Diffusion Models for Visual Content Creation

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Daniel Cohen-Or, Or Patashnik, Chun-Hao Huang, Minhyuk Sung

Part 6: 3D Generation

UCL Adobe TEL AVIV UNIVERSITY KAIST

https://geometry.cs.ucl.ac.uk/courses/diffusion4ContentCreation_sigg24/

Presentation Schedule

Introduction to Diffusion Models

Guidance and Conditioning Sampling

Attention

Break

Personalization and Editing

Beyond Single Images

Diffusion Models for 3D Generation

3D Generative Model – 6 Years Ago

Achlioptas et al., Learning Representations and Generative Models for 3D Point Clouds, ICML 2018.

3D Generative Model – 1 Year Ago

Koo et. al., SALAD: Part-Level Latent Diffusion for 3D Shape Generation and Manipulation, ICCV 2023.

Diversity of *Imaginable* 3D Shapes

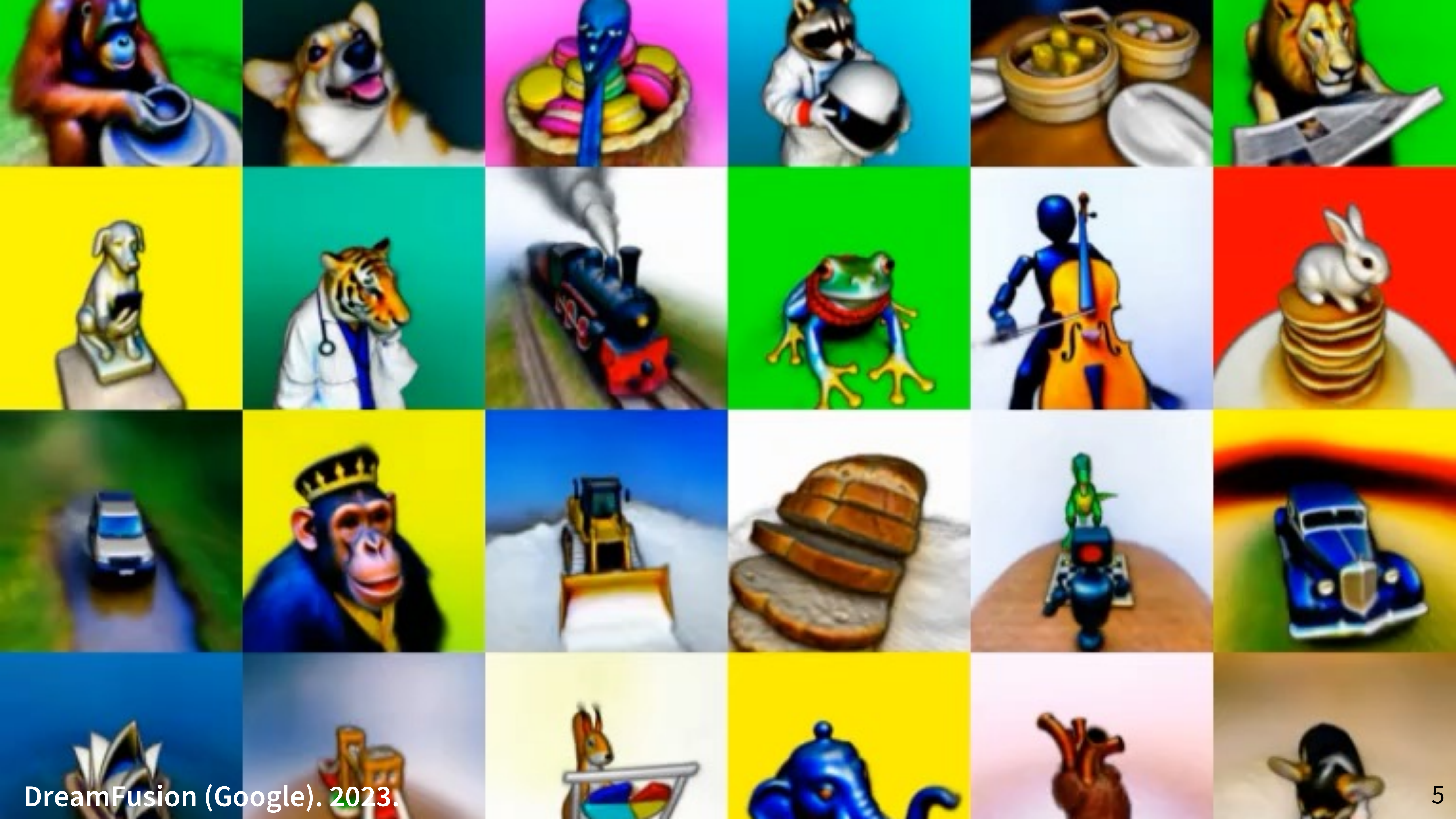
“frog wearing a sweater”

“eggshell broken in two with an adorable chick standing next to it”

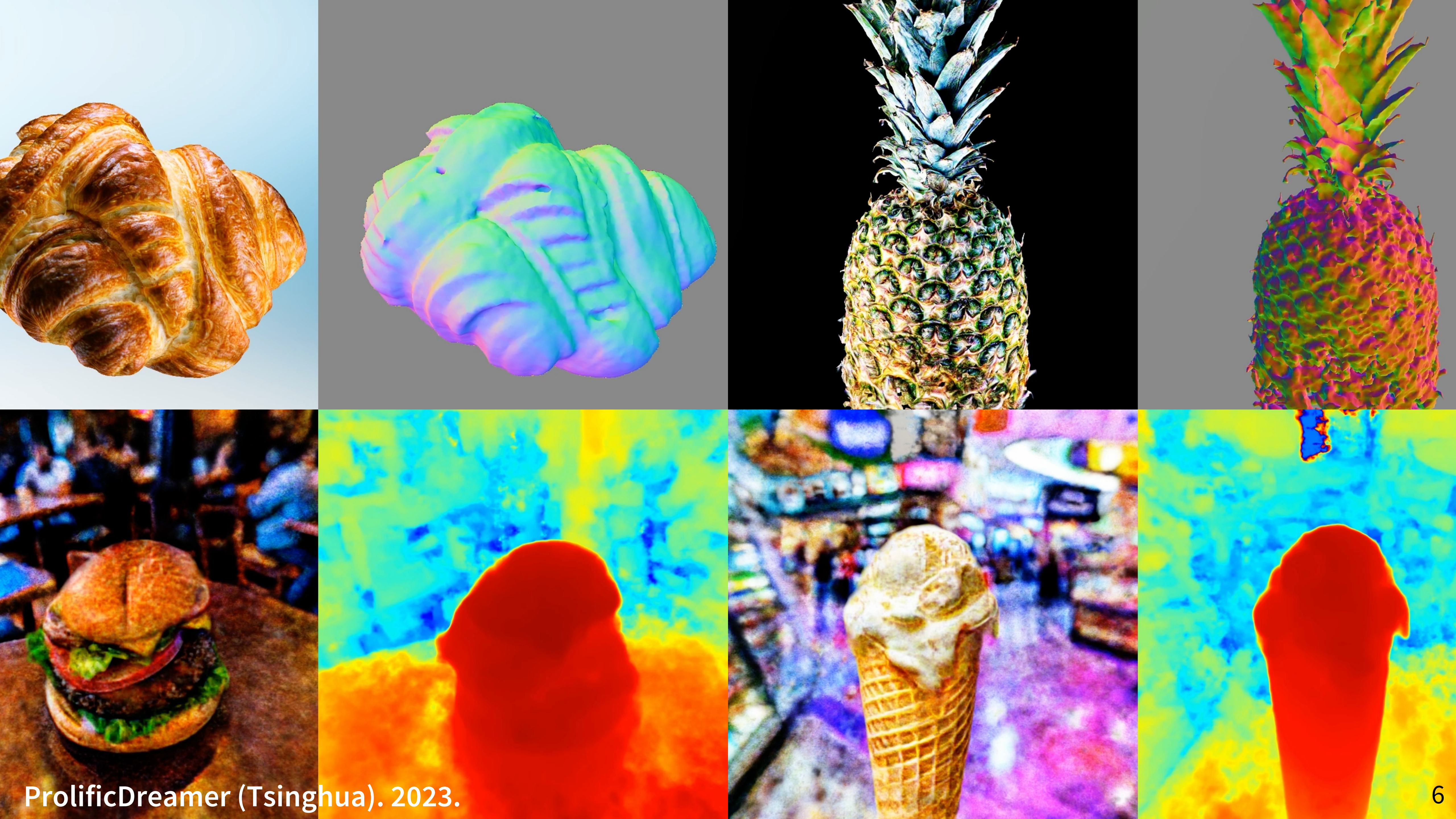
“ghost eating a hamburger”

“a pig wearing a backpack”

DreamFusion (Google)



DreamFusion (Google). 2023.



ProlificDreamer (Tsinghua). 2023.

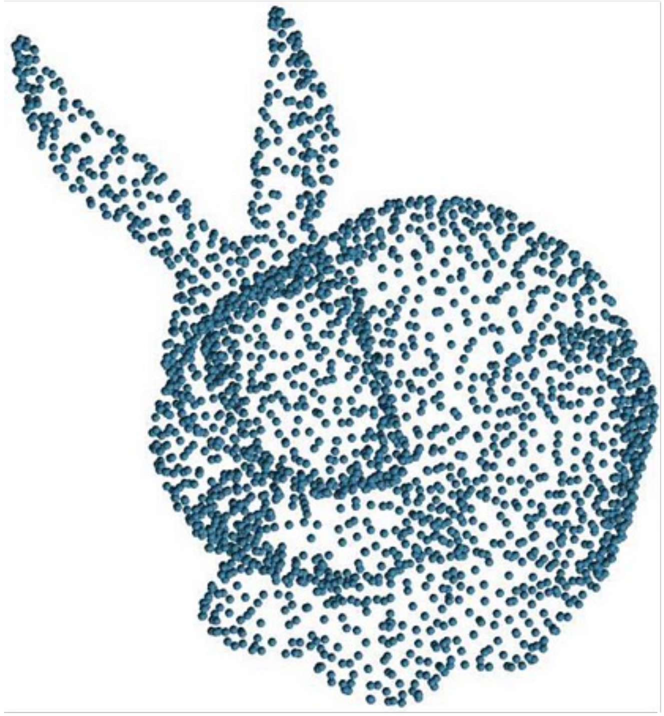
Zhang et al., CLAY: A Controllable Large-scale Generative Model for Creating High-quality 3D Assets, SIGGRAPH 2024.

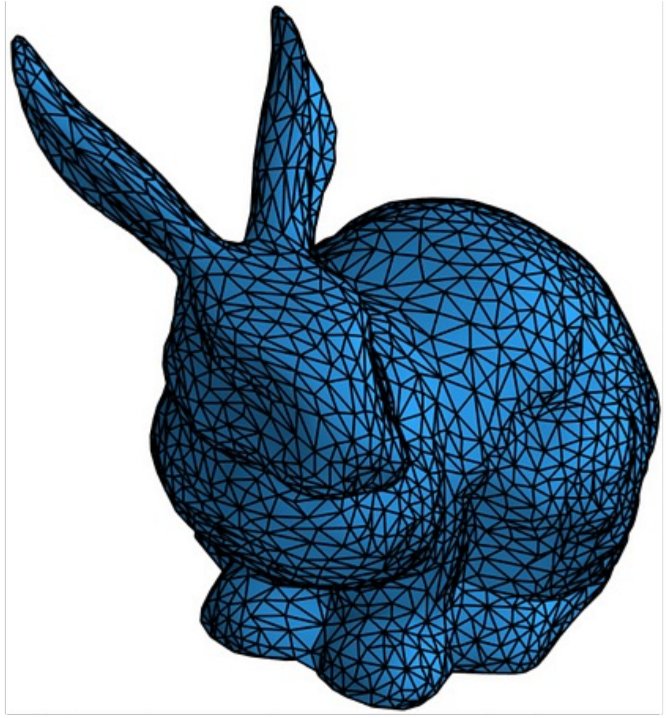
Content

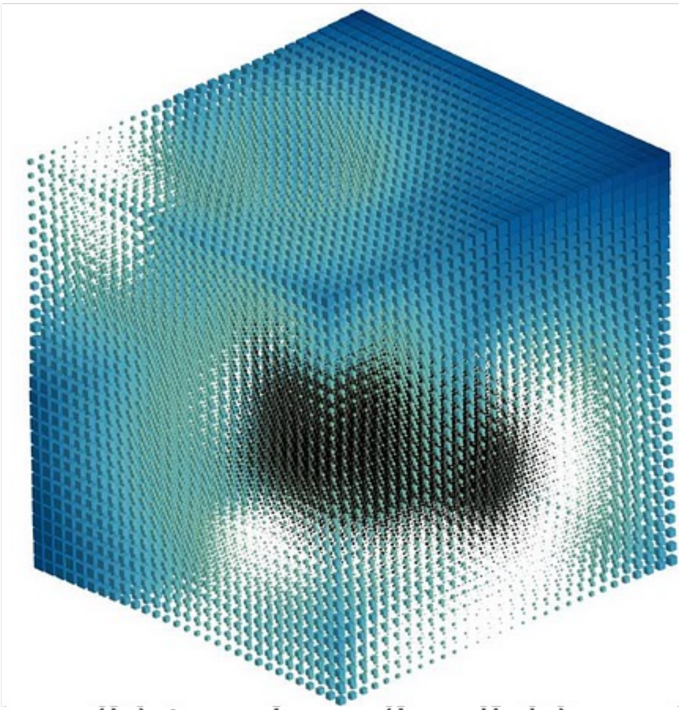
1. 3D diffusion models trained with 3D data
2. 3D generation using 2D image priors
3. Future directions

3D Diffusion Models

3D Representations


(a) Point set


(b) Triangulated mesh (parametric)

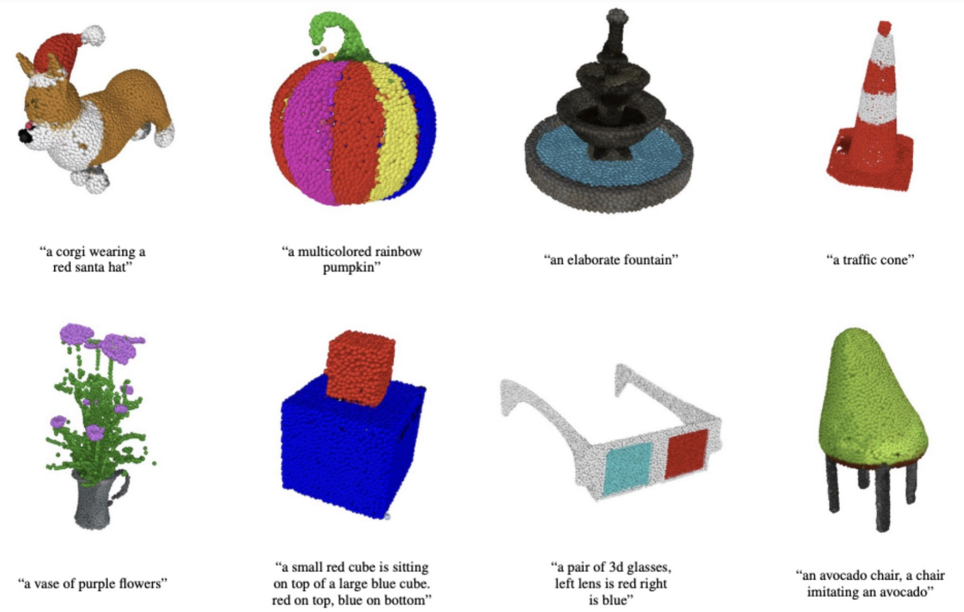

(b) Level set (implicit)

https://medium.com/@sunil7545/implicit-vs-parametric-3d-shape-representation-9d4c01c8c60c

3D Diffusion Models

Point clouds

- ShapeGF (Cai et al., 2020)
- DPM (Luo and Hu, 2021)
- LION (Nichol et al., 2022)

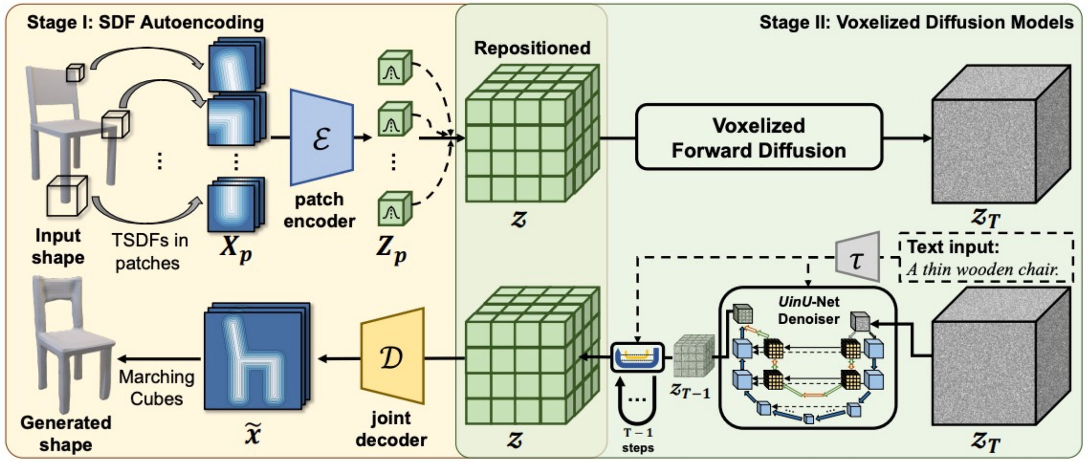


LION, Nichol et al. 2022.

3D Diffusion Models

Voxel representation

- PVD (Zhou et al., 2022)
- Diffusion-SDF (Li et al, 2022)

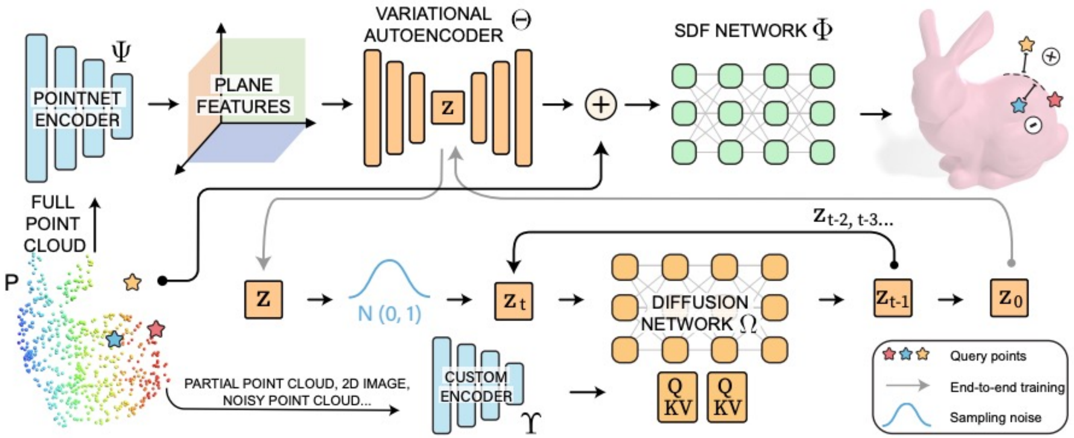


Diffusion-SDF, Li et al., 2022.

