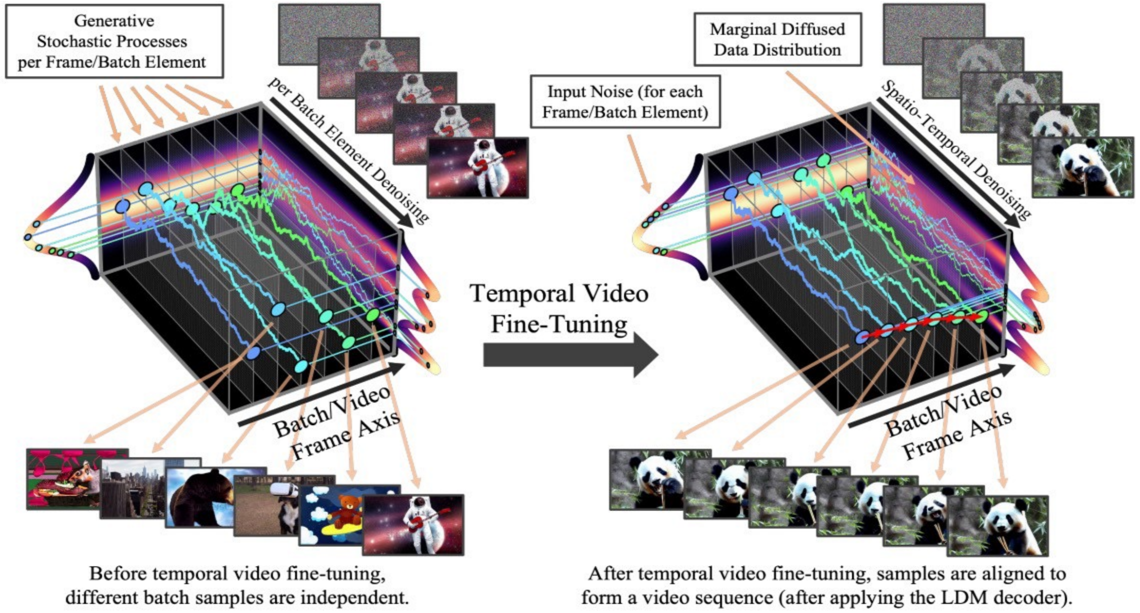


Figure 3: **The architecture and initialization scheme of the Pseudo-3D convolutional and attention layers, enabling the seamless transition of a pre-trained Text-to-Image model to the temporal dimension. (left)** Each spatial 2D conv layer is followed by a temporal 1D conv layer. The temporal conv layer is initialized with an identity function. **(right)** Temporal attention layers are applied following the spatial attention layers by initializing the temporal projection to zero, resulting in an identity function of the temporal attention blocks.

Video LDM





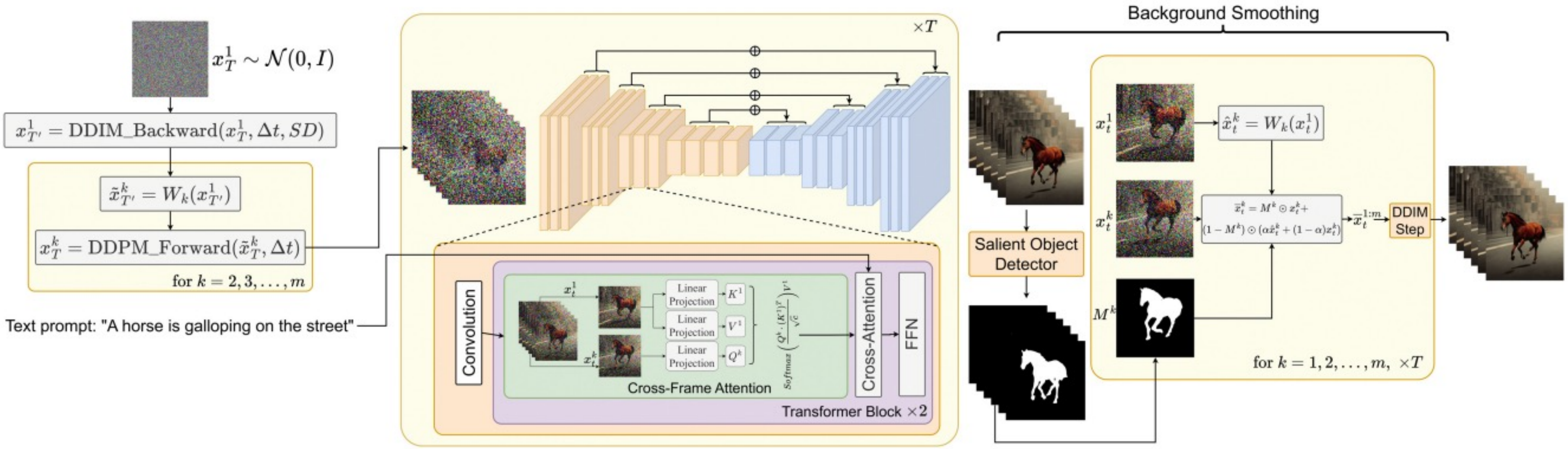
- Fine-tune the decoder to be video-aware, keeping encoder frozen
- Interleave spatial and temporal layers.
- The spatial layers are frozen, whereas temporal layers are trained.
- Temporal layers can be Conv3D or Temporal attentions.
- Context can be added for autoregressive generation.

Blattmann et al., "Align your Latents: High-Resolution Video Synthesis with Latent Diffusion Models", CVPR 2023

Text2Video-Zero: Text-to-Image Diffusion Models are Zero-Shot Video Generators

A pretrained text-to-image diffusion model **without any further fine-tuning or optimization**

1. Encode motion dynamics in the latent codes
2. Reprogram each frame’s self-attention using a new cross-frame attention



Conditional and Specialized Text-to-Video

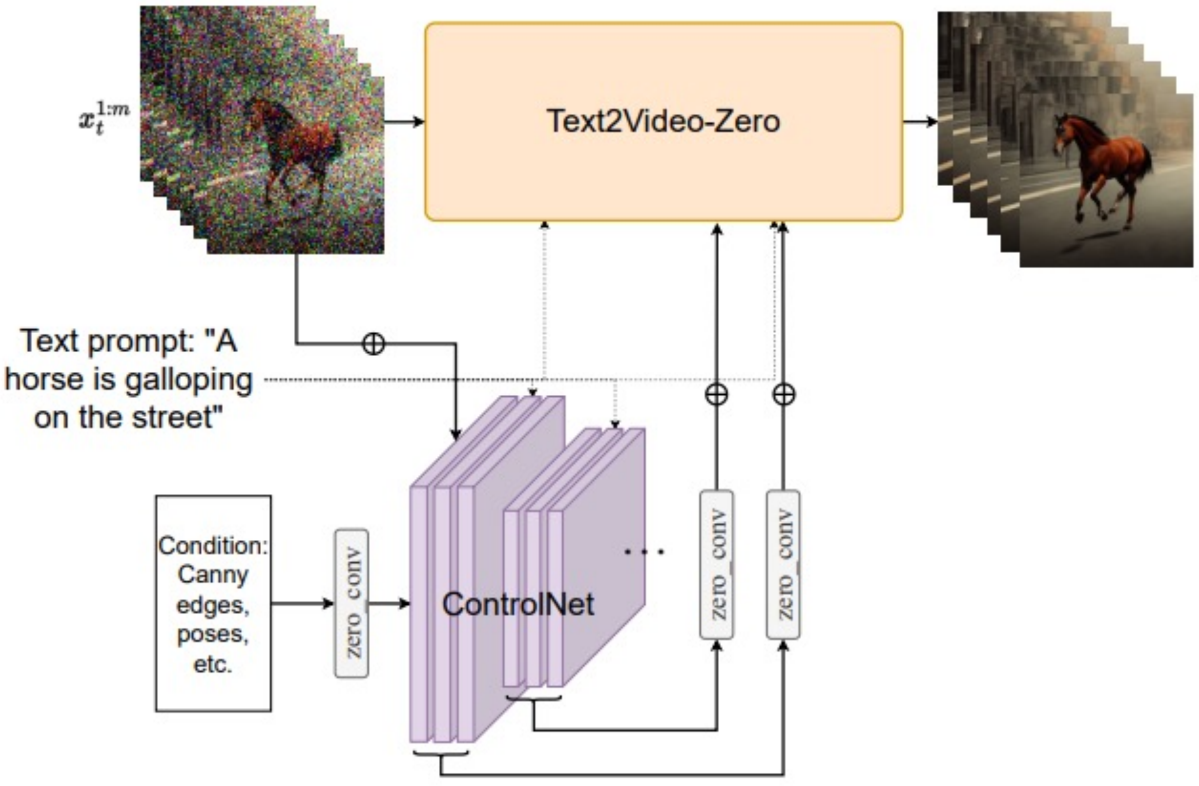
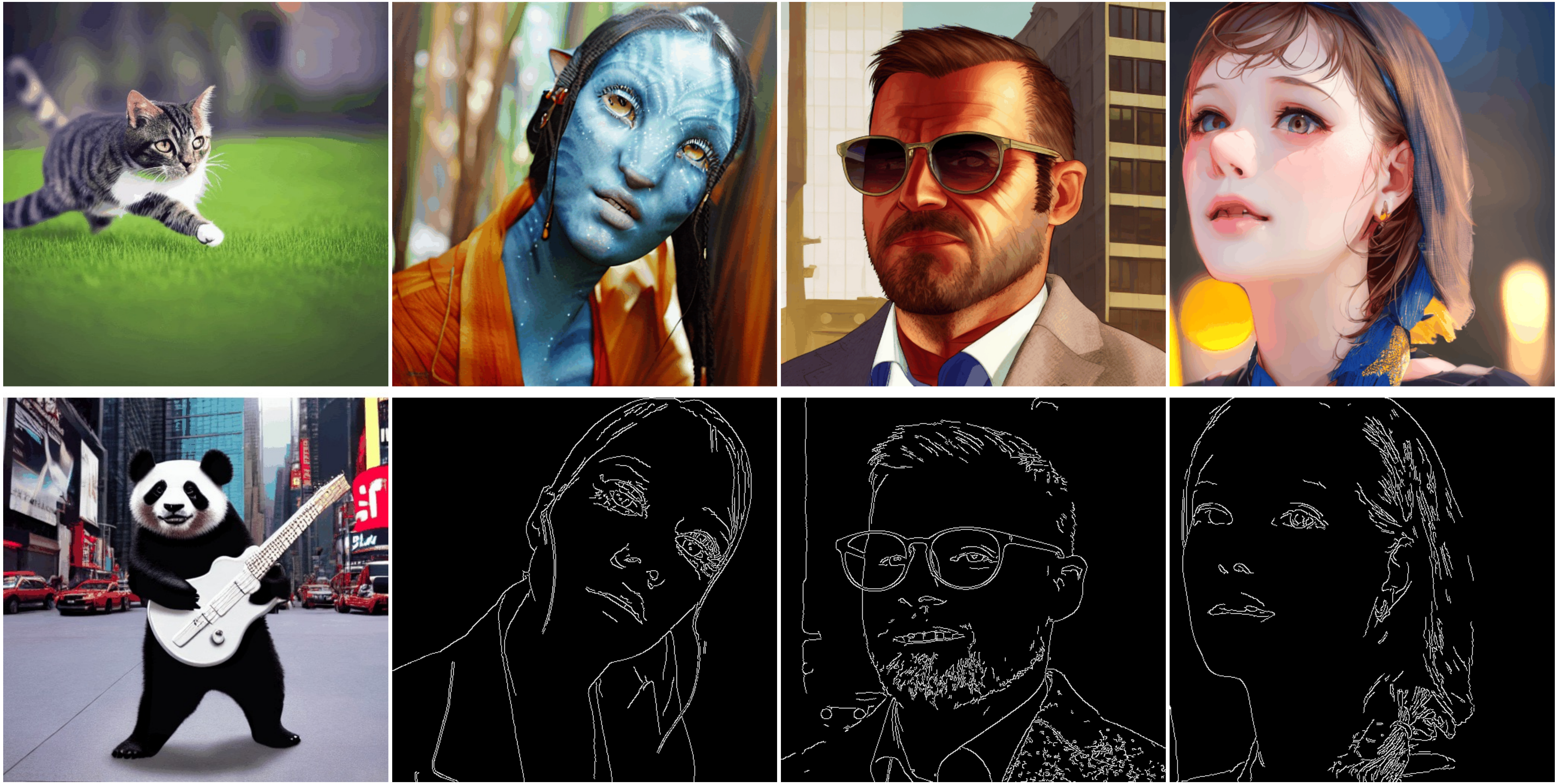
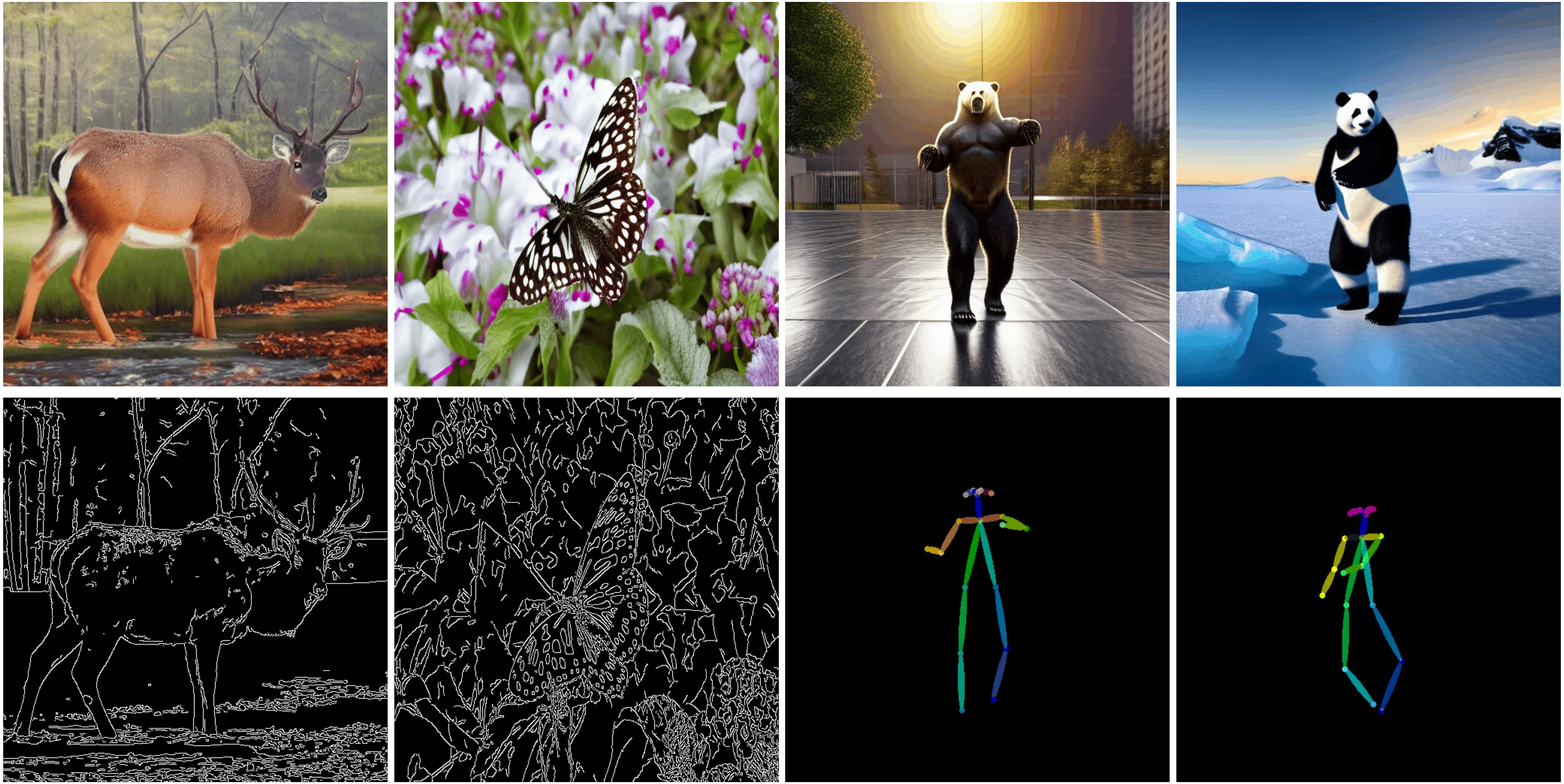