3D Diffusion Models

Latent representation

- SDFusion (Cheng et al., 2022)
- DiffusionSDF (w/o *hyphen*, Chou et al., 2023)
- 3DShape2VecSet (Zhang et al., 2023)



DiffusionSDF, Chou et al., 2023

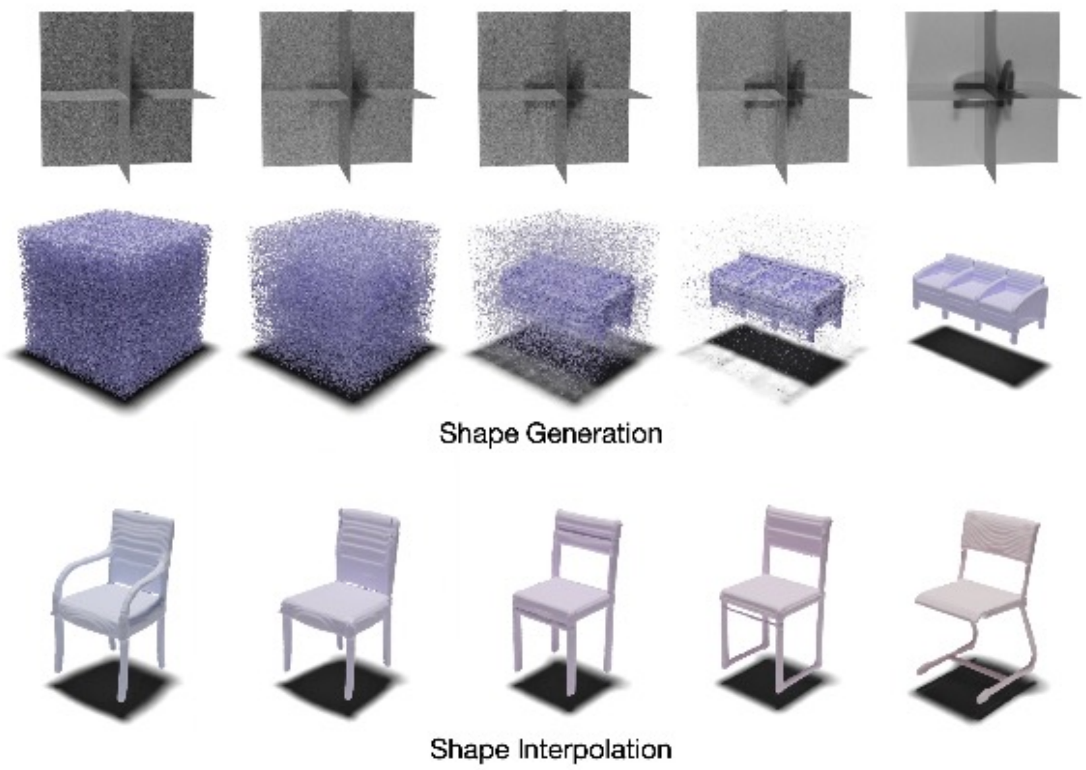
3D Diffusion Models

Triplane representation

- NFD (Shue et al., 2022)

Diffusion in the spectral domain:

- NeuralWavelet (Hui et al., 2022)



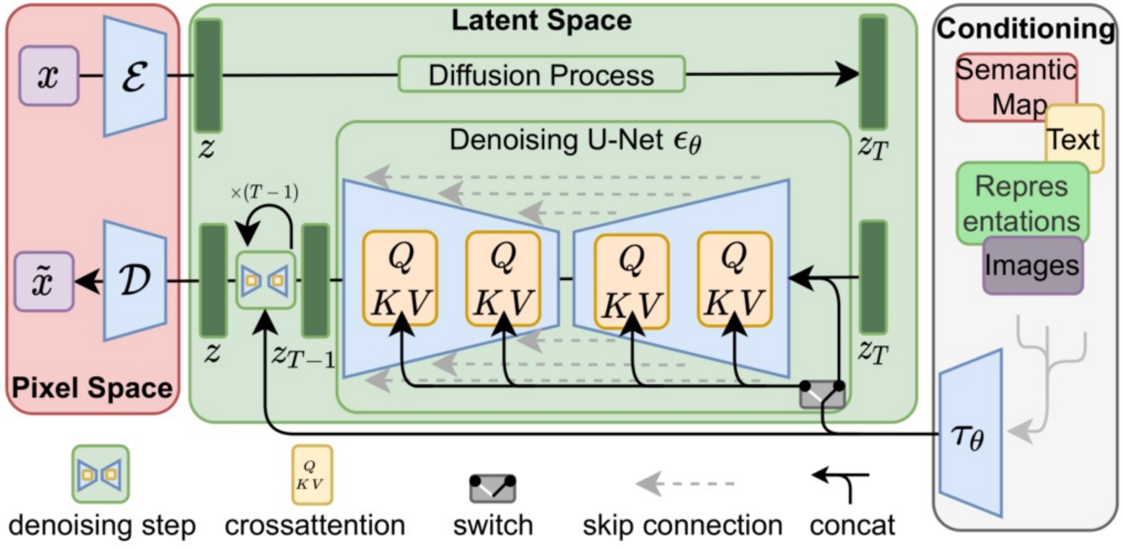
NFD, Shue et al., 2022.

Diffusion w/ Different Representations

- **Implicit (latent)** representation
- **Explicit** representation

Diffusion w/ Different Representations

- **Implicit** representation (i.e., latent features)
  - (+) Best quality of the generated data.
  - (–) Requires retraining for each conditional generation setup.



Latent Diffusion, Rombach et al., 2022.

Diffusion w/ Different Representations

- **Explicit** representation (e.g., pixels in images)
  - (–) Suboptimal performance due to the high dimensionality.
  - (–) Cannot change the resolution of the data.
  - (+) Can be directly leveraged in conditional generation setups in a zero-shot manner.

SDEdit [Meng et al., 2022]

Image editing using a pretrained pixel-space diffusion model.

$$\mathbf{x}^{(0)} = m \odot \mathbf{x}_a^{(0)} + (1 - m) \odot \mathbf{x}_b^{(0)}$$

$$\mathbf{x}^{(t)} = \text{denoise}\left(\mathbf{x}^{(0)}, t\right)$$

$$\mathbf{x}'^{(0)} = \text{add\_noise}\left(\mathbf{x}^{(t)}, t\right)$$

RePaint [Lugmayr et al., 2022]

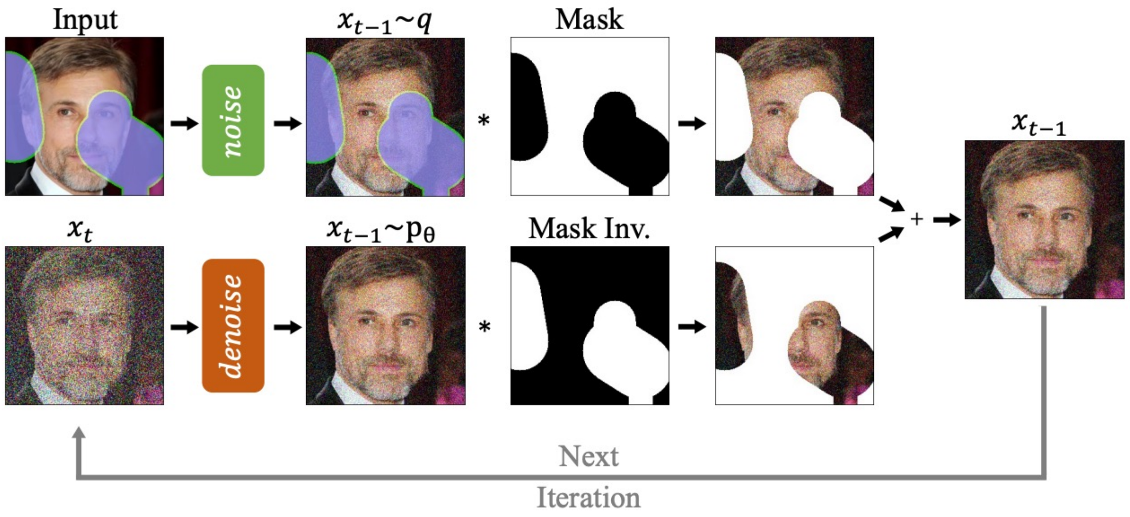
Image inpainting using a pretrained pixel-space diffusion model.

$$\mathbf{x}_f^{(t-1)} = \text{denoise}\left(\mathbf{x}^{(t)}, 1\right)$$

$$\mathbf{x}_b^{(t-1)} = \text{add\_noise}\left(\mathbf{x}^{(0)}, t\right)$$

$$\mathbf{x}^{(t-1)} = m \odot \mathbf{x}_f^{(t-1)} + (1-m) \odot \mathbf{x}_b^{(t-1)}$$

Repeat for $t = T, \cdots, 1$.



Hybrid Representation

Leverages a novel hybrid representation describing

- global part-level structure explicitly, and
- local geometry implicitly.

Part-Level Representation

For each part of an object learned in an unsupervised way,

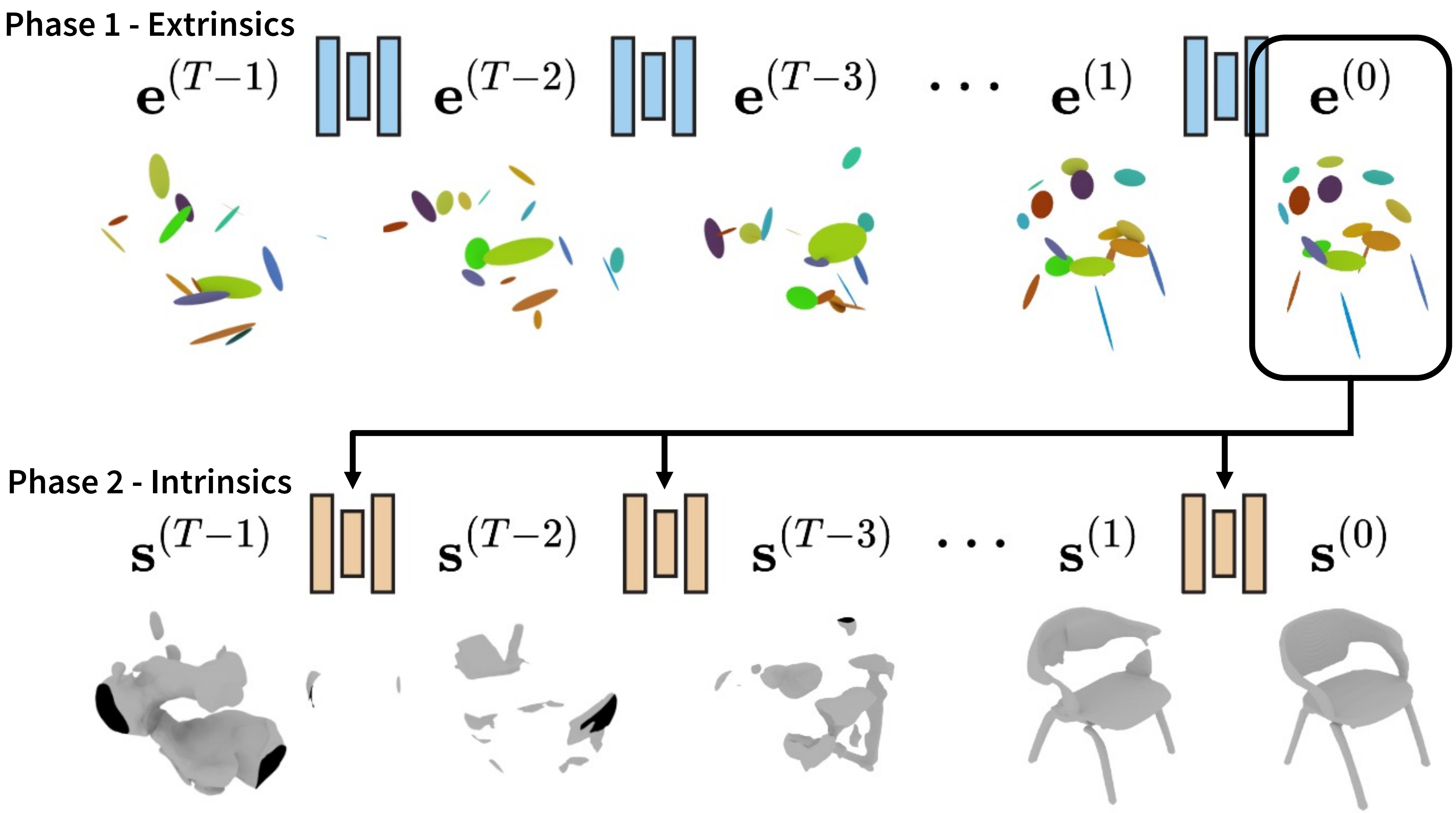
- Explicit parameters of Gaussian blubs indicate position, scale, and rotation.

Part-Level Representation

For each part of an object learned in an unsupervised way,

- Implicit latent feature is decoded into an occupancy function.

Two-Phase Cascaded Diffusion

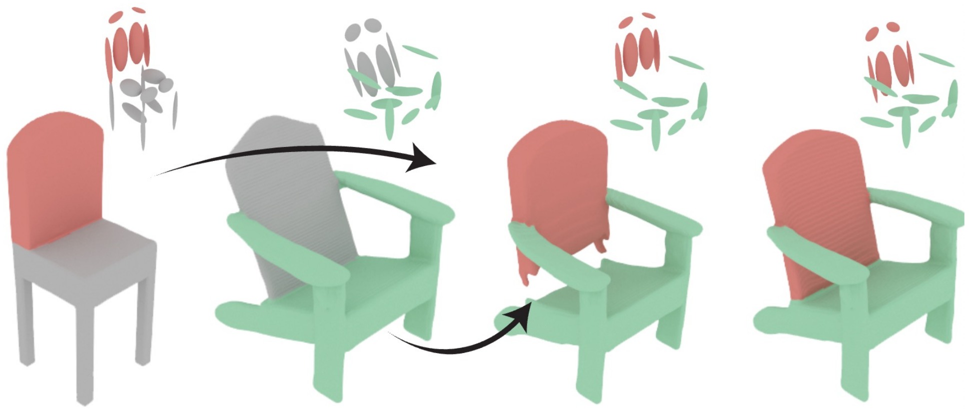


Diversity of 3D Shapes

Koo et al., SALAD: Part-Level Latent Diffusion for 3D Shape Generation and Manipulation, ICCV 2023.

Applications

Part Completion

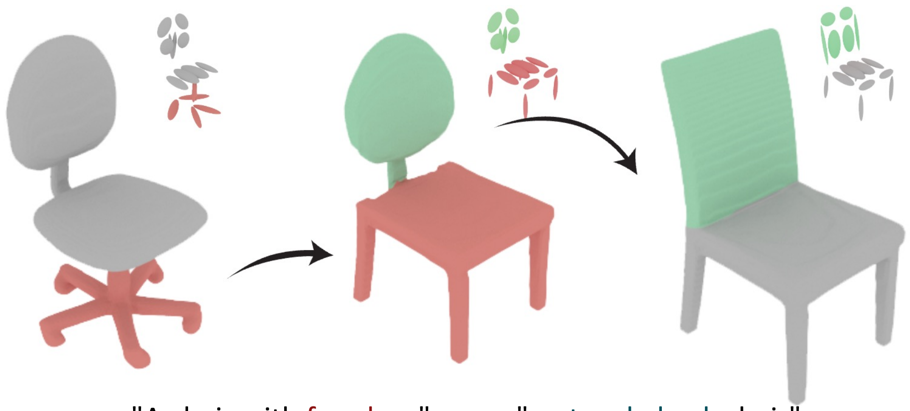


Part Mixing

”Chair has round arms and wheels."

”Its the one with gaps in the back."

Text-to-3D Generation



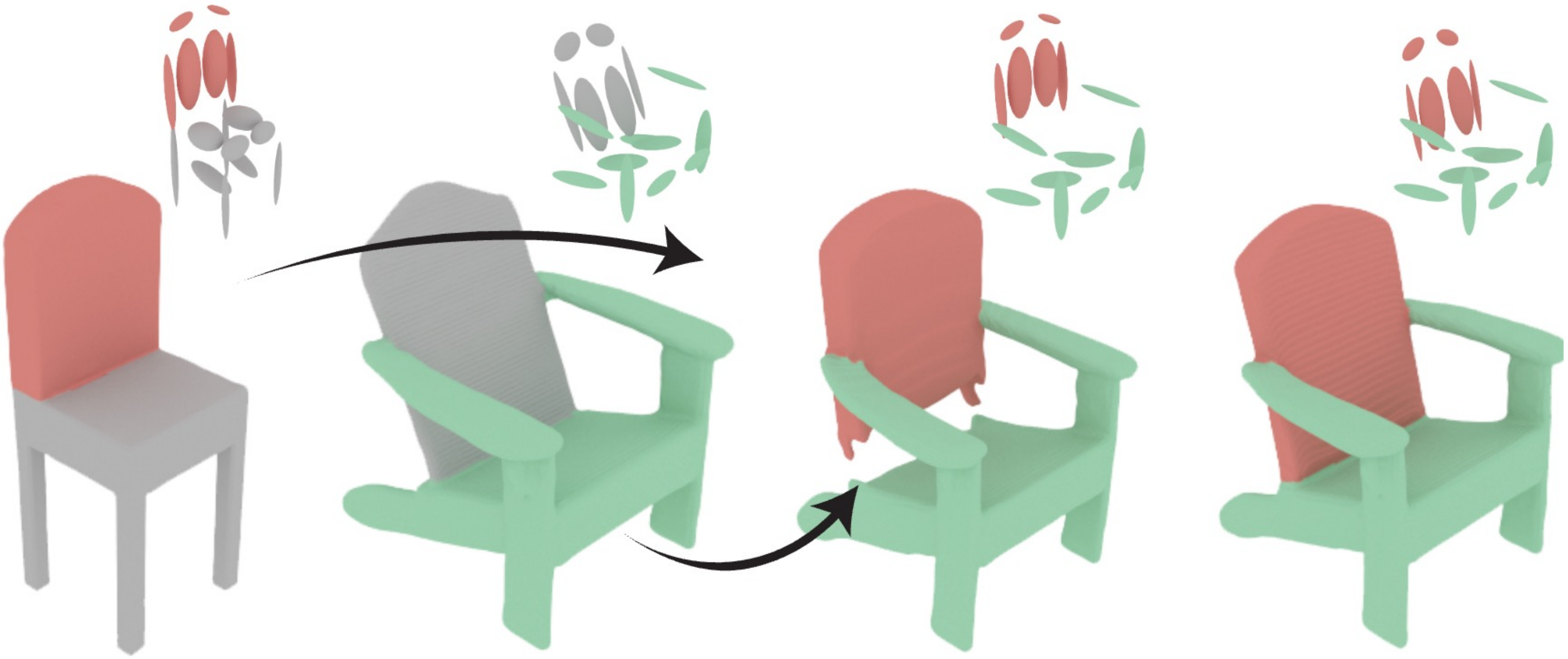
"A chair with four legs"