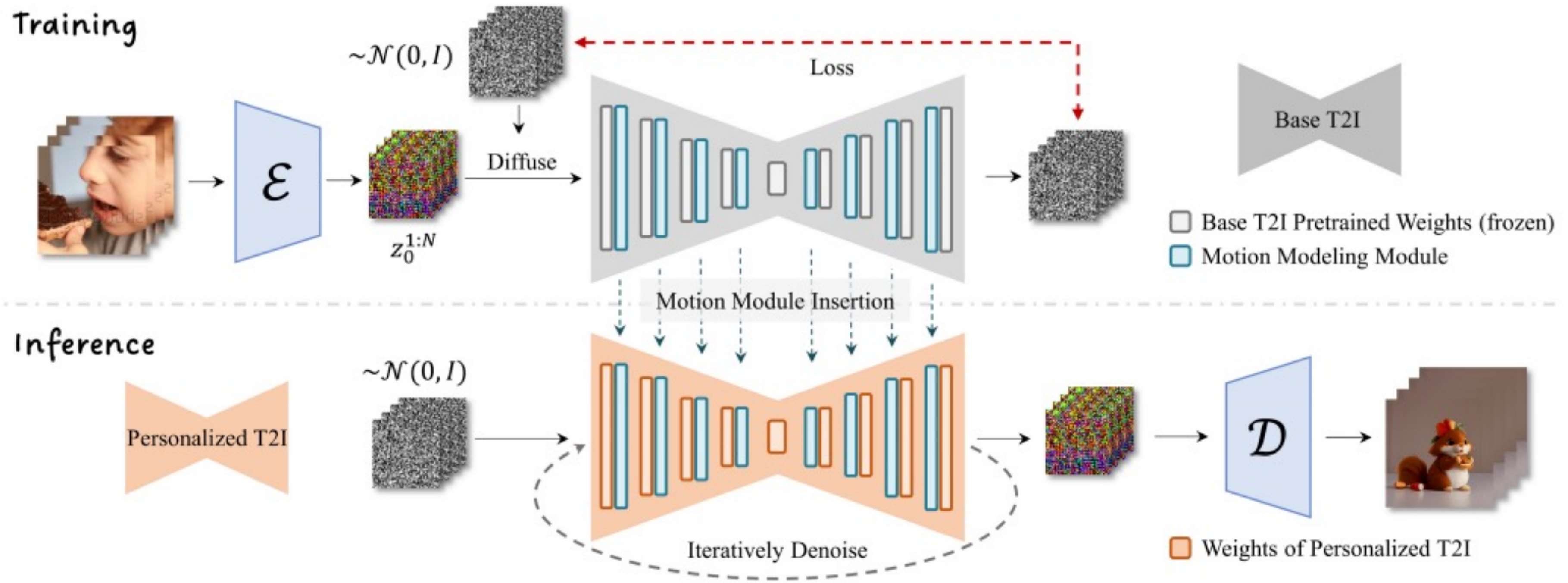
Figure 4: The overview of Text2Video-Zero + ControlNet





AnimateDiff: Animate Your Personalized Text-to-Image Diffusion Models without Specific Tuning

Base T2I contributes to the appearance and train an additional module for the motion