"rectangle back chair"

Text-Guided Part Editing

Part Mixing

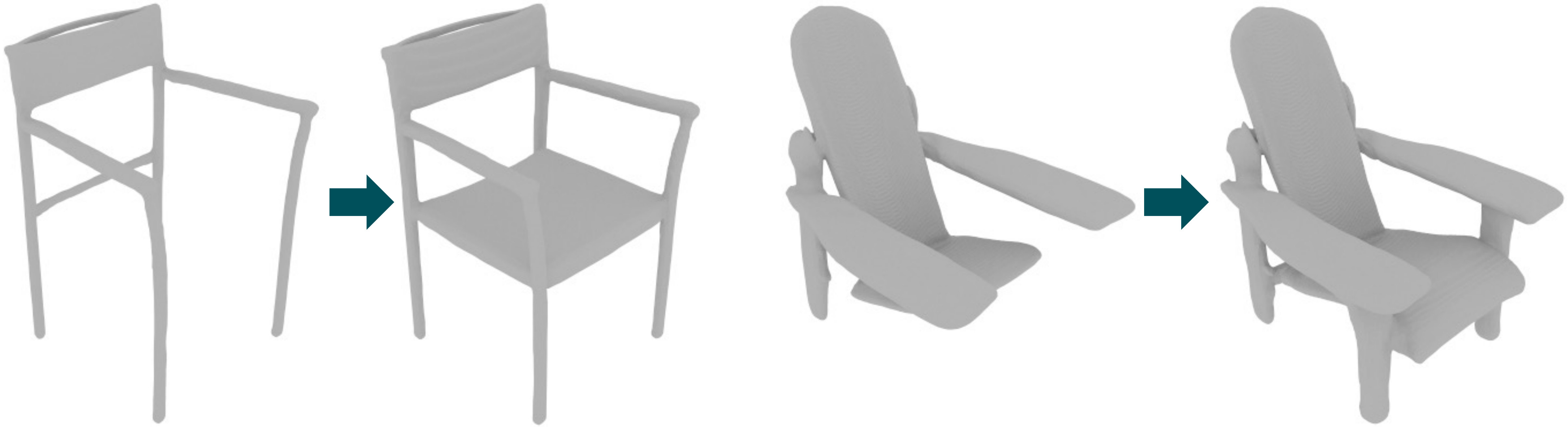
$$\mathbf{x}^{(0)} = m \odot \mathbf{x}_a^{(0)} + (1-m) \odot \mathbf{x}_b^{(0)}$$
$$\mathbf{x}^{(t)} = \text{denoise}\left(\mathbf{x}^{(0)}, t\right)$$
$$\mathbf{x}'^{(0)} = \text{add\_noise}\left(\mathbf{x}^{(t)}, t\right)$$



Part Completion

$$\mathbf{x}_f^{(t-1)} = \text{denoise}\left(\mathbf{x}^{(t)}, 1\right)$$
$$\mathbf{x}_b^{(t-1)} = \text{add\_noise}\left(\mathbf{x}^{(0)}, t\right)$$
$$\mathbf{x}^{(t-1)} = m \odot \mathbf{x}_f^{(t-1)} + (1-m) \odot \mathbf{x}_b^{(t-1)}$$

Repeat for $t = T, \cdots, 1$.



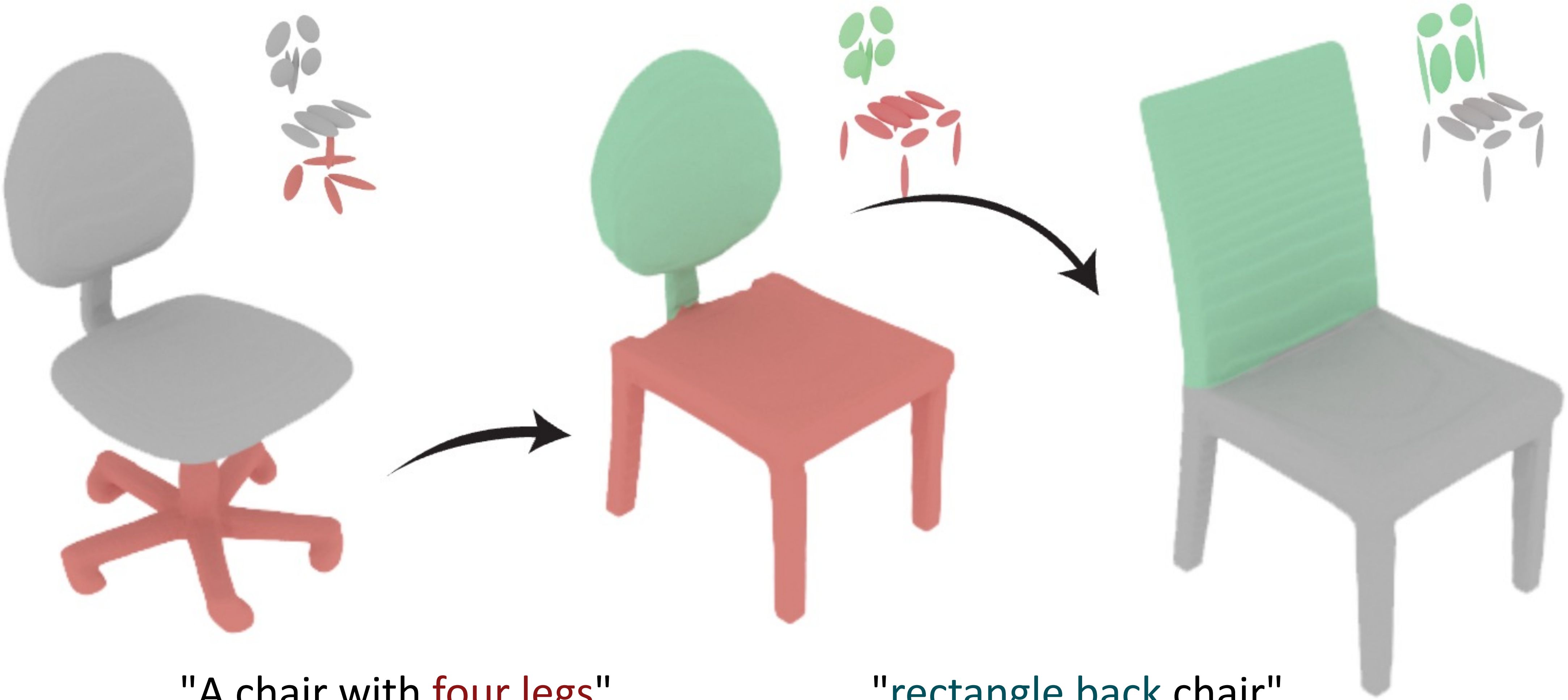
Koo et al., SALAD: Part-Level Latent Diffusion for 3D Shape Generation and Manipulation, ICCV 2023.

Text-to-3D Generation

”Chair has round arms and wheels."

”Its the one with gaps in the back."

Text-Guided Part Editing



"A chair with four legs" "rectangle back chair"

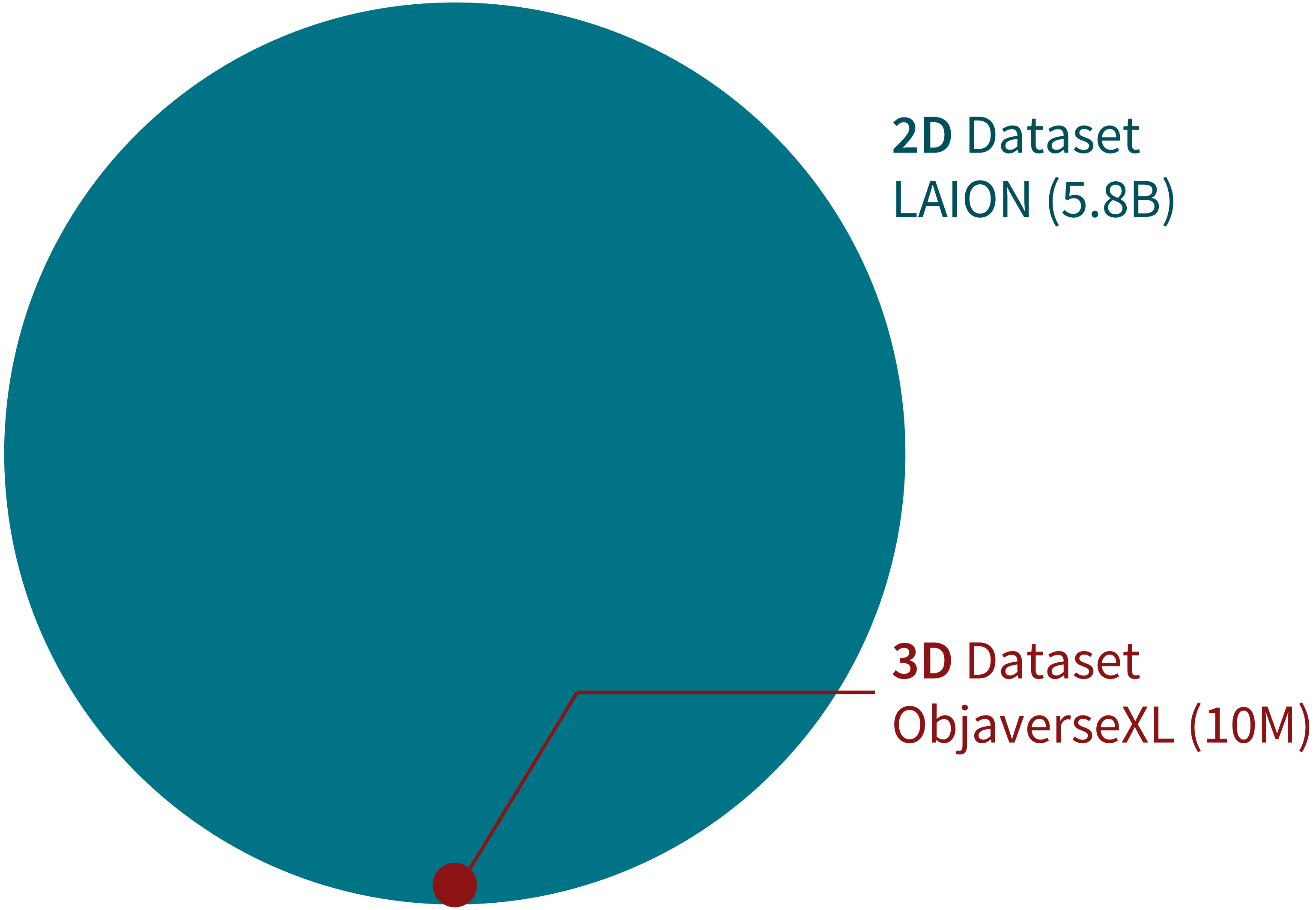
Limitation?

Koo et al., SALAD: Part-Level Latent Diffusion for 3D Shape Generation and Manipulation, ICCV 2023.

Challenge: Lack of Large-Scale 3D Dataset

Objaverse-XL
Allen Institute

Data Deficiency



Diversity of *Imaginable* 3D Shapes

"frog wearing a sweater"

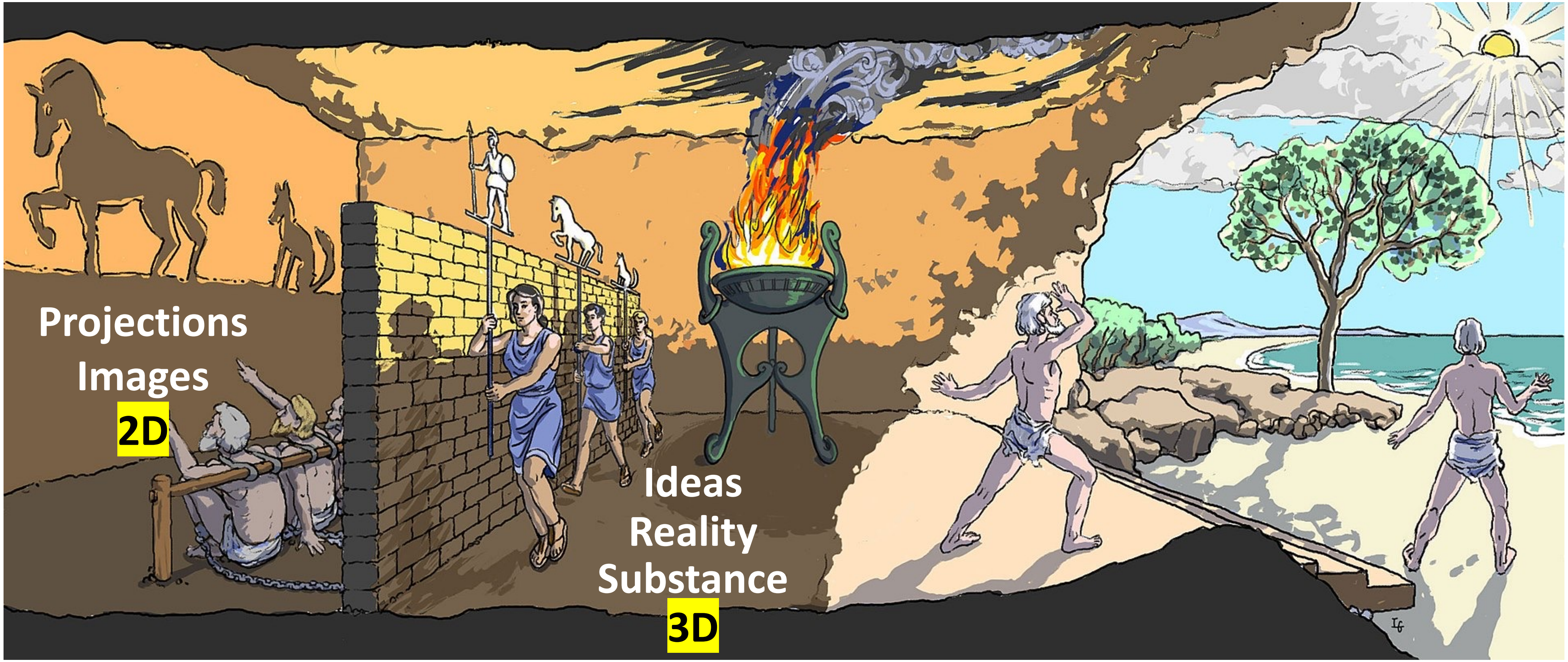
"eggshell broken in two with an adorable chick standing next to it"

"ghost eating a hamburger"

"a pig wearing a backpack"

How can we leverage an internet-scale image dataset for 3D generation?

Platonic Perspective



Wikipedia

3D Generation

How to generate a 3D object

from a collection of 2D images?

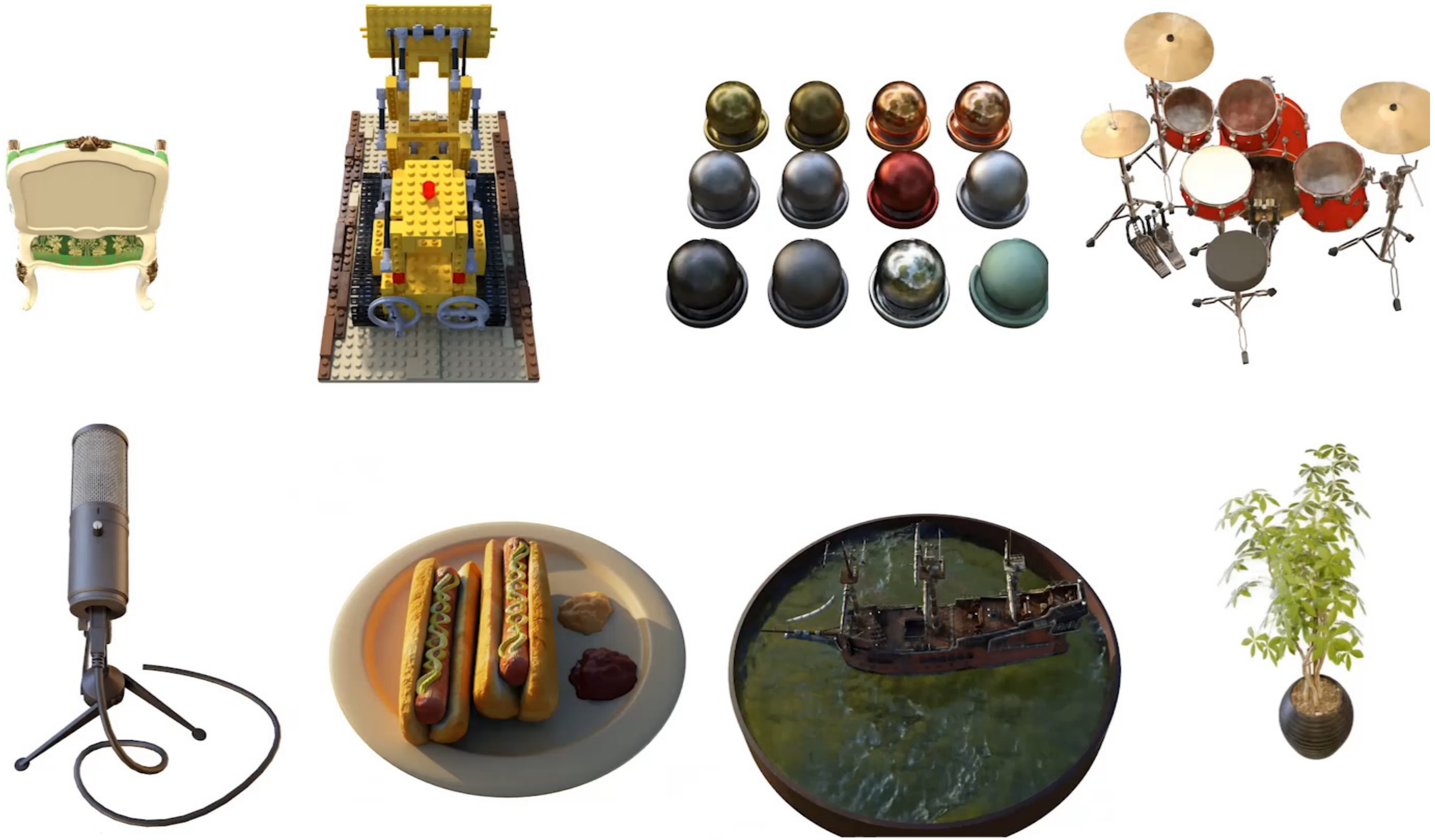
3D Reconstruction

How to reconstruct a 3D object

from a collection of 2D images

of a specific object?