Training Pipeline of AnimateDiff

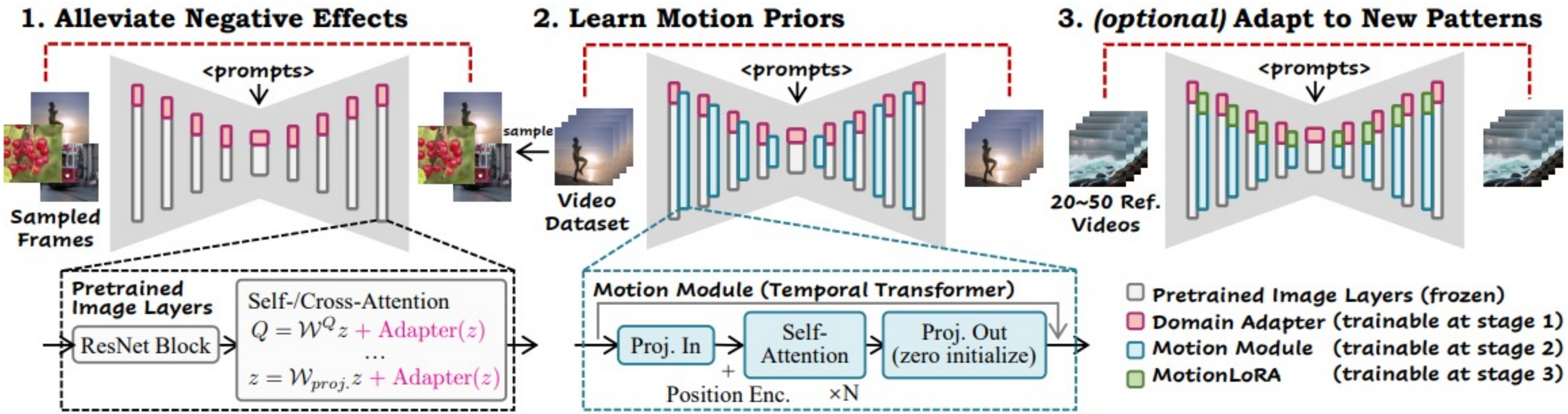
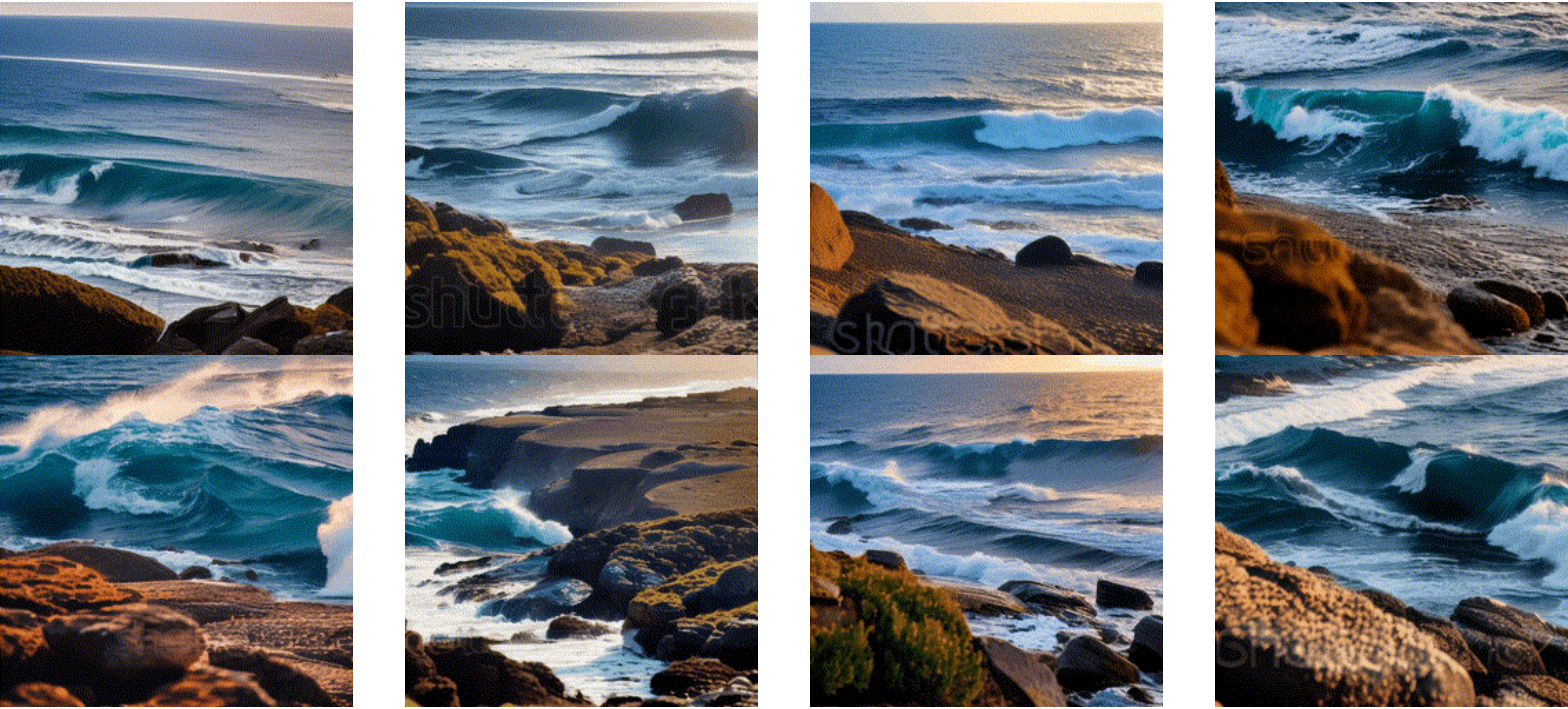
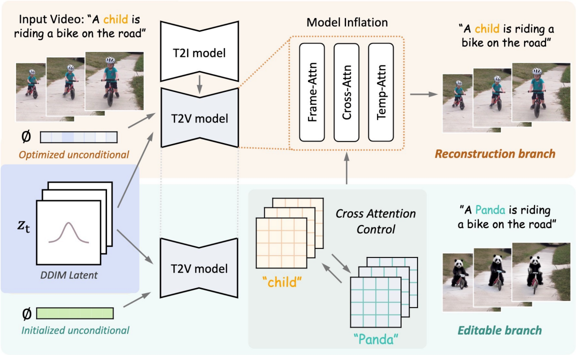


Figure 3: **Training pipeline of AnimateDiff.** AnimateDiff consists of three training stages for the corresponding component modules. Firstly, a domain adapter (Sec. 4.1) is trained to alleviate the negative effects caused by training videos. Secondly, a motion module (Sec. 4.2) is inserted and trained on videos to learn general motion priors. Lastly, MotionLoRA (Sec. 4.3) is trained on a few reference videos to adapt the pre-trained motion module to new motion patterns.

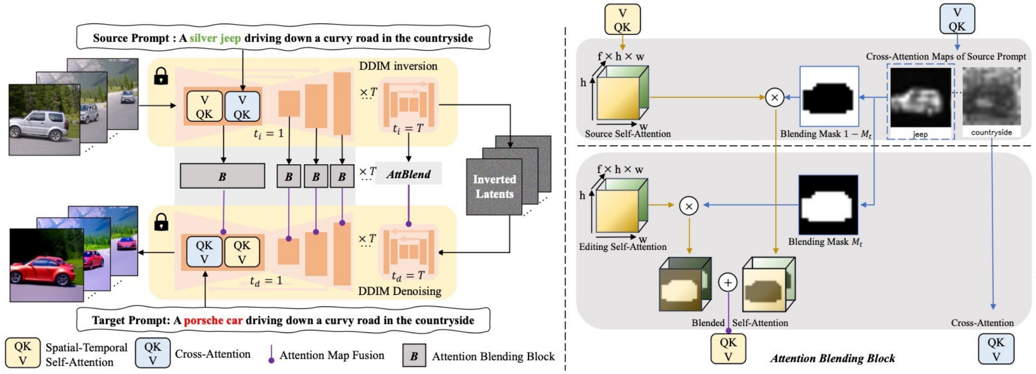
Fine-grained Control of Camera



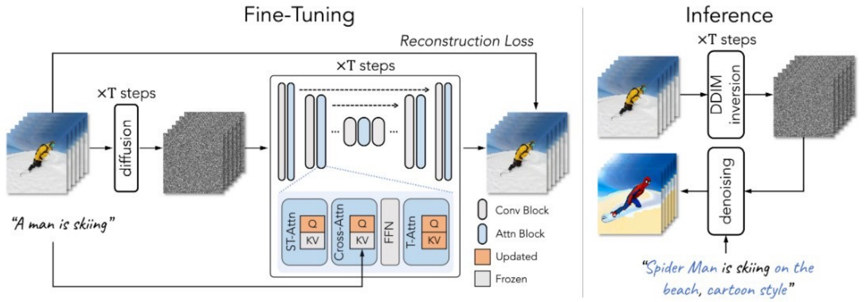
More Concurrent / Related Works



Video-P2P: Cross-Attention Control on text-to-video model

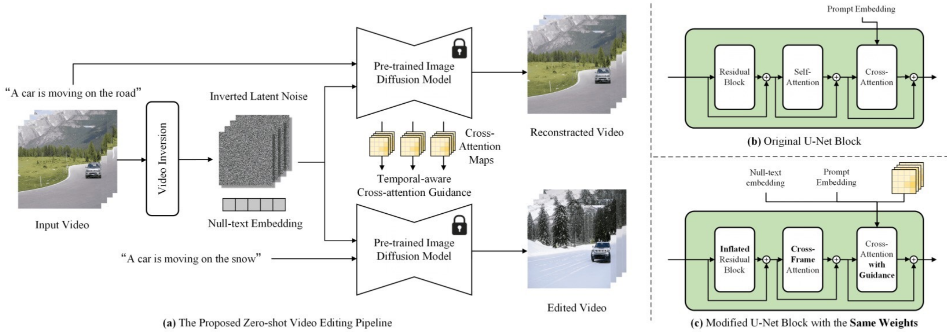


FateZero: Store attention maps from DDIM inversion for later use



Given a text-video pair (e.g., "a man is skiing") as input, our method leverages the pretrained T2I diffusion models for T2V generation. During fine-tuning, we update the projection matrices in attention blocks using the standard diffusion training loss. During inference, we sample a novel video from the latent noise inverted from the input video, guided by an edited prompt (e.g., "Spider Man is surfing on the beach, cartoon style").

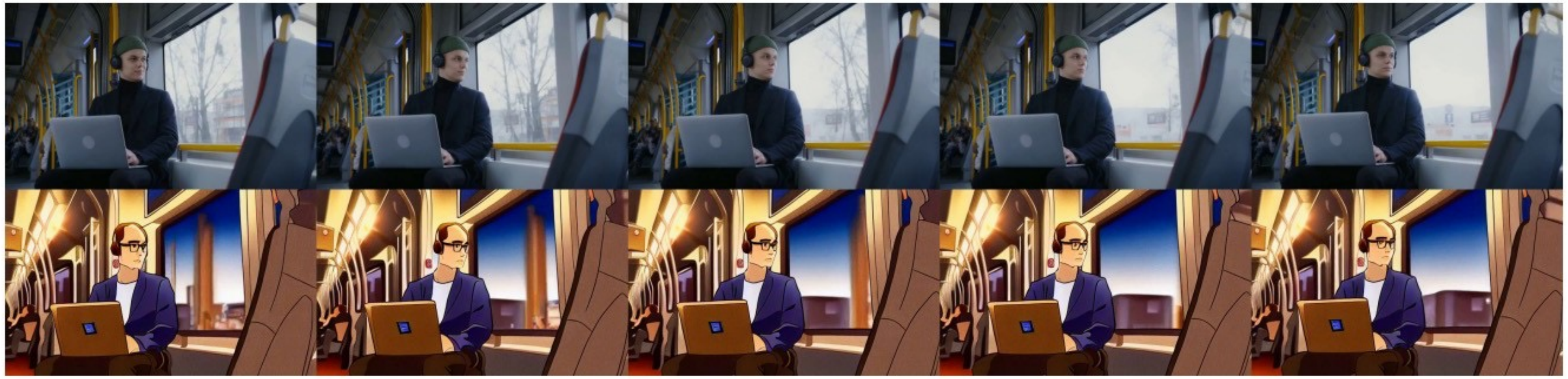
Tune-A-Video: Fine-tune projection matrices of the attention layers, from text2image model to text2video model.



Vid2vid-zero: Learn a null-text embedding for inversion, then use cross-frame attention with original weights.