NeRF



3D Reconstruction

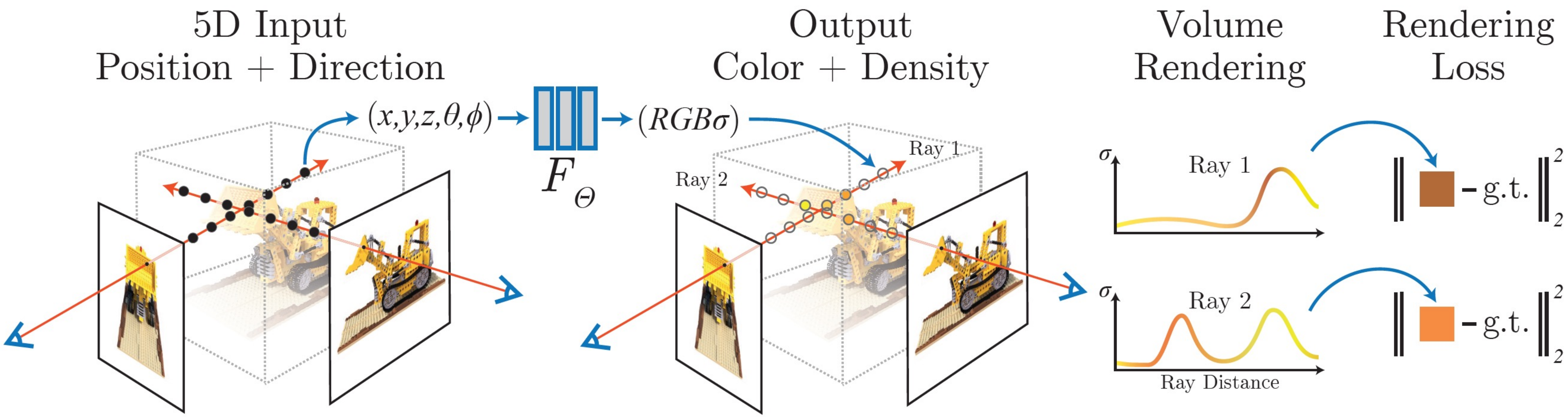
- **Input:** A set of images with camera poses.
- **Output:** A representation of the 3D object.

Kerbl et al., 3D Gaussian Splatting for Real-Time Radiance Field Rendering, SIGGRAPH 2023.

Gaussian Splatting

NeRF Optimization

1. Render a NeRF representation into a specific view.
2. Compute the difference with the given image.
3. Update the NeRF using gradient descent.



Can we perform NeRF reconstruction

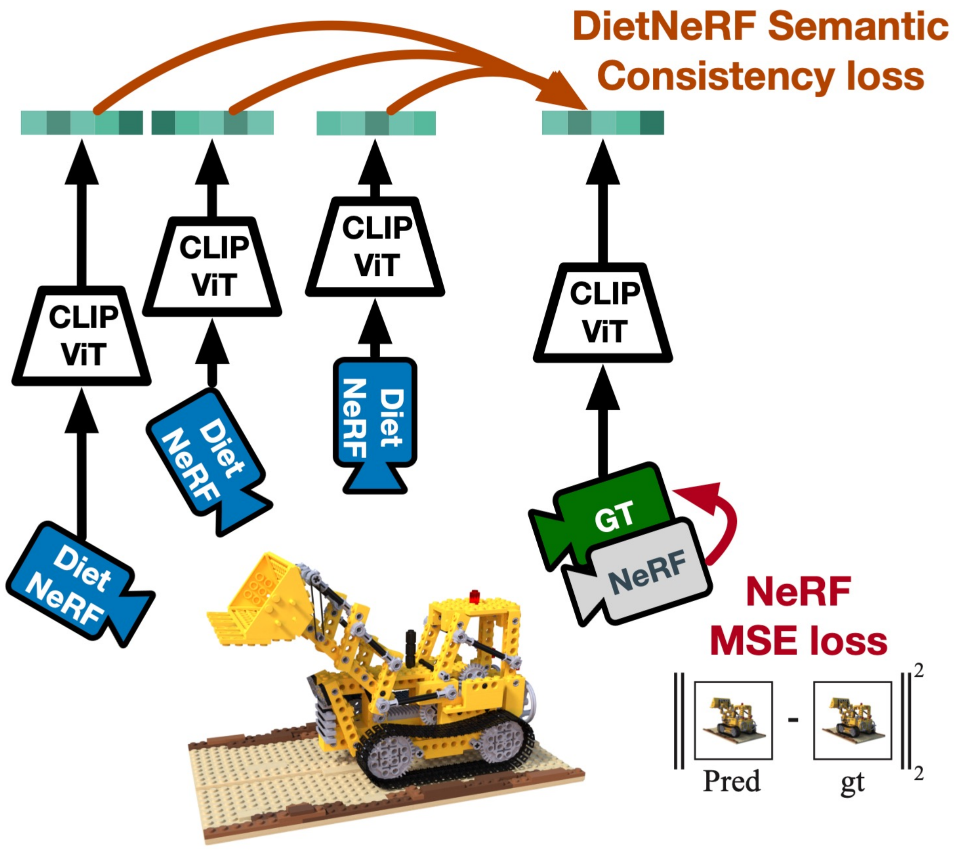
with a few images?

Then, we need additional information!

Few-Shot NeRF

DietNeRF [Jain et al., ICCV 2021]

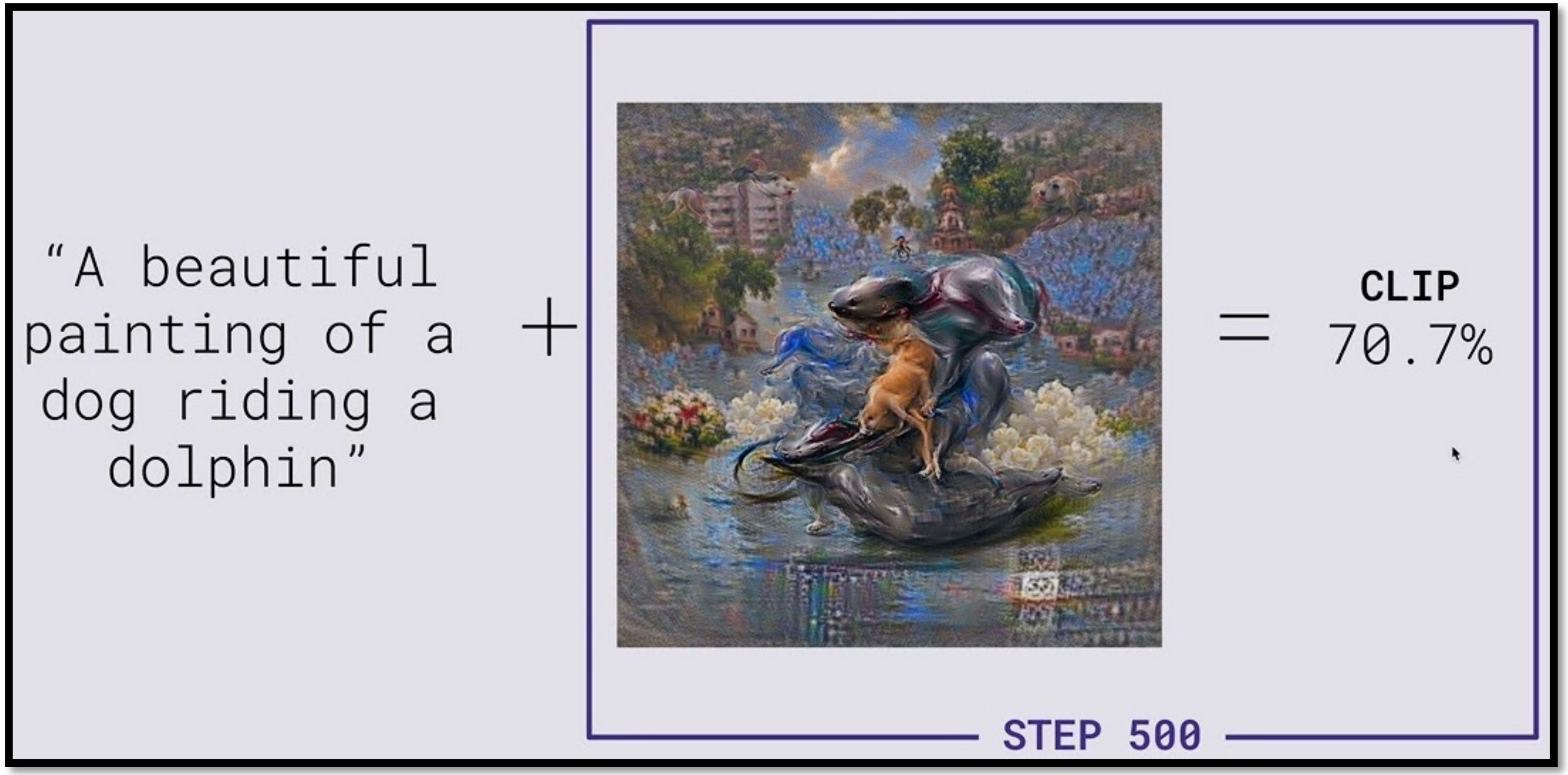
Use priors learned by CLIP [Radford et al., 2021], a text-image model.



"a bulldozer is a bulldozer from any perspective"

CLIP [Radford et al., 2021]

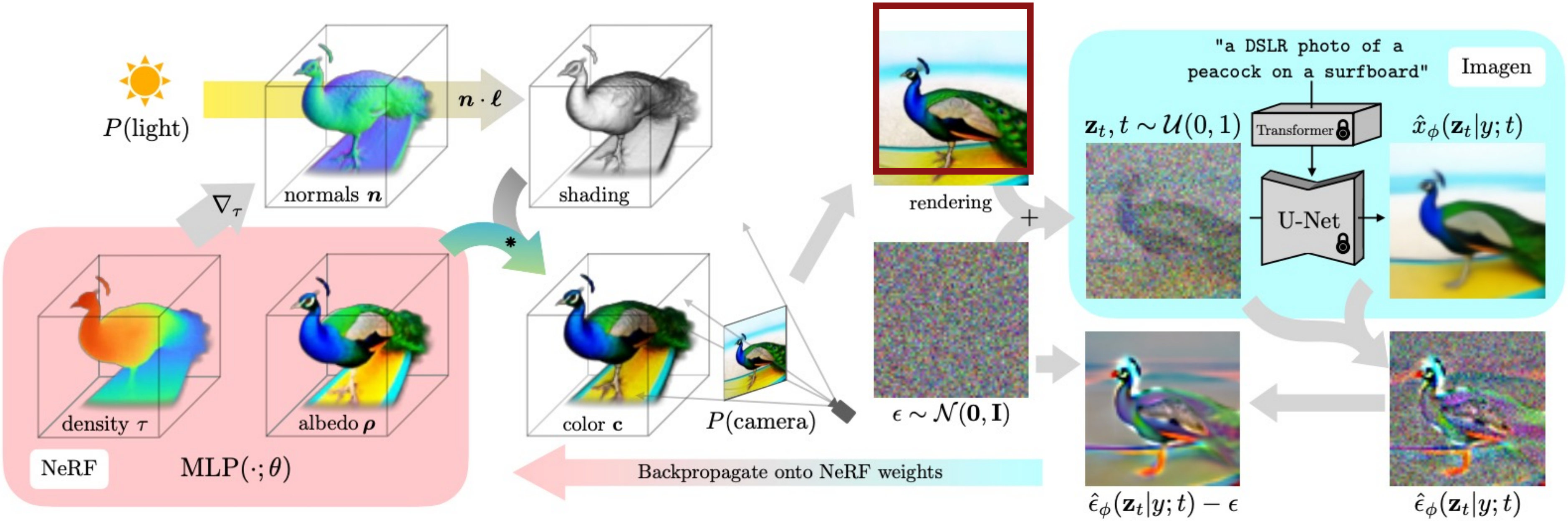
CLIP takes a text-image pair as input and assesses the alignment between the text and the image.



https://www.youtube.com/watch?app=desktop&v=-b7xKWeADHQ

Knowledge Distillation in 3D Generation

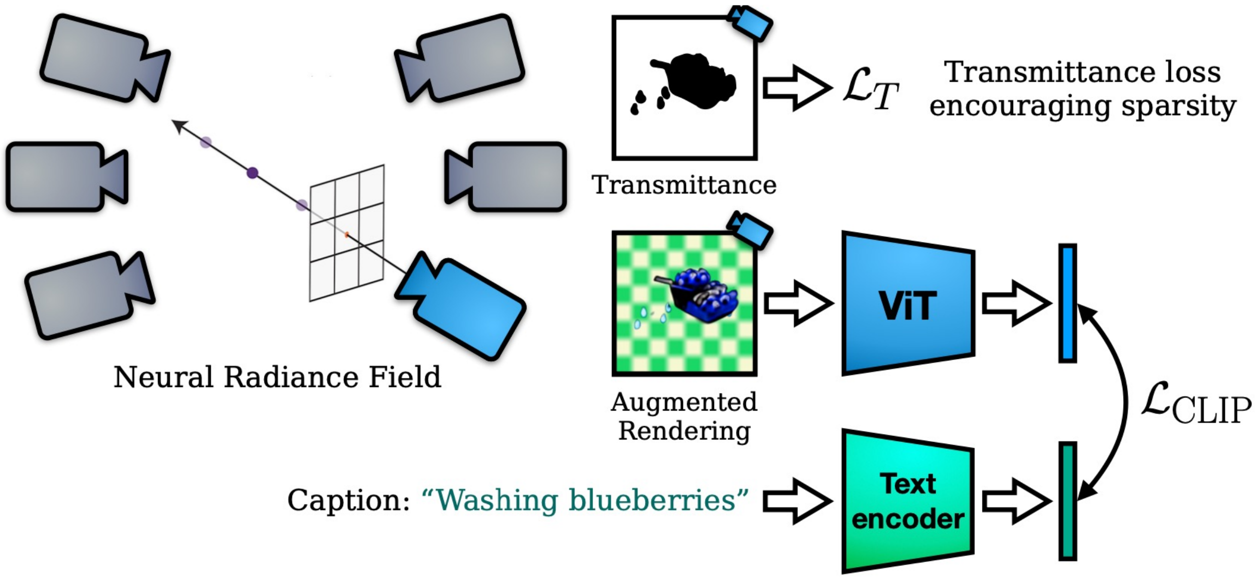
1. Render the NeRF representation into a specific view
2. **Compute the alignment to the other images.**
3. Update the NeRF using the gradient descent.

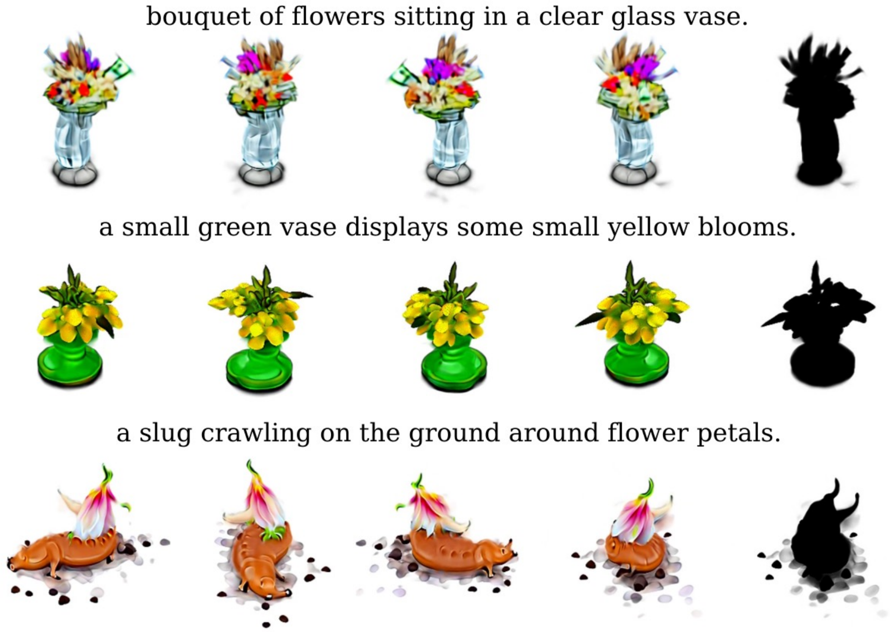


Extrem Case: Zero-Shot NeRF

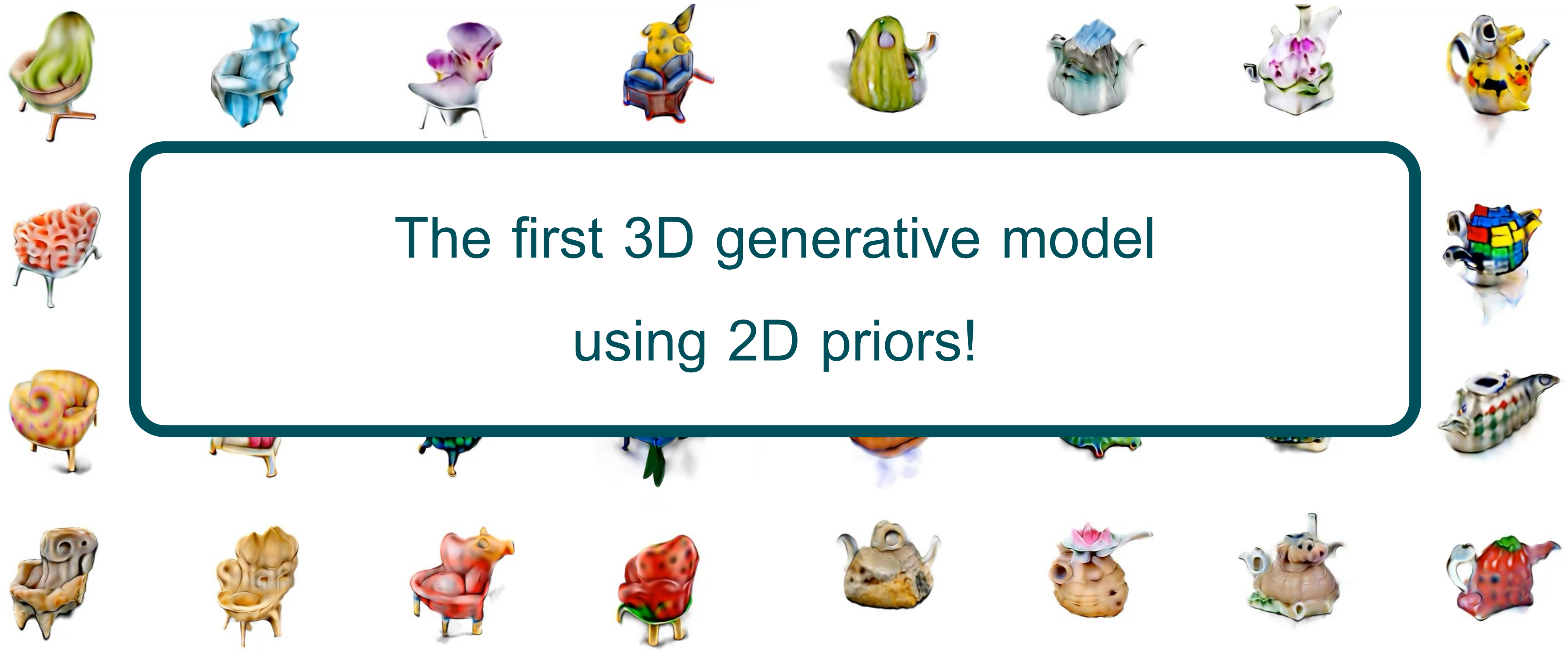
DreamFields [Jain et al., CVPR 2022]

Given a text prompt but no images, generate a 3D shape by maximizing similarity between a rendered image and the input prompt in the CLIP embedding space.





DreamFields [Jain et al., CVPR 2022]

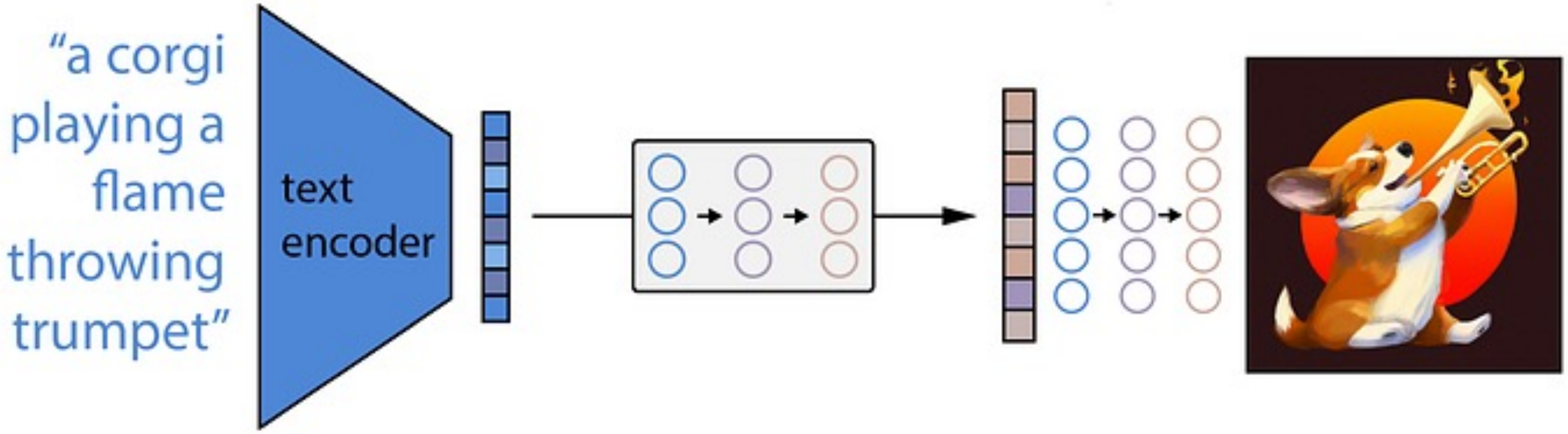


The first 3D generative model
using 2D priors!

an archair in the shape of a ____.
an archair imitating a ____.

a teapot in the shape of a ____.
a teapot imitating a ____.

Can we use a pretrained **image diffusion model** instead of CLIP?

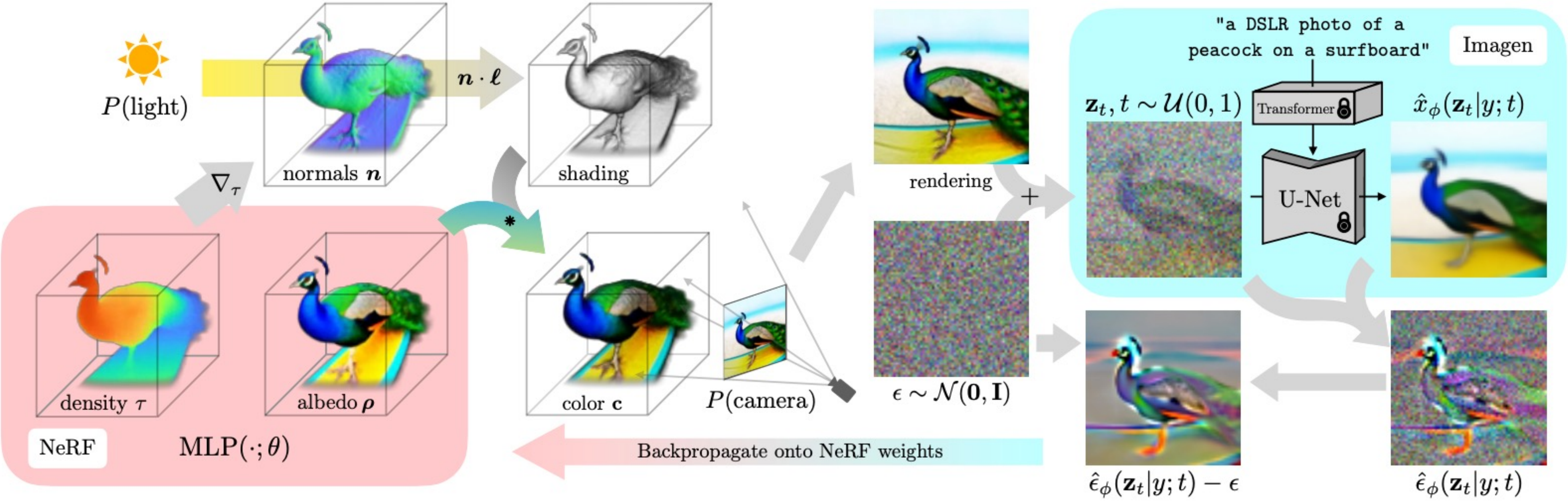


https://medium.com/latinxinai/text-to-image-with-stable-diffusion-4df16da2cfd5

Score Distillation Sampling (SDS)

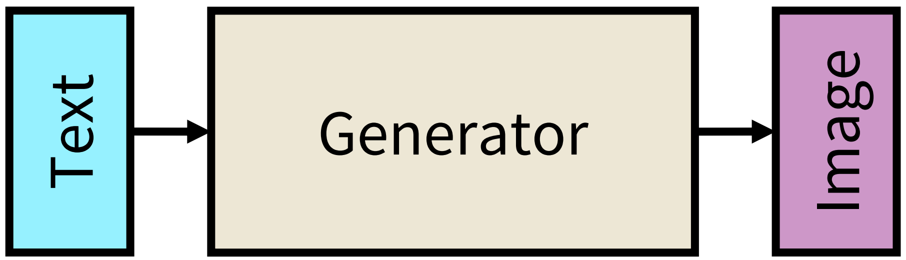
DreamFusion [Poole et al., ICLR 2023]

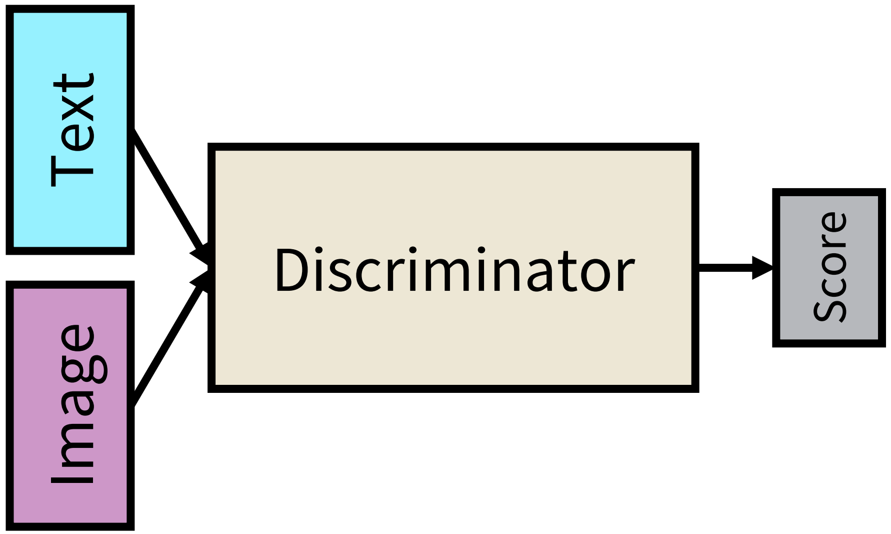
Proposed the idea of Score Distillation Sampling (SDS), leveraging a pretrained diffusion model to measure the plausibility of rendered images.



Knowledge Distillation

- **Use a generator as a discriminator.**
- **Generator**: Takes text as input and generates an image.
- **Discriminator**: Takes a pair of text and image as input and outputs the alignment score.

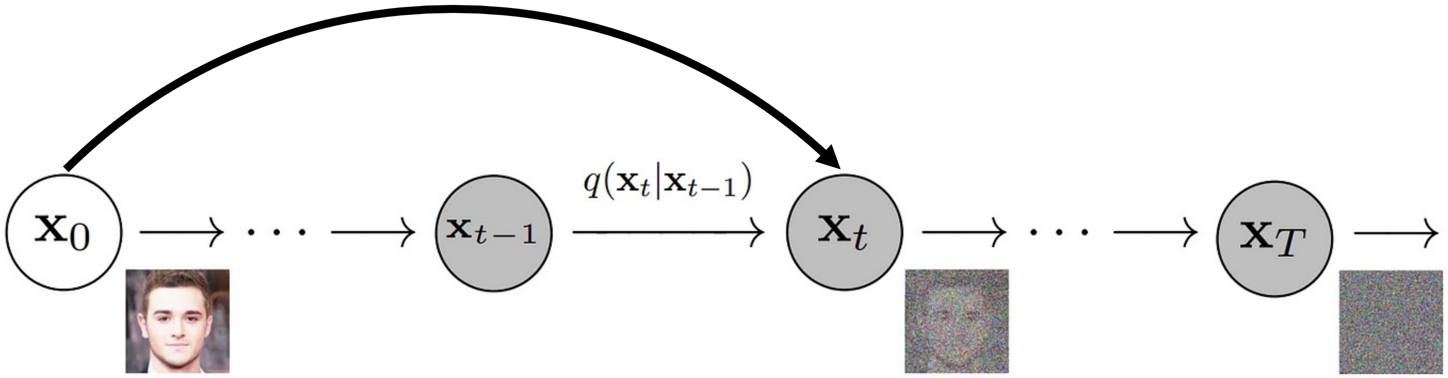




Diffusion Model Training

Given $\mathbf{x}_0$ and random timestep t,

1. Sample $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}, \mathbf{I})$.
2. Compute the forward jump: $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\boldsymbol{\varepsilon}_t$.
3. Predict $\hat{\boldsymbol{\varepsilon}}_t = \boldsymbol{\varepsilon}_\theta(\mathbf{x}_t, t)$.
4. Backpropagate through $\mathcal{L} = \mathbb{E}_{t\sim[1,T],\mathbf{x}_0,\boldsymbol{\varepsilon}_t}\left[\|\boldsymbol{\varepsilon}_\theta(\mathbf{x}_t, t) - \boldsymbol{\varepsilon}_t\|^2\right]$.



Score Distillation Sampling (SDS)

- How can we utilize a pretrained diffusion model to measure the plausibility of rendered images?

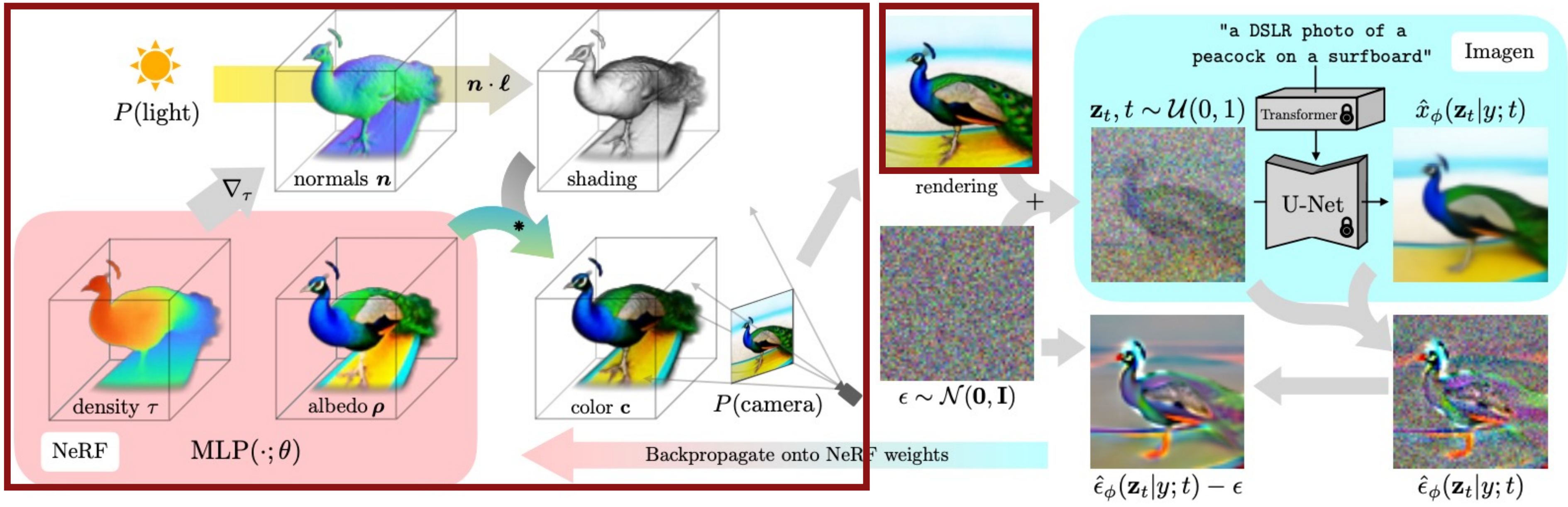
- Review the loss function:

$$\mathcal{L} = \mathbb{E}_{t\sim[1,T],\mathbf{x}_0,\boldsymbol{\varepsilon}_t}\left[\left\|\boldsymbol{\varepsilon}_t - \boldsymbol{\varepsilon}_\theta\left(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\varepsilon}_t, t\right)\right\|^2\right]$$

If the training of the diffusion model has converged, the loss for real data $\mathbf{x}_0$ will be close to zero.

Score Distillation Sampling (SDS)

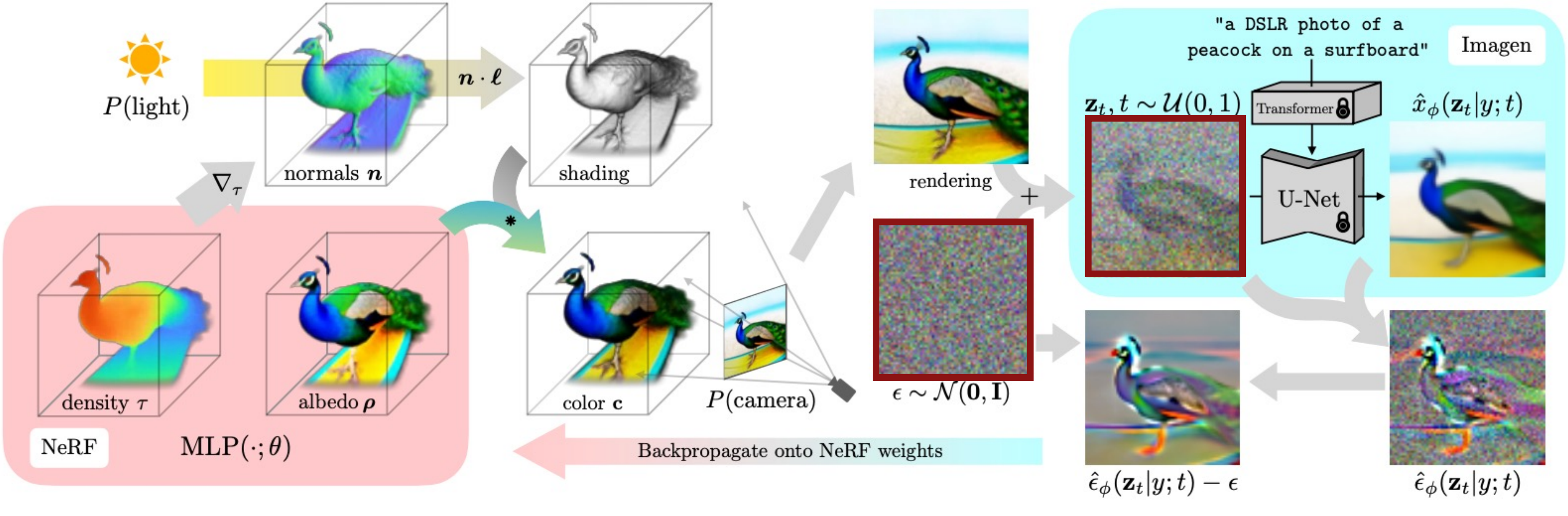
1. Render the NeRF representation into a specific view. Let ϕ denote the NeRF parameter, and $\mathbf{x}_0 = g(\phi)$ denote the rendered image.



Score Distillation Sampling (SDS)

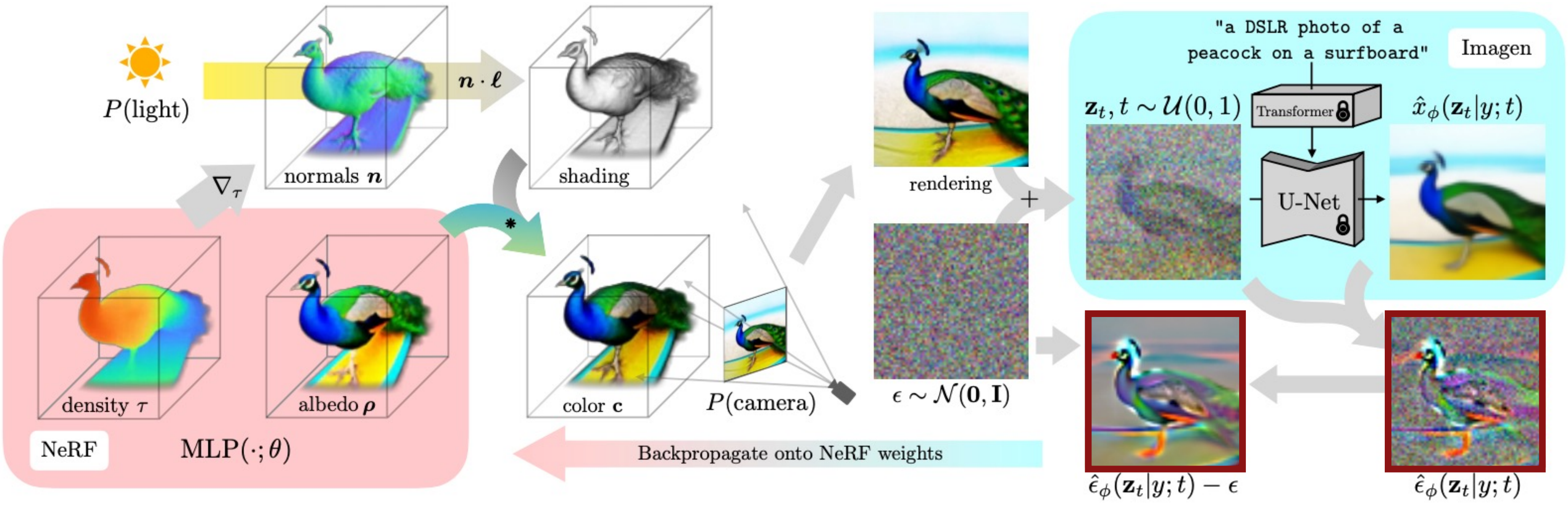
2. Add noise to the rendered image $\mathbf{x}_0$:

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\varepsilon}_t.$$



Score Distillation Sampling (SDS)

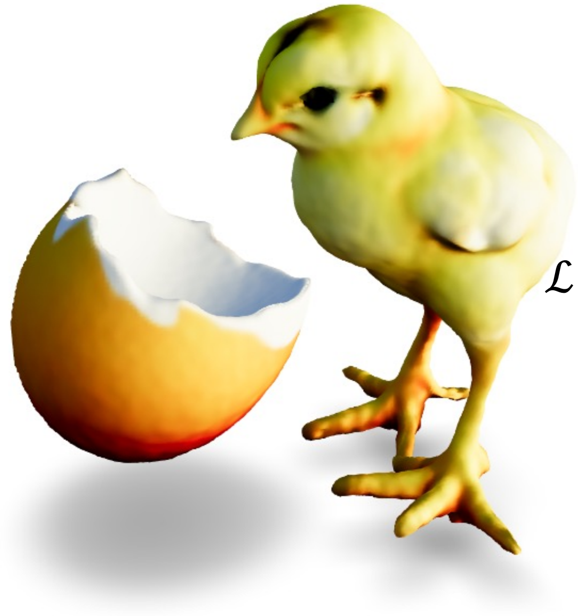
3. Compute the loss $\mathcal{L}$ and perform gradient descent on $\mathcal{L}$ with respect to the NeRF parameters ϕ.



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

DreamFusion Results

“frog wearing a sweater”



“eggshell broken in two with an adorable chick standing next to it”

“ghost eating a hamburger”

“a pig wearing a backpack”

Why SDS Instead of Reverse Diffusion?

This is a scenario where the images are parameterized differently from how they were represented during the training of the diffusion model.

- **Training**: Per-pixel colors.
- **Inference**: NeRF rendering.

Jain et al., VectorFusion: Text-to-SVG by Abstracting Pixel-Based Diffusion Models, CVPR 2023.

Example: Vector Images / Sketches

The same idea but with a different parameterization of images.

Example: Mesh Editing

The same idea but with a different parameterization of images.

Source

ARAP
[Sorkine and Alexa, 2007]

APAP
[Yoo et al., 2024]

Stable-DreamFusion

Stable-Dreamfusion

A pytorch implementation of the text-to-3D model **Dreamfusion**, powered by the Stable Diffusion text-to-2D model.

ADVERTISEMENT: Please check out threestudio for recent improvements and better implementation in 3D content generation!

NEWS (2023.6.12):

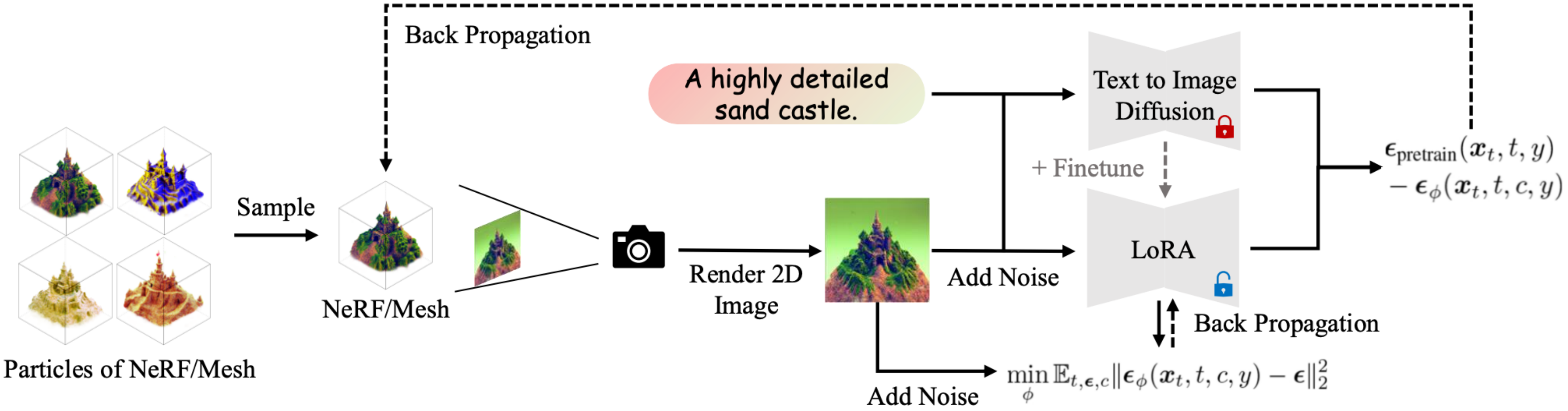
- Support of Perp-Neg to alleviate multi-head problem in Text-to-3D.
- Support of Perp-Neg for both Stable Diffusion and DeepFloyd-IF.

Text-to-3D

a rabbit, animated movie character, high detail 3d model | a DSLR photo of a delicious hamburger | a highly detailed stone bust of Theodoros Kolokotronis | a small saguaro cactus planted in a clay pot

ProlificDreamer [Wang et al., arXiv 2023]

- Minimize the SDS loss for the multiple samples of the NeRF parameters ϕ.
- Finetune the diffusion model with the Low Rank Adaptation (LoRA) technique.

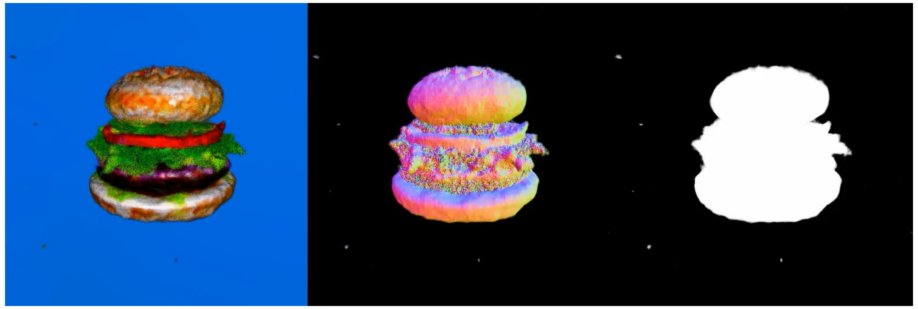


Limitation of SDS

It does not converge well without a high CFG weight (e.g., $w = 400$) and thus suffers from model collapse.

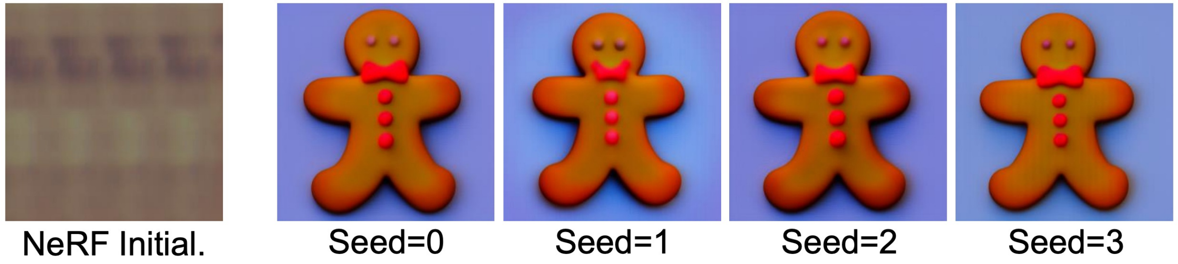
"a delicious hamburger"

$w = 400$



$w = 7.5$

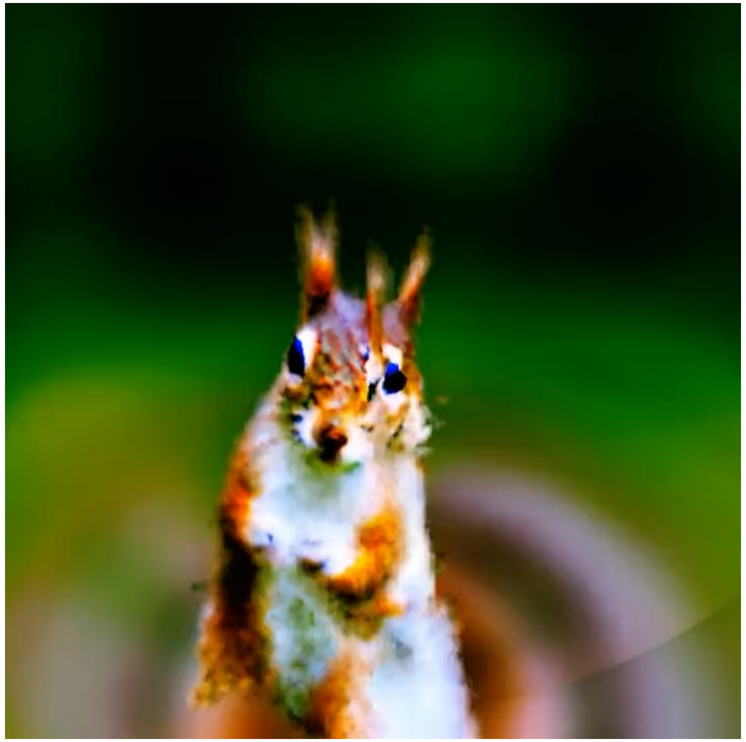
Credit: Jaihoon Kim

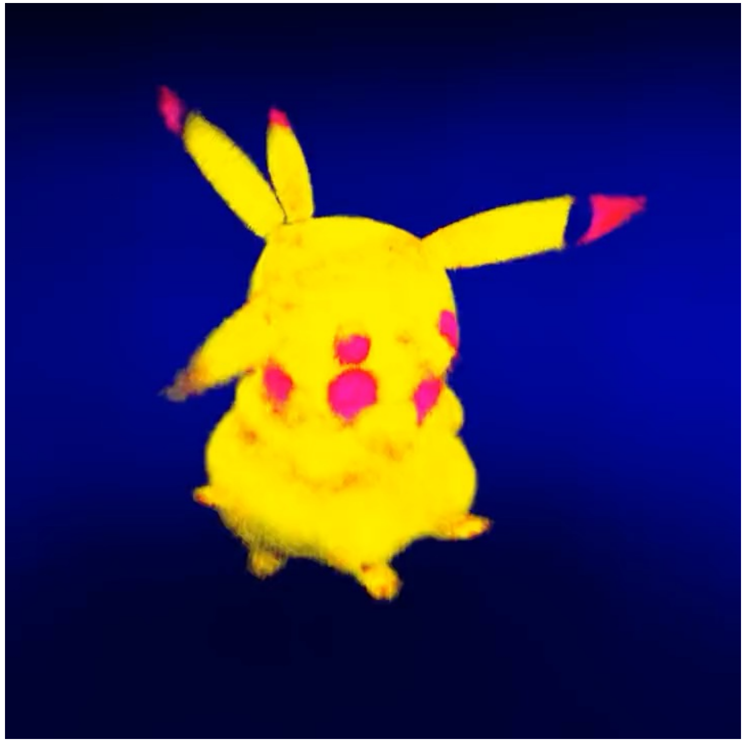


"gingerbread man"

Huang et al., DreamTime: An Improved Optimization Strategy for Text-to-3D Content Creation, arXiv 2023.

Limitation of 3D Generation from 2D Priors





Twitter @_akhaliq

Limitation of 3D Generation from 2D Priors

Supervision for geometry is still needed!

ProlificDreamer, Wang et al., 2023.

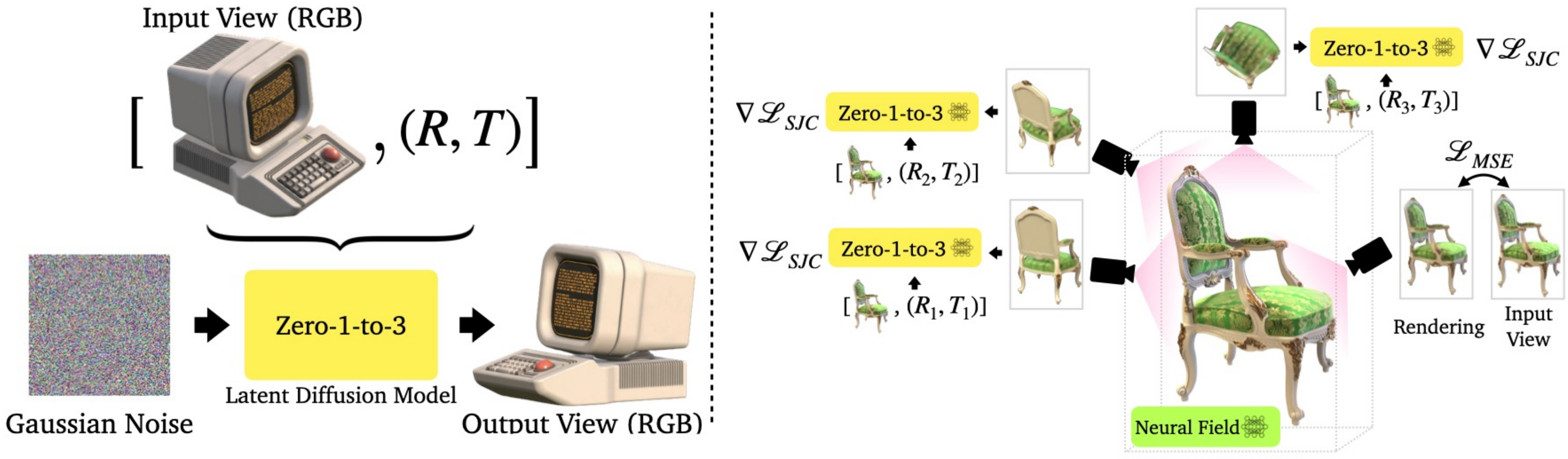
StableDreamFusion

Multi-View Diffusion Models

Zero-1-to-3 [Liu et al., 2023]

Novel view generation

An image diffusion model generating a novel view image conditioned by another view image and camera pose.

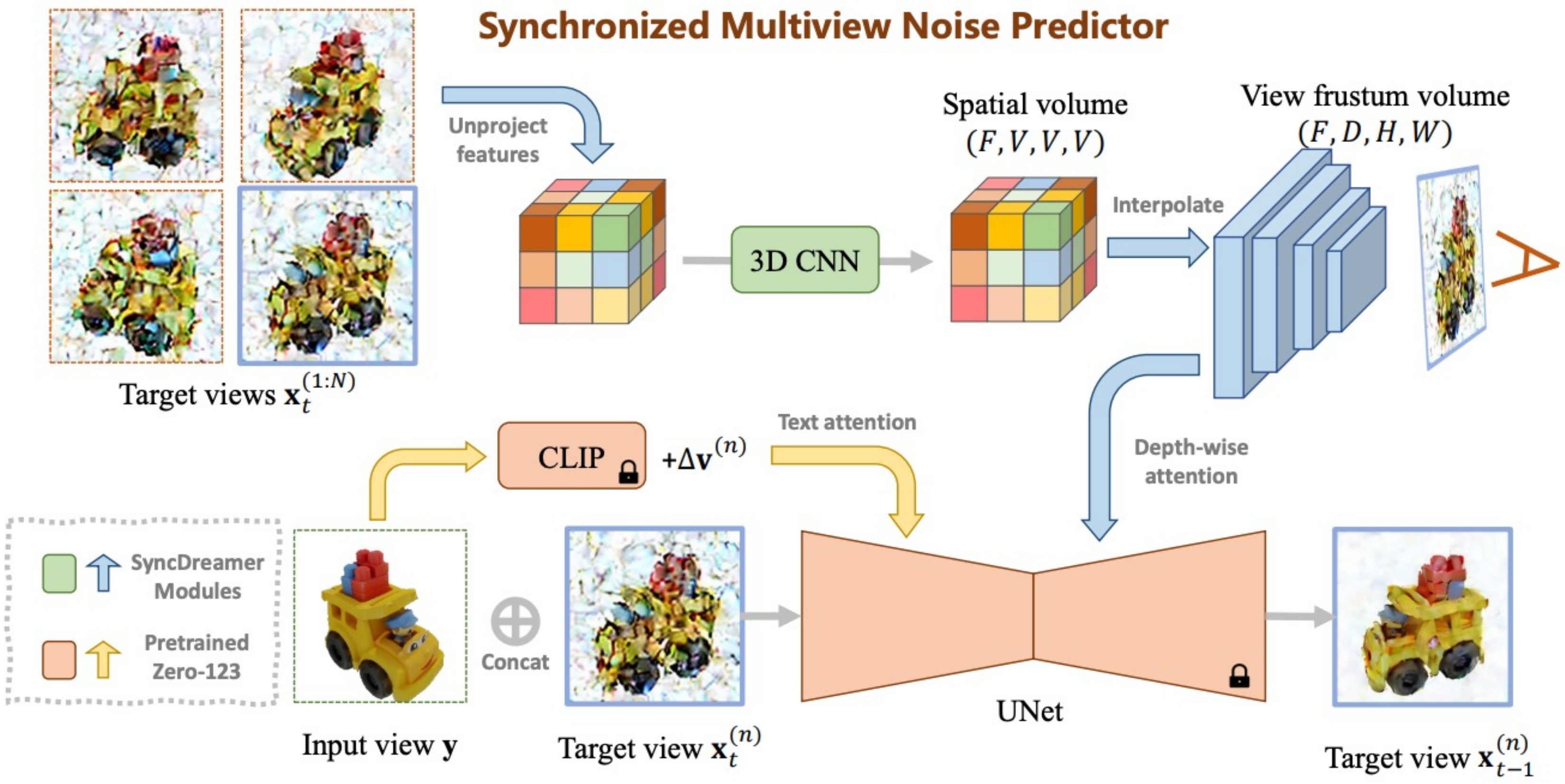


Novel View Synthesis

3D Reconstruction

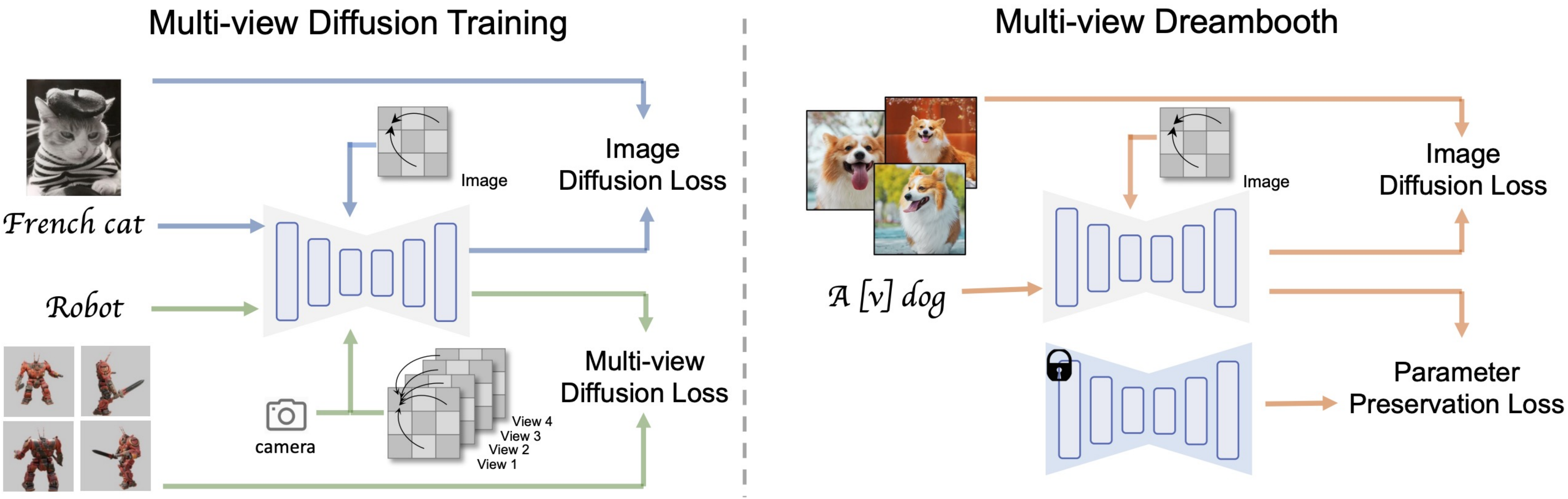
SyncDreamer [Liu et al., 2023]

Utilize Zero 1-to-3 to learn the joint probability distribution of multi-view images.



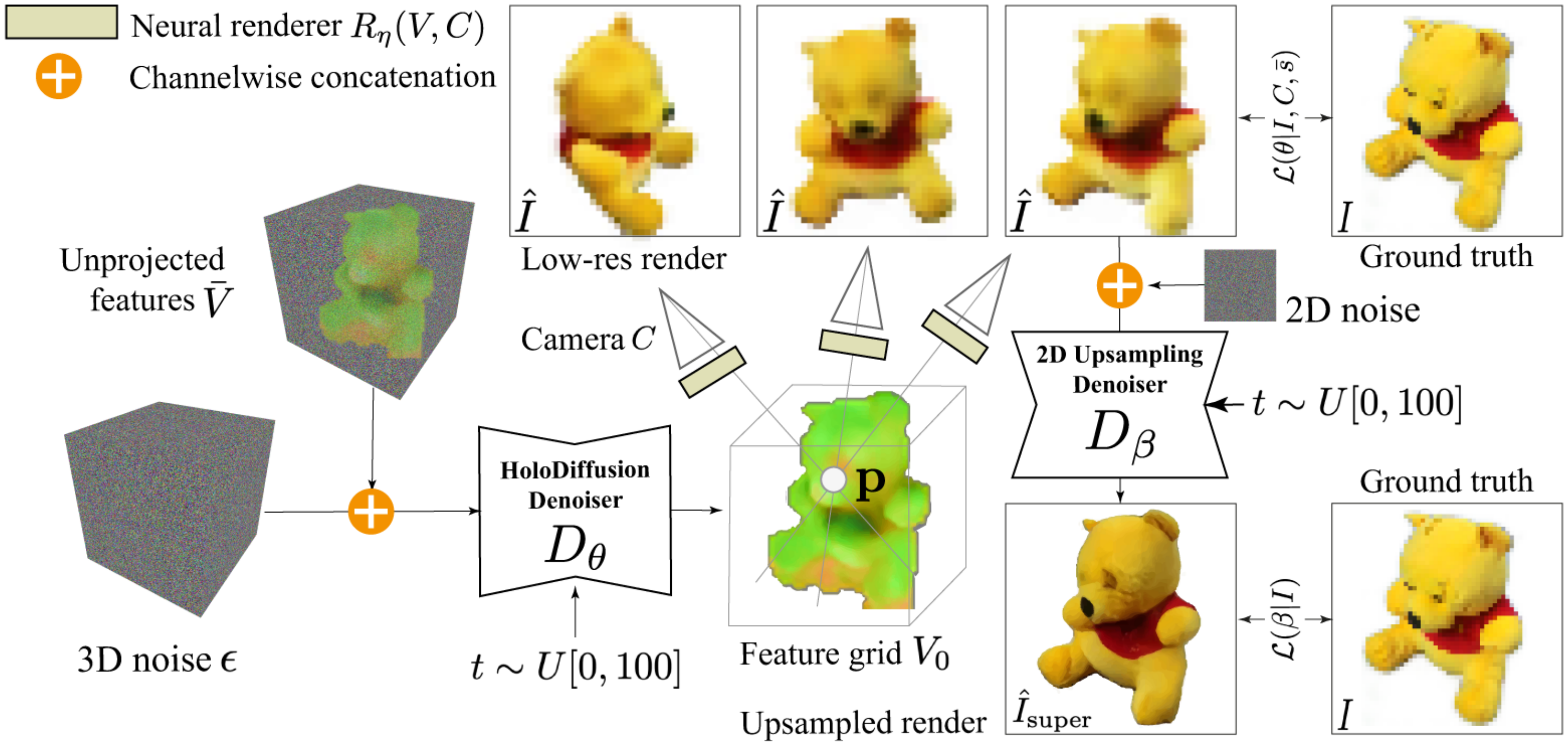
MVDream [Liu et al., 2023]

A diffusion model generating multi-view images.



HoloFusion [Karnewar et al., 2023]

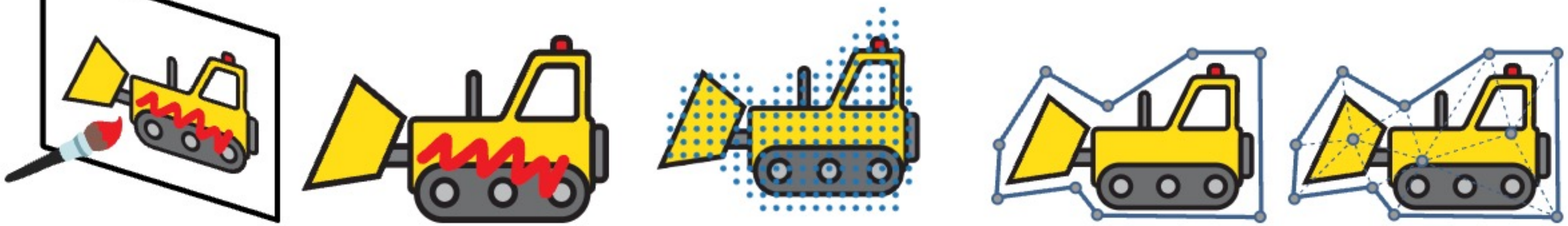
- Train a 3D diffusion model using multi-view images only.
- Can be extended to integrate 2D priors.



Future Directions

Generation → Editing

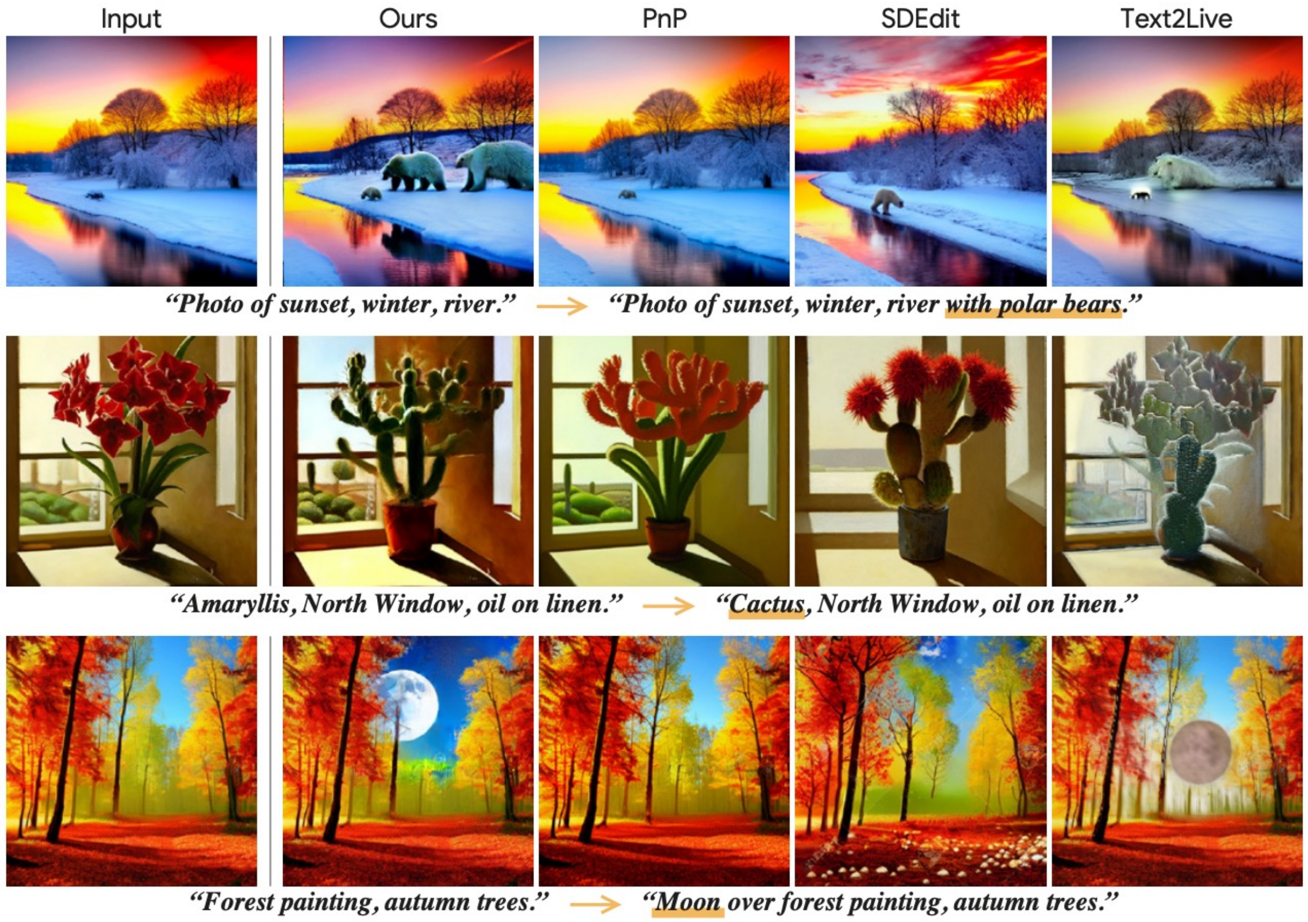
The focus of 3D generative models will shift towards creating versatile models capable of not only generating but editing and manipulating 3D shapes.



NeRFshop, Jambon et al., I3D 2023.

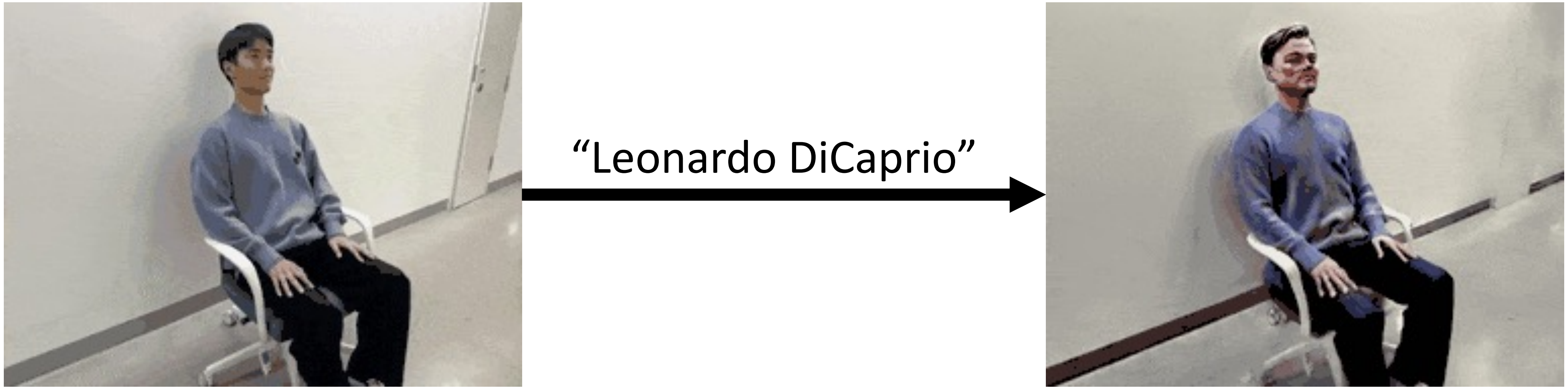
Delta Denoising Score [Hertz et al., 2023]

A new loss function for zero-shot image editing.



Posterior Distillation Sampling [Koo et al., 2024]

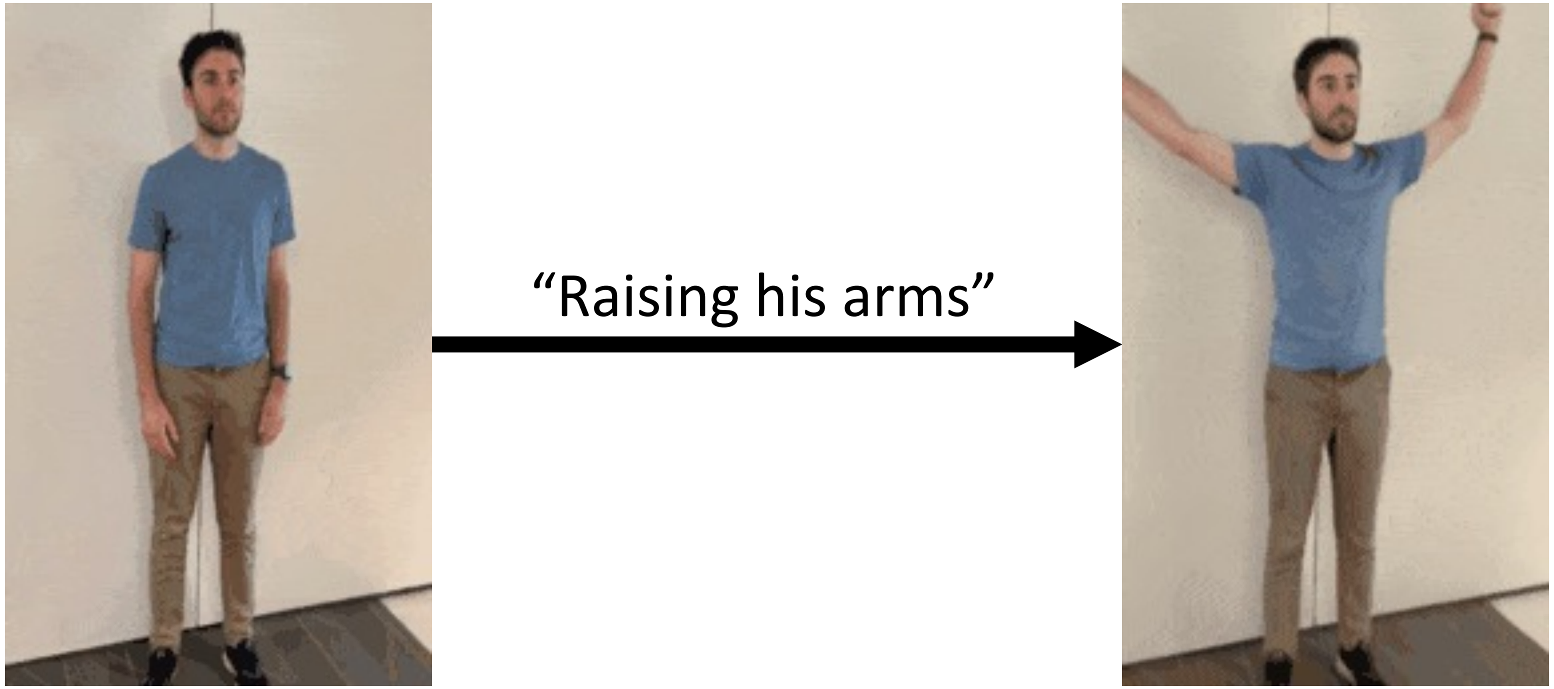
A new loss function for zero-shot NeRF editing.



Koo et al., Posterior Distillation Sampling, CVPR 2024.

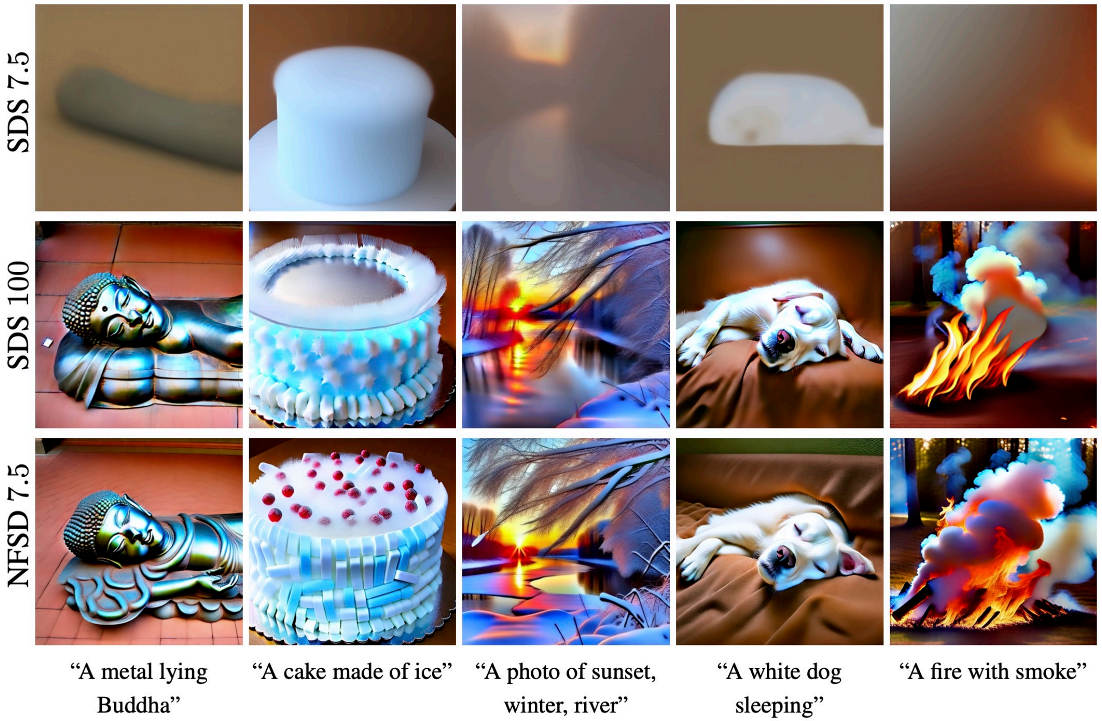
Posterior Distillation Sampling [Koo et al., 2024]

A new loss function for zero-shot NeRF editing.



Limitations of SDS

- Highly saturated colors due to high CFG weight.
- Somewhat cartoonish images.
- Lack of diversity.



Katzir et al., Noise Free Score Distillation, ICLR 2024.

Hertz et al., Delta Denoising Score, ICCV 2023.

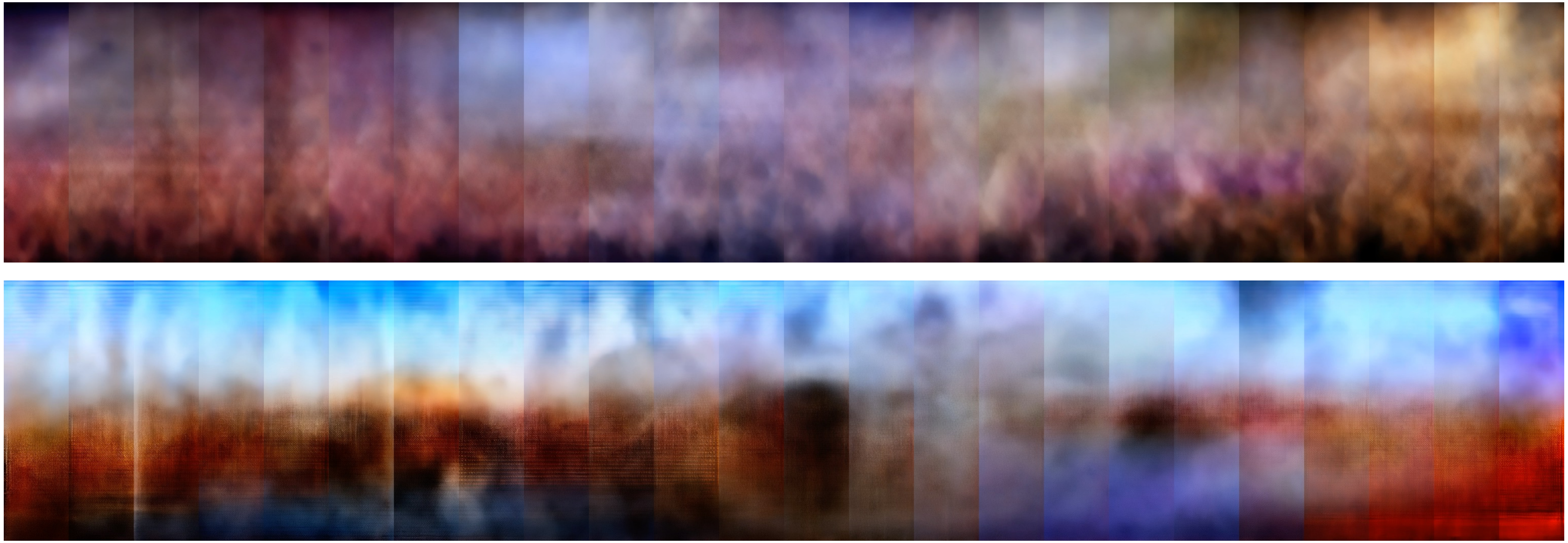
SDS → Joint Diffusion

Can we generate various visual data using image diffusion models while using them *"as is"* – performing reverse diffusion?

Kim et al., SyncTweedies: A General Generative Framework Based on Synchronized Diffusions, arXiv 2024.

SDS → Joint Diffusion

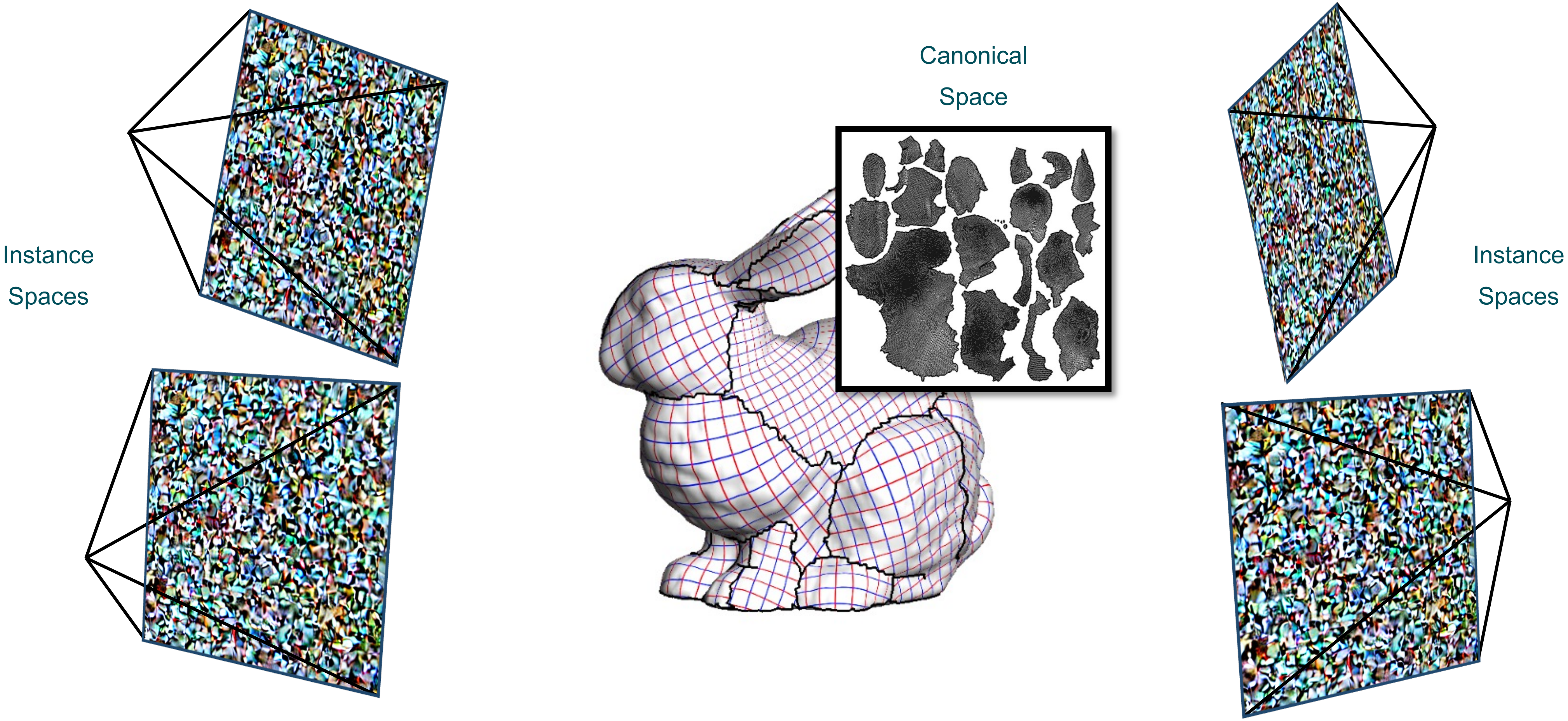
Can we generate various visual data using image diffusion models while using them *“as is”* – performing reverse diffusion?



Lee et al., SyncDiffusion: Coherent Montage via Synchronized Joint Diffusions, NeurIPS 2023.

SDS → Joint Diffusion

Can we generate various visual data using image diffusion models while using them *“as is”* – performing reverse diffusion?



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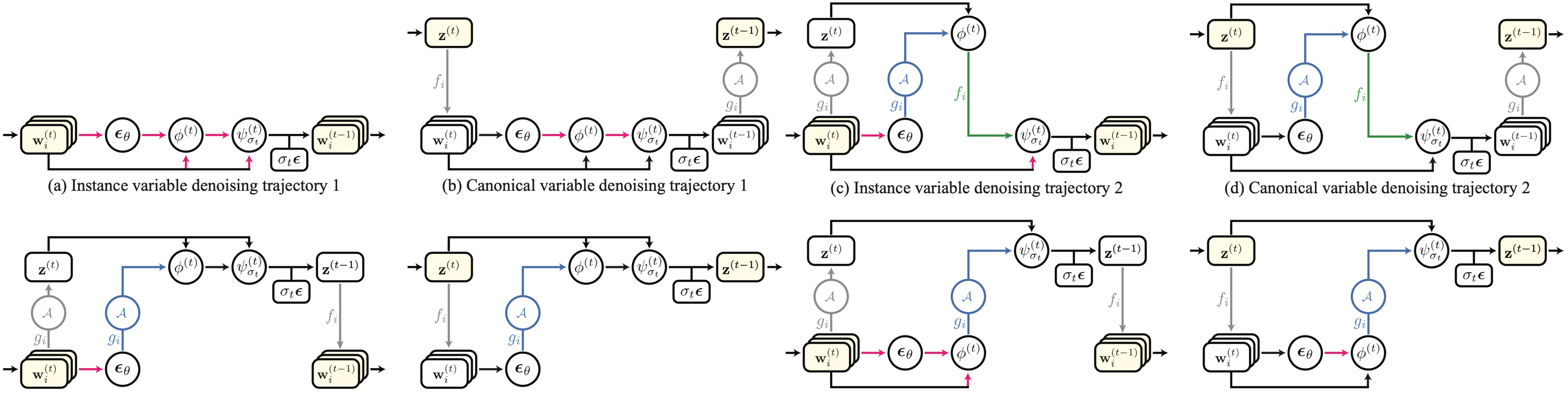


(a) Instance variable denoising trajectory 1

(b) Canonical variable denoising trajectory 1

(c) Instance variable denoising trajectory 2

(d) Canonical variable denoising trajectory 2

(e) Instance variable denoising trajectory 3

(f) Canonical variable denoising trajectory 3

(g) Instance variable denoising trajectory 4

(h) Canonical variable denoising trajectory 4

Kim et al., SyncTweedies: A General Generative Framework Based on Synchronized Diffusions, arXiv 2024.

SDS → Joint Diffusion

Can we generate various visual data using image diffusion models while using them *"as is"* – performing reverse diffusion?

"A hand carved wood turtle"

"A dumpster"

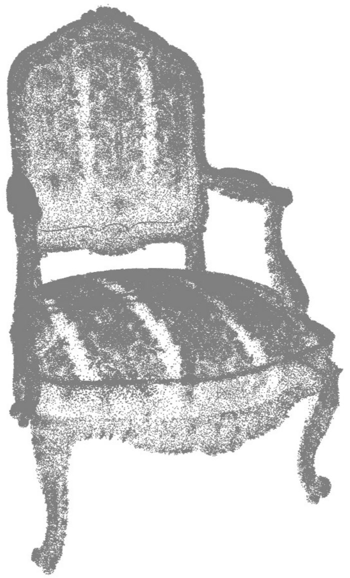
"A Chinese style lantern"

"A car with graffiti"

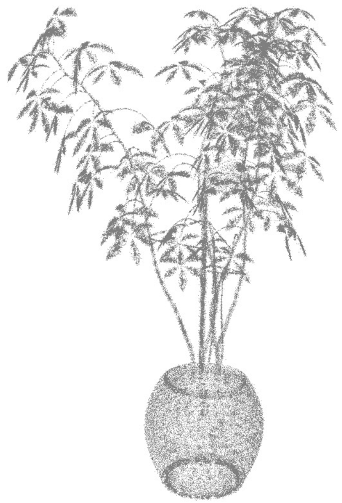
Kim et al., SyncTweedies: A General Generative Framework Based on Synchronized Diffusions, arXiv 2024.

SDS → Joint Diffusion

Can we generate various visual data using image diffusion models while using them *“as is”* – performing reverse diffusion?



"A majestic red chair"



"A photo of a tree with multicolored leaves"

More results are available on https://synctweedies.github.io/.

SDS → Joint Diffusion

Can we generate various visual data using image diffusion models while using them *"as is"* – performing reverse diffusion?

a painting of a horse

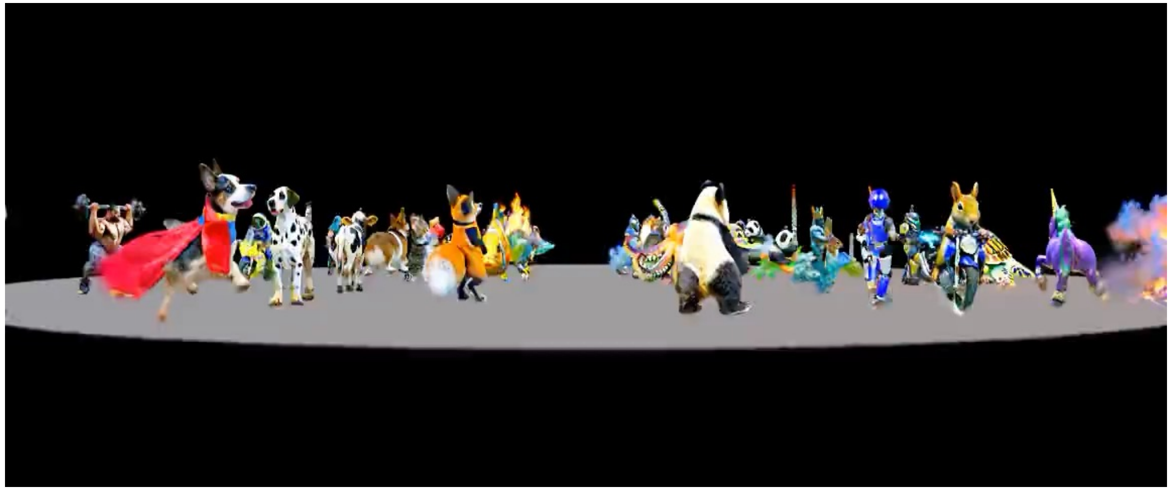
a painting of a truck

a painting of a truck

More results are available on https://synctweedies.github.io/.

Video Generative Models as Priors

Will video generative models be the ultimate priors for 3D and other visual content generation?



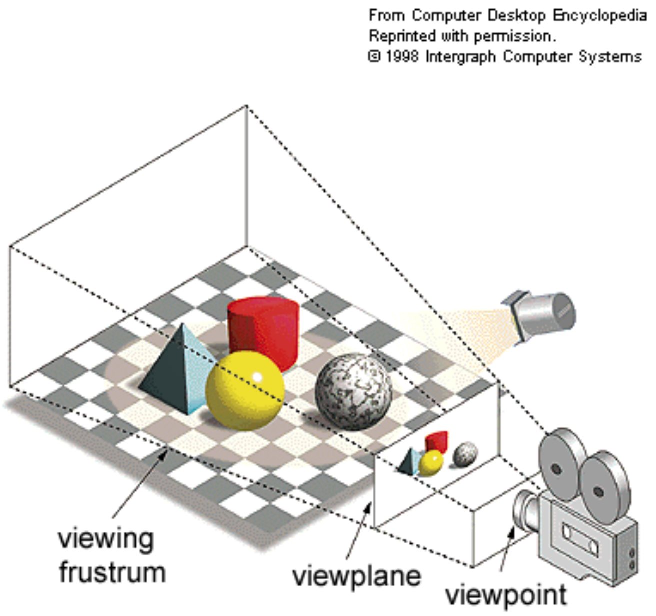
Align Your Gaussians

Stable Video 3D

Video Generative Models as Priors

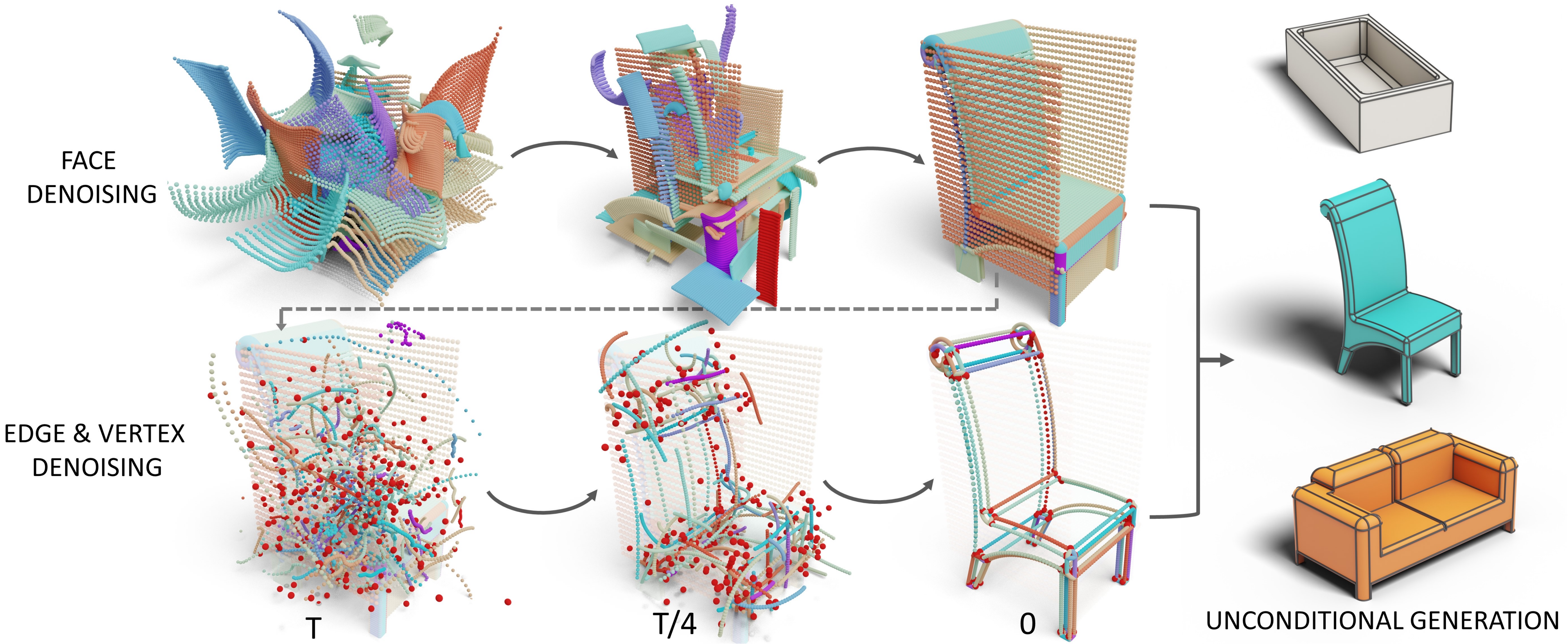
Videos still lack:

- camera pose information
- separation of geometry and appearance
- physical information
- structural 3D information
- cross-frame correspondence



3D Structure Generation

Can we generate 3D structure using diffusion models?



Xu et al., BrepGen: A B-rep Generative Diffusion Model with Structured Latent Geometry, SIGGRAPH 2024.

Summary

1. 3D diffusion models
2. Score distillation sampling
    1. Issues with high CFG
    2. Janus problem
3. Multi-view diffusion models
4. Future directions: 3D editing, synchronization, video priors, structure generation, etc.

Presentation Schedule

Introduction to Diffusion Models

Guidance and Conditioning Sampling

Attention

Break

Personalization and Editing

Beyond Single Images

Diffusion Models for 3D Generation