Gen-1 (video-to-video)

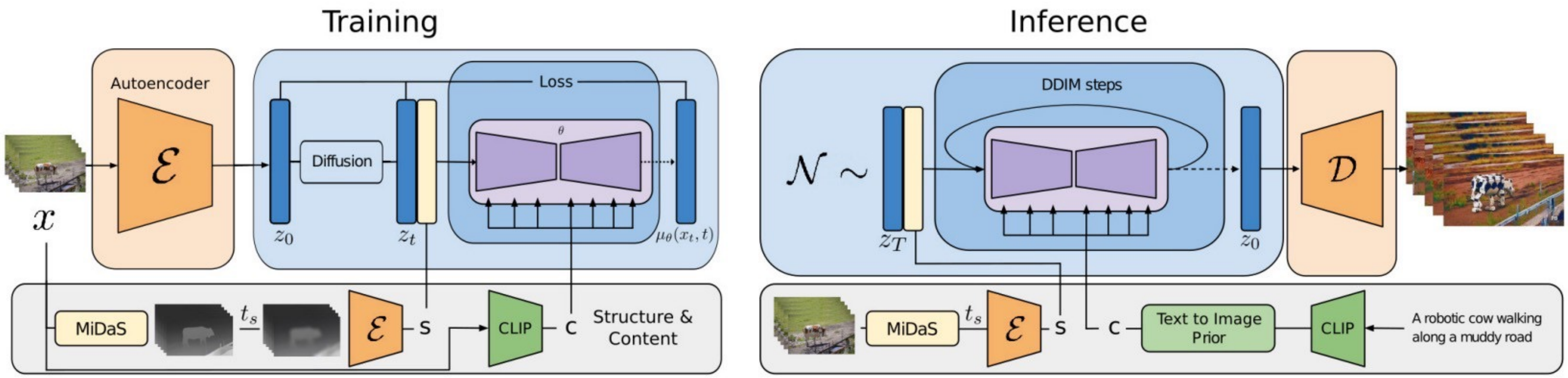
- Transfer the style of a video using text prompts given a “driving video”

Prompt	Driving Video (top) and Result (bottom)
a man using a laptop inside a train, anime style	
a woman and man take selfies while walking down the street, claymation	

Esser et al., ["Structure and Content-Guided Video Synthesis with Diffusion Models"](), arXiv 2023

Gen-1 (video-to-video)

- Condition on structure (depth) and content (CLIP) information.
- Depth maps are passed with latents as input conditions.
- CLIP image embeddings are provided via cross-attention blocks.
- During inference, CLIP text embeddings are converted to CLIP image embeddings.



Esser et al., "Structure and Content-Guided Video Synthesis with Diffusion Models", arXiv 2023

Gen-2 (text-to-video, and more)

Gen-2 (the latest release, Nov 02 2023)

Gen AI in Film Making?

- From simple animation and quality enhancement, to nowadays Scriptwriting, Visual Effects (CGI), Subtitling, Scheduling, Trailers...
- **Next billion-dollar question:** end-to-end automated?

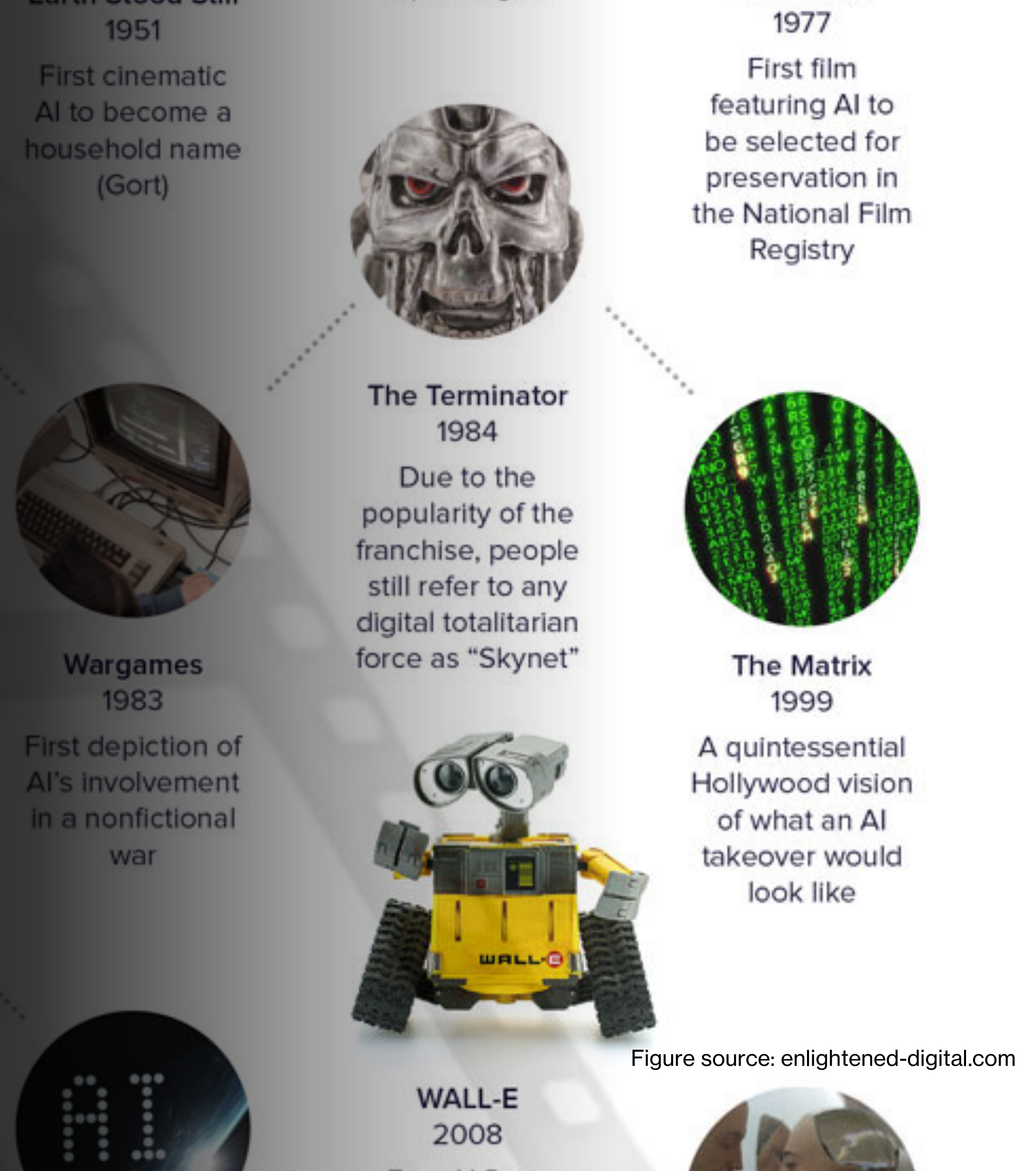


Figure source: enlightened-digital.com

Short Realistic Videos with Generative AI

- Rapidly generate assets
- Tell coherent stories and even evoke emotions
- Even surprise us with its creativity!

Sci-Fi Trailer Made with Generative AI

"**AI Star Wars Teaser**", made by the community with current available Generative AI techniques

Challenges Along the Road

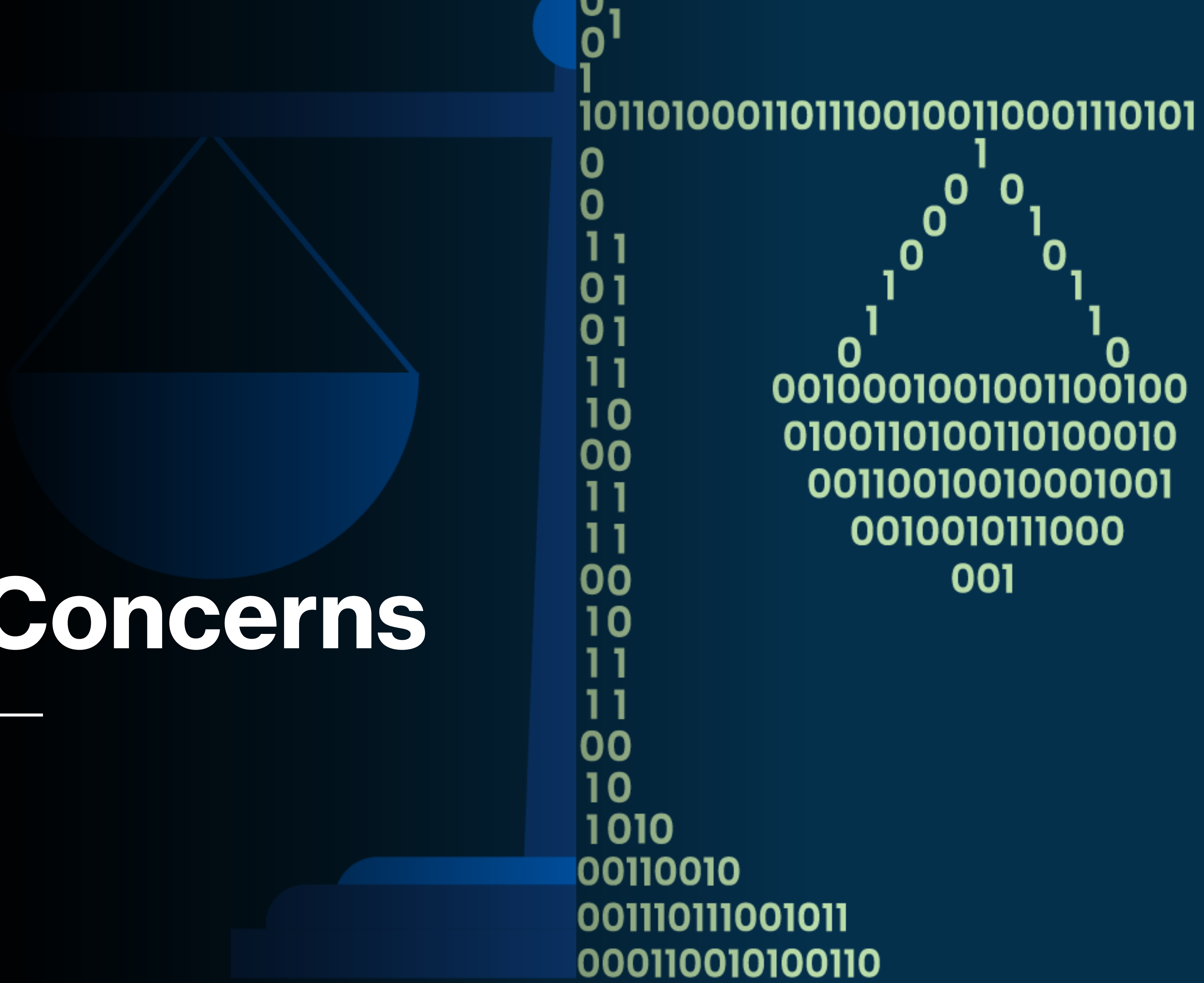
- Generating highly accurate objects especially human faces and bodies, and their nuanced motions

- Creating complex, physically grounded motions

- Maintaining a cohesive narrative over the long time range

The Human Touch

The Ethical Concerns



The Future of GenAI Film Making

The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering