Text to Image Generation: Pretraining and Applications

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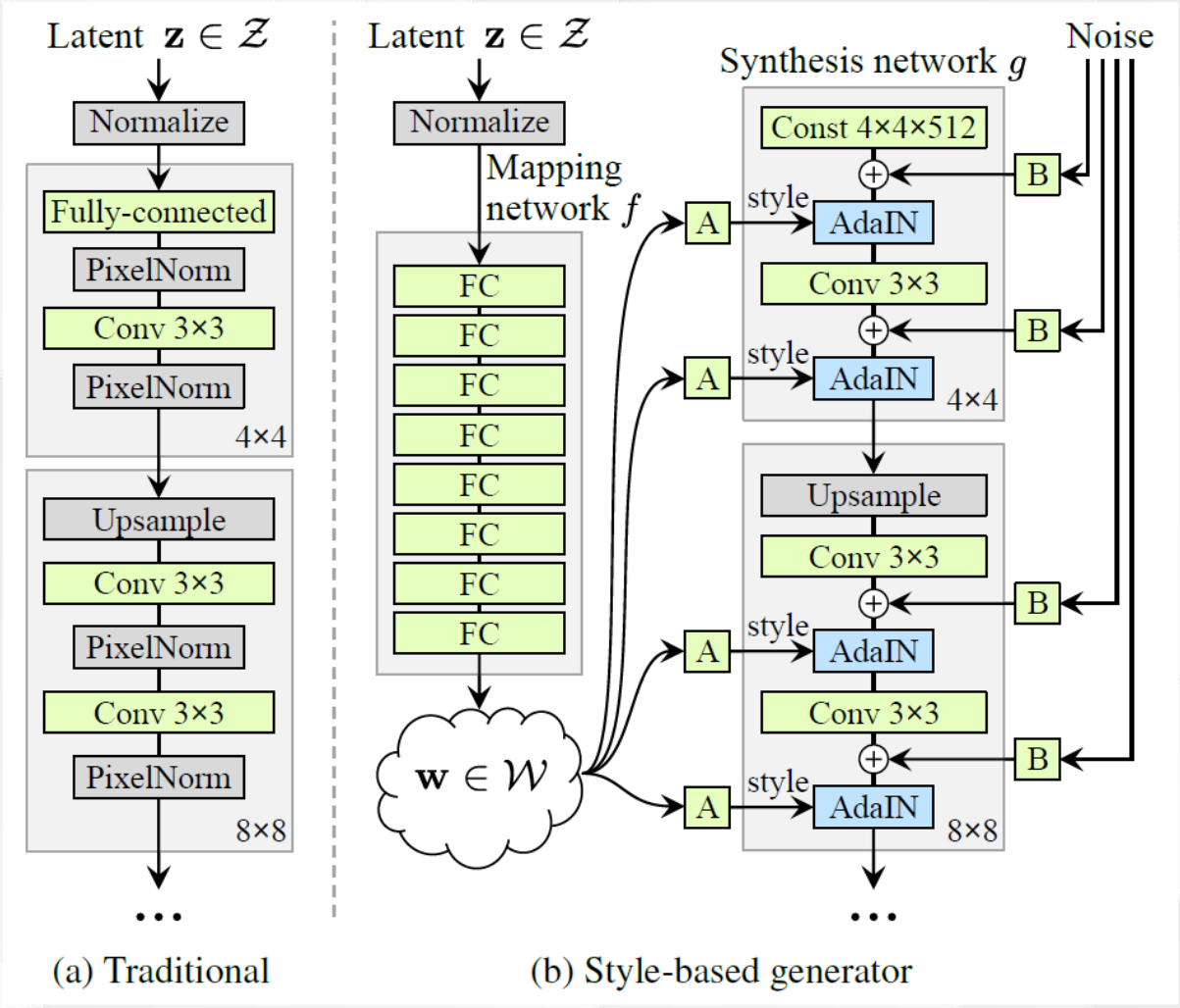
Content

- Large Scale Pretraining Models
  - GAN
  - Auto-autoregressive models
  - Diffusion models
  - Return of GAN and AR Models
  - From T2I to 3D/Video Generation

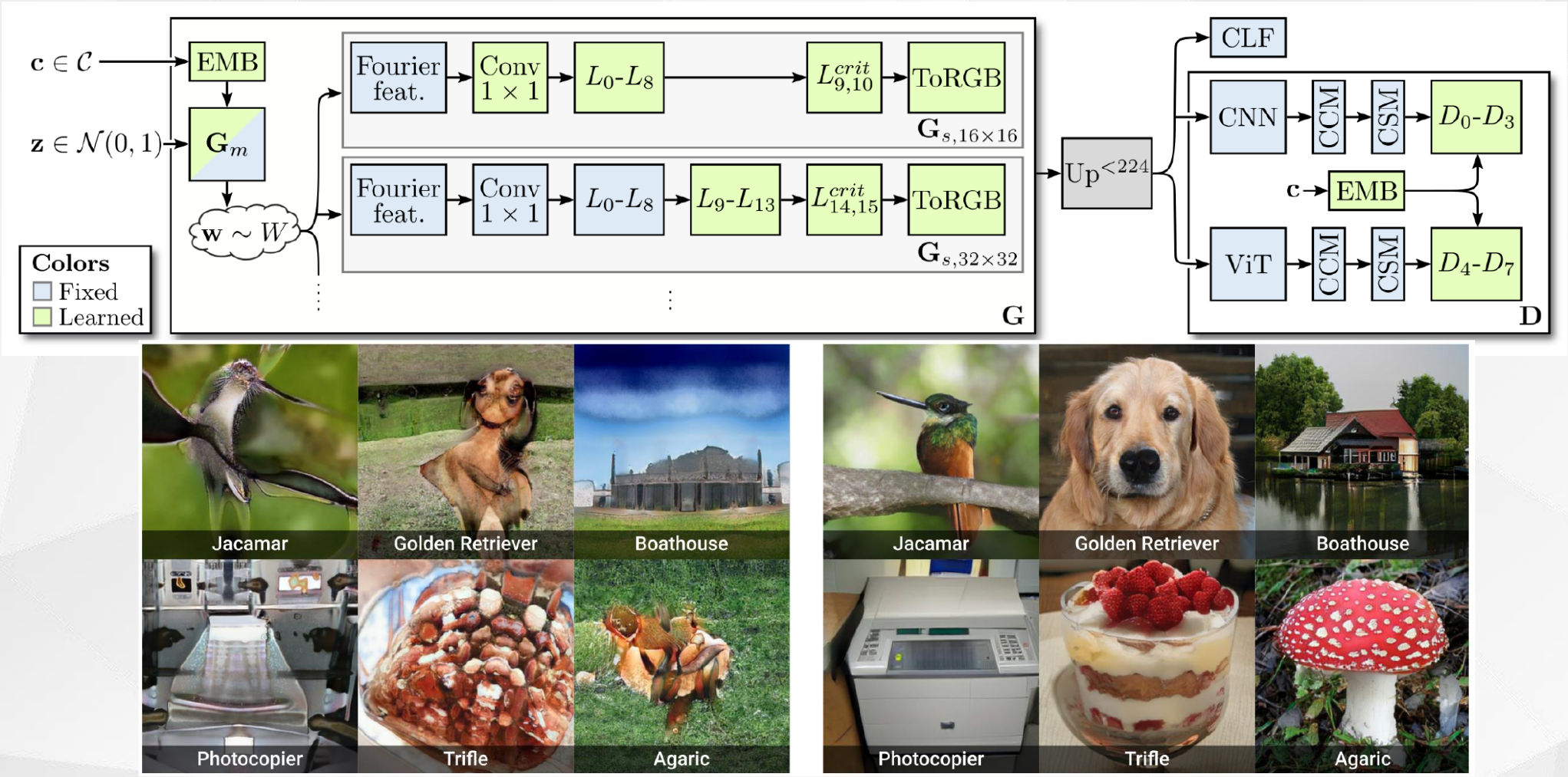
- Applications

StyleGAN 1~3 (Karras, CVPR 2019)

- Progressive GAN
- Multi-layer manipulation on style and noise
- Truncation trick



StyleGAN-XL



StyleGAN-XL: Scaling StyleGAN to Large Diverse Datasets, Siggraph 2022.

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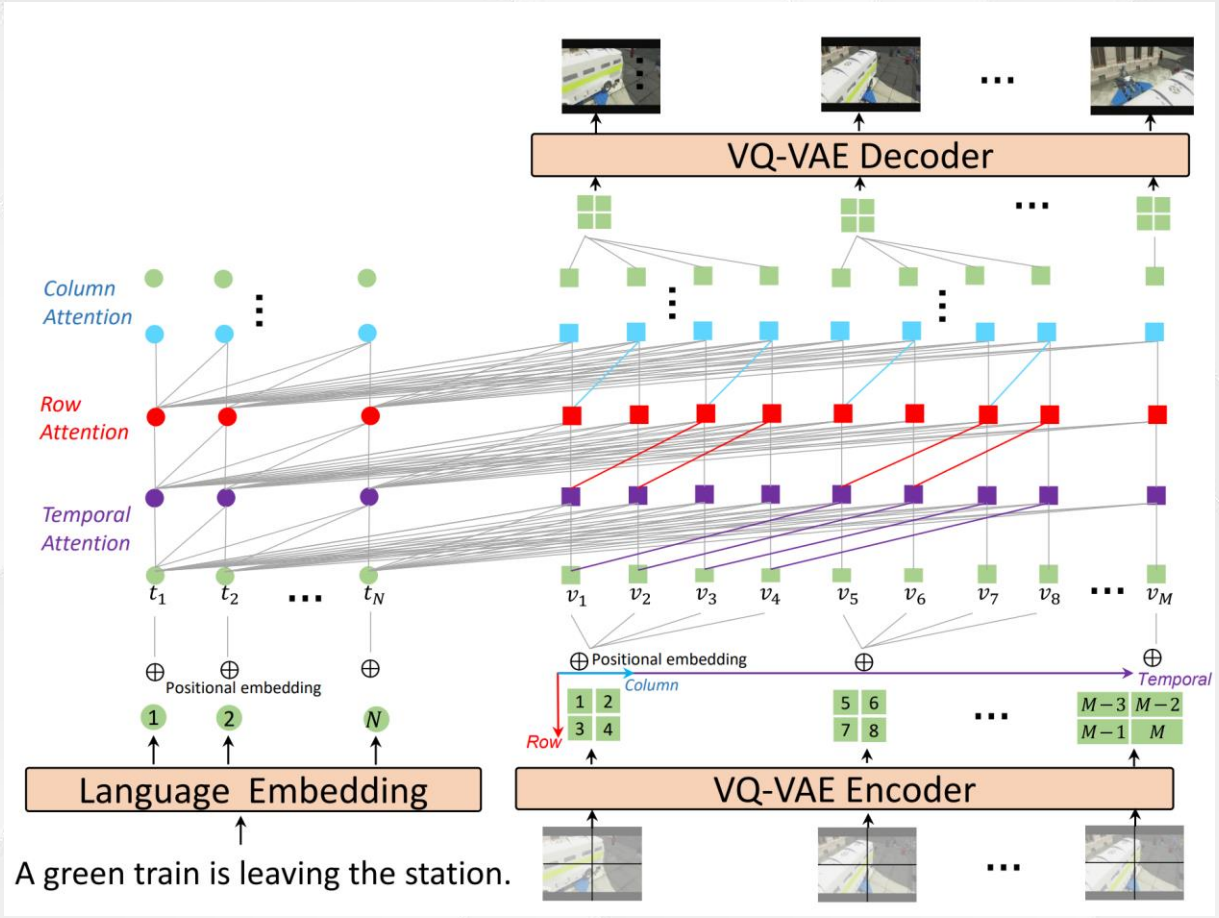
DALL-E: Text-to-Image Generation

- Sufficient data and scale
  - 250 million text-images pairs
  - A discrete variational autoencoder (**dVAE**) to compress each 256x256 RGB image into a 32x32 grid of image tokens.
  - An autoregressive transformer to model the joint distribution over the text and image tokens

Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, Ilya Sutskever, Zero-Shot Text-to-Image Generation, Arxiv 2021.

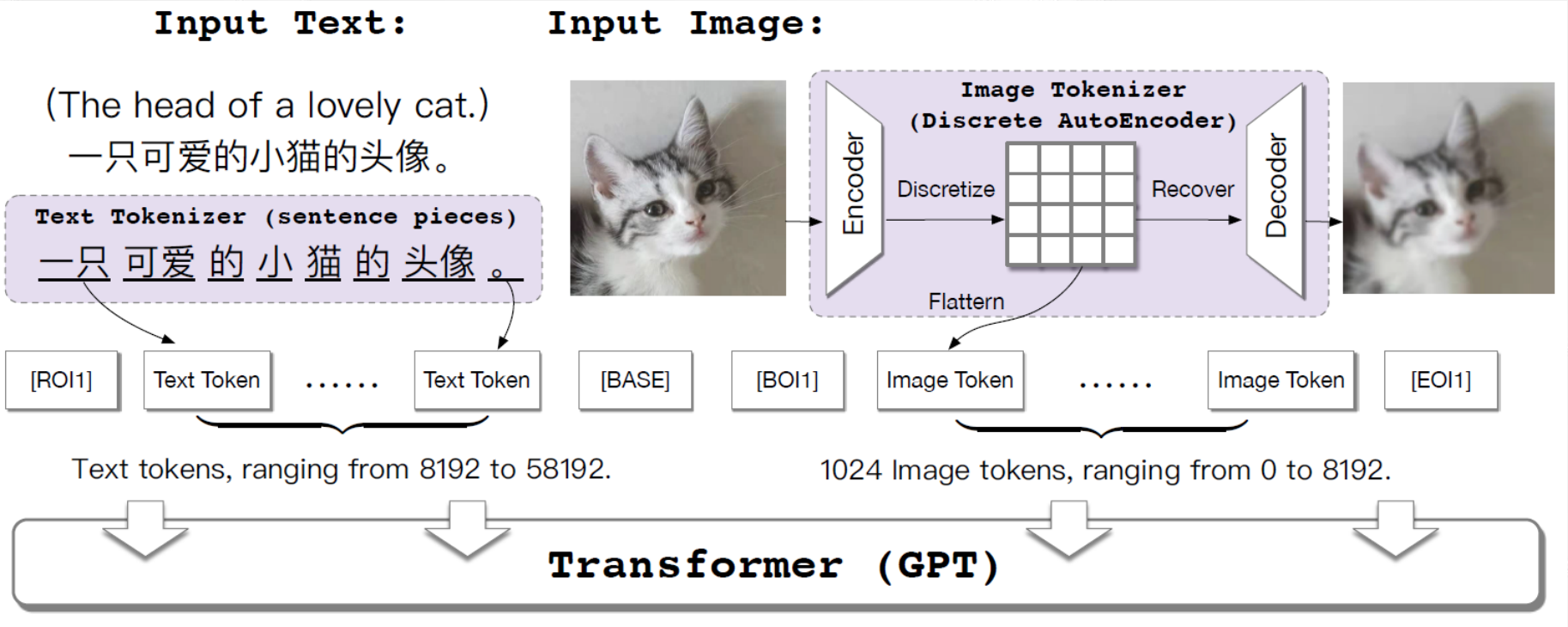
GODIVA Model



GODIVA: Generating Open-DomaIn Videos from nAtural Descriptions, arXiv 2021

CogView: Text-to-Image Generation

- **VQ-VAE** Tokenizer

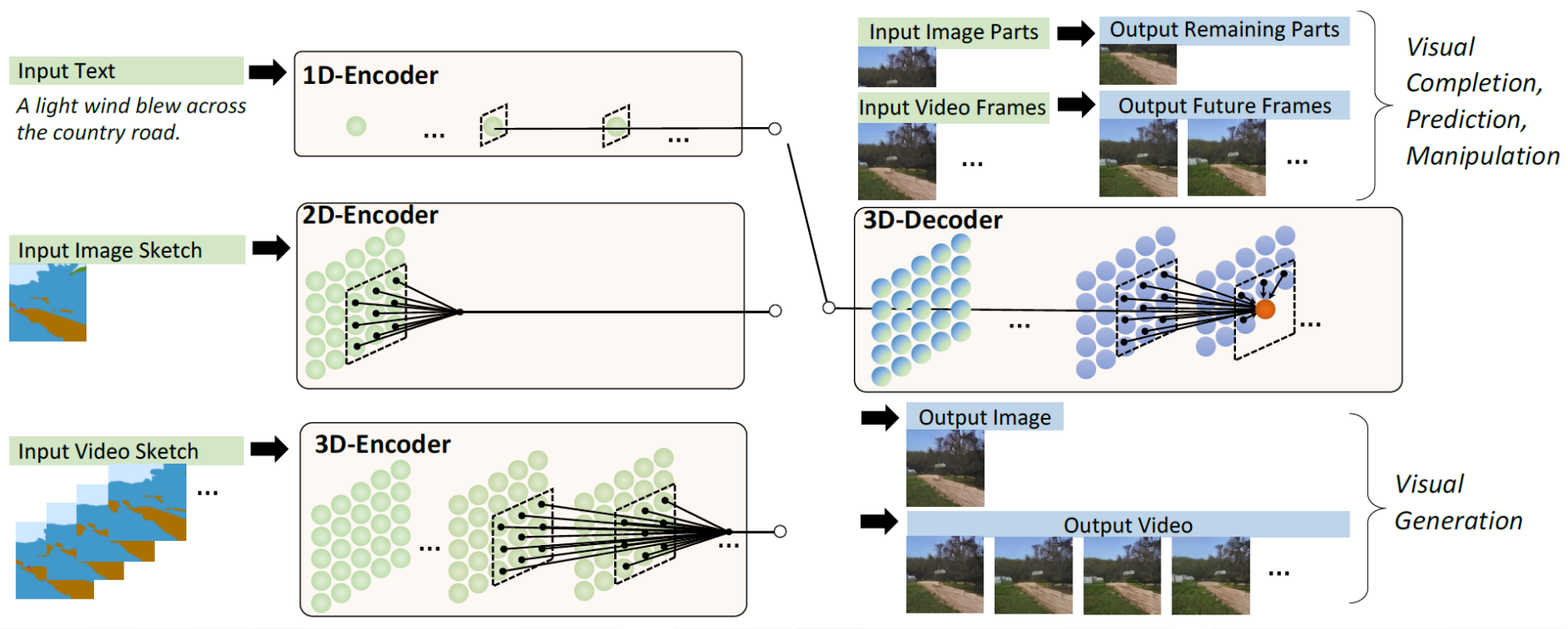


Ming Ding, Zhuoyi Yang, Wenyi Hong, Wendi Zheng, Chang Zhou, Da Yin, Junyang Lin, Xu Zou, Zhou Shao, Hongxia Yang, and Jie Tang. CogView: Mastering Text-to-Image Generation via Transformers. Arxiv 2021

CogView: Text-to-Image Generation

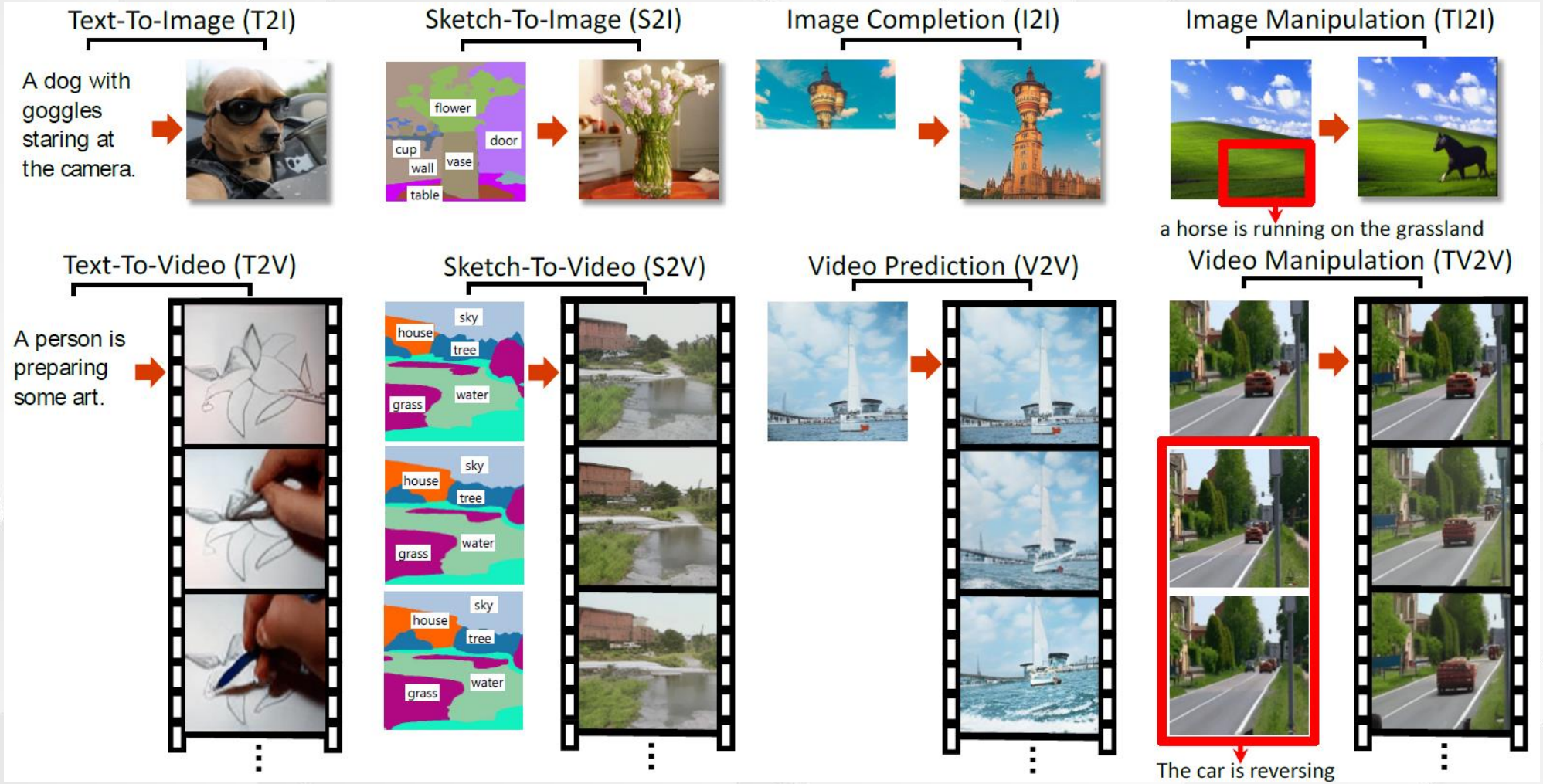
NÜWA: Neural visUalWorld creAtion

- Adaptive encoder and pre-trained decoder, many applications



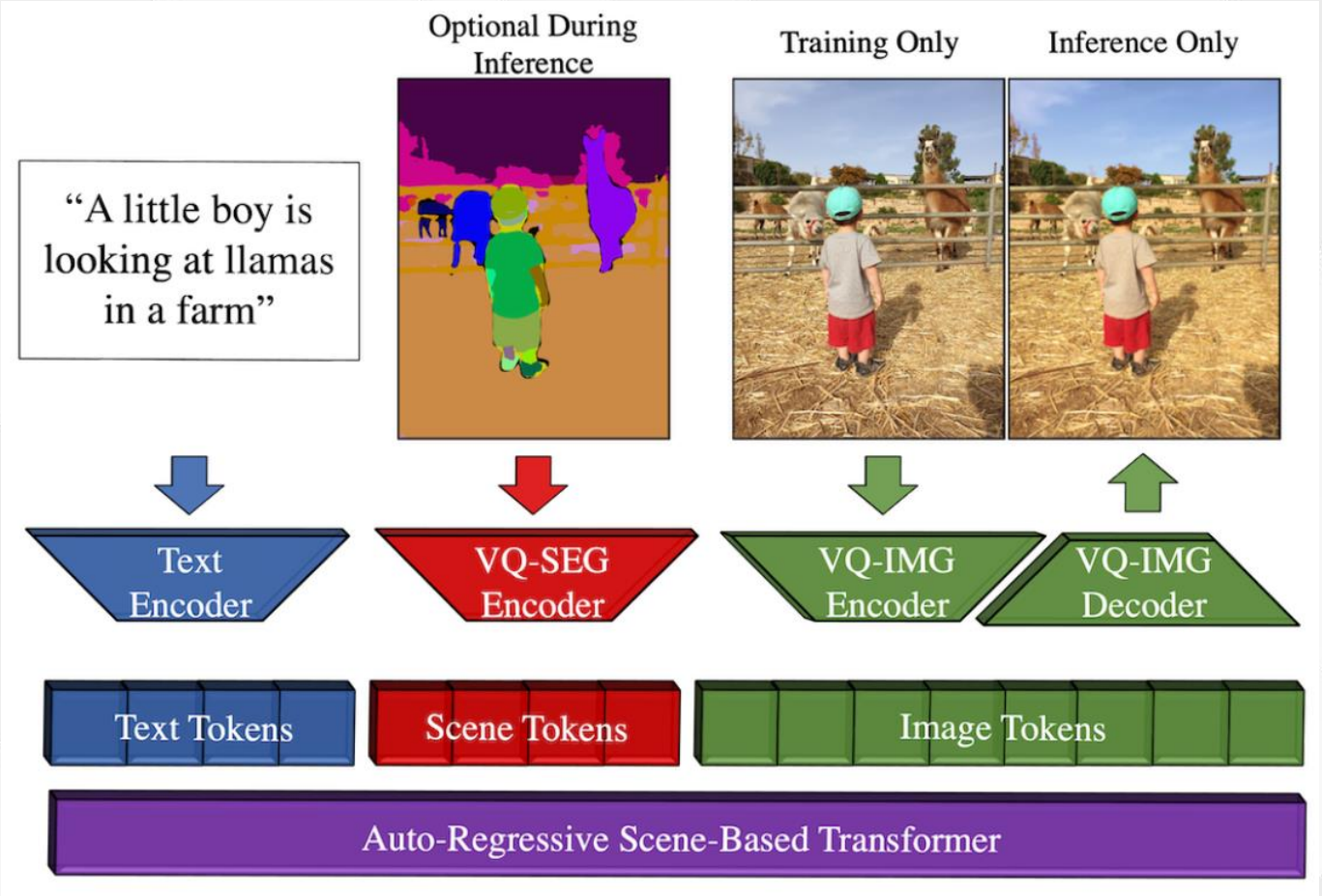
Chenfei Wu, Jian Liang, Lei Ji, Fan Yang, Yuejian Fang, Daxin Jiang, Nan Duan, NÜWA: Visual Synthesis Pre-training for Neural visUalWorld creation, Arxiv 2021.

NÜWA: Many Possible Applications



Make-A-Scene

- Segmentation mask: domain-specific knowledge
- Face/Object emphasis
- Classifier-free guidance



Make-A-Scene: Scene-Based Text-to-Image Generation with Human Priors, Arxiv 2022

Samples on MS-COCO Prompts

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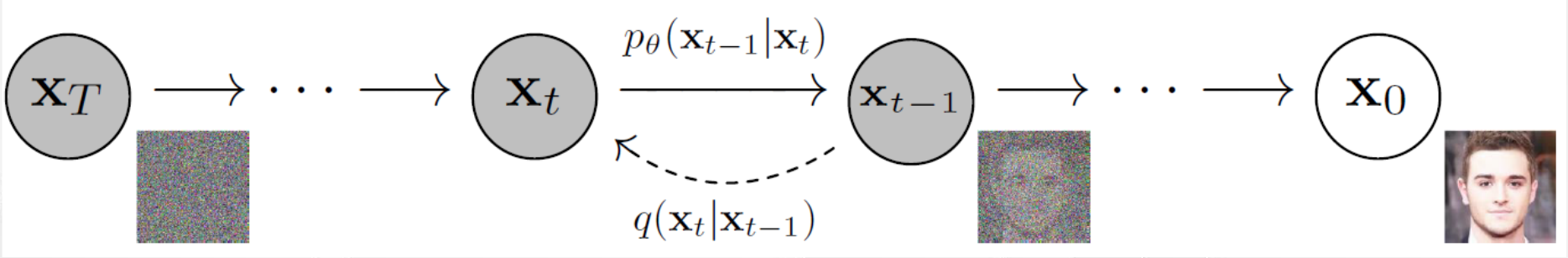
DDPM



- Forward process or diffusion process

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

- Reverse process

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

Jonathan Ho , Ajay Jain, Pieter Abbeel, Denoising Diffusion Probabilistic Models, NeurIPS 2020

DDPM: Learning Objective

- Forward process

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I})$$

$$q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}_t(\mathbf{x}_t, \mathbf{x}_0), \tilde{\beta}_t\mathbf{I}),$$
$$\text{where} \quad \tilde{\boldsymbol{\mu}}_t(\mathbf{x}_t, \mathbf{x}_0) := \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t}\mathbf{x}_0 + \frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}\mathbf{x}_t \quad \text{and} \quad \tilde{\beta}_t := \frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t}\beta_t$$

- Reverse process

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

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

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

$$\mathbb{E}_{\mathbf{x}_0, \boldsymbol{\epsilon}}\left[\frac{\beta_t^2}{2\sigma_t^2\alpha_t(1-\bar{\alpha}_t)}\left\|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t)\right\|^2\right]$$

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right) + \sigma_t\mathbf{z}, \text{ where } \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

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

DDPM: Results

- Training

$$\epsilon_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\epsilon, t)$$

- Generation

$$\epsilon_\theta(\mathbf{x}_t, t)$$

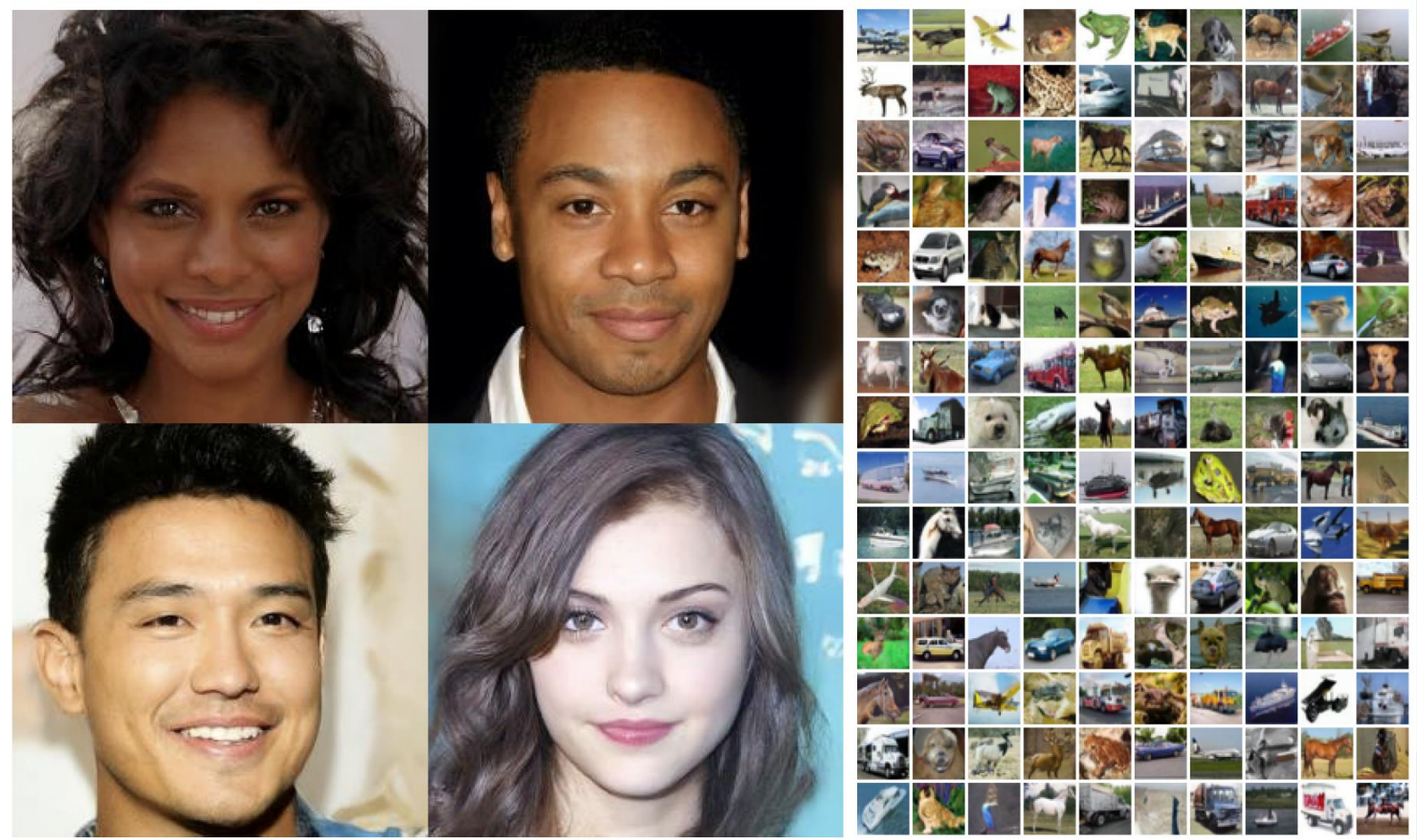
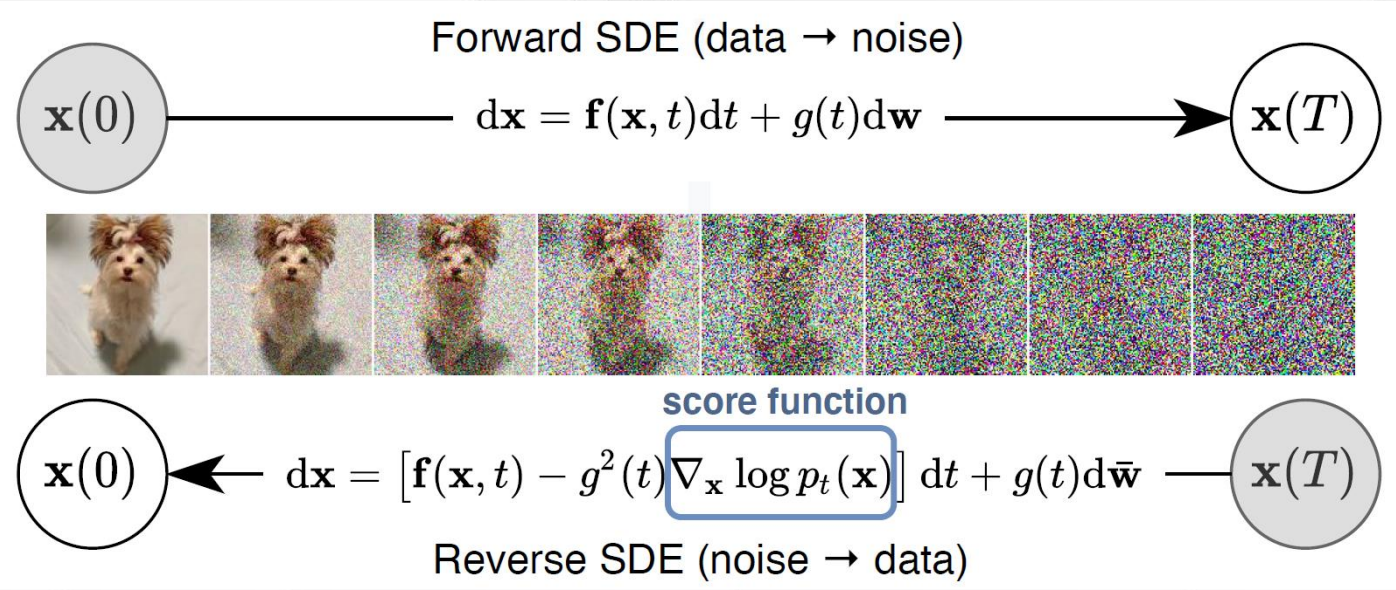


Figure 1: Generated samples on CelebA-HQ 256 × 256 (left) and unconditional CIFAR10 (right)

Score-based Generative Modeling

- Score: time-dependent gradient field
- Accurately estimate these scores with neural networks

$$\mathrm{d}\mathbf{x} = \left[\mathbf{f}(\mathbf{x}, t) - \frac{1}{2} g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})\right] \mathrm{d}t$$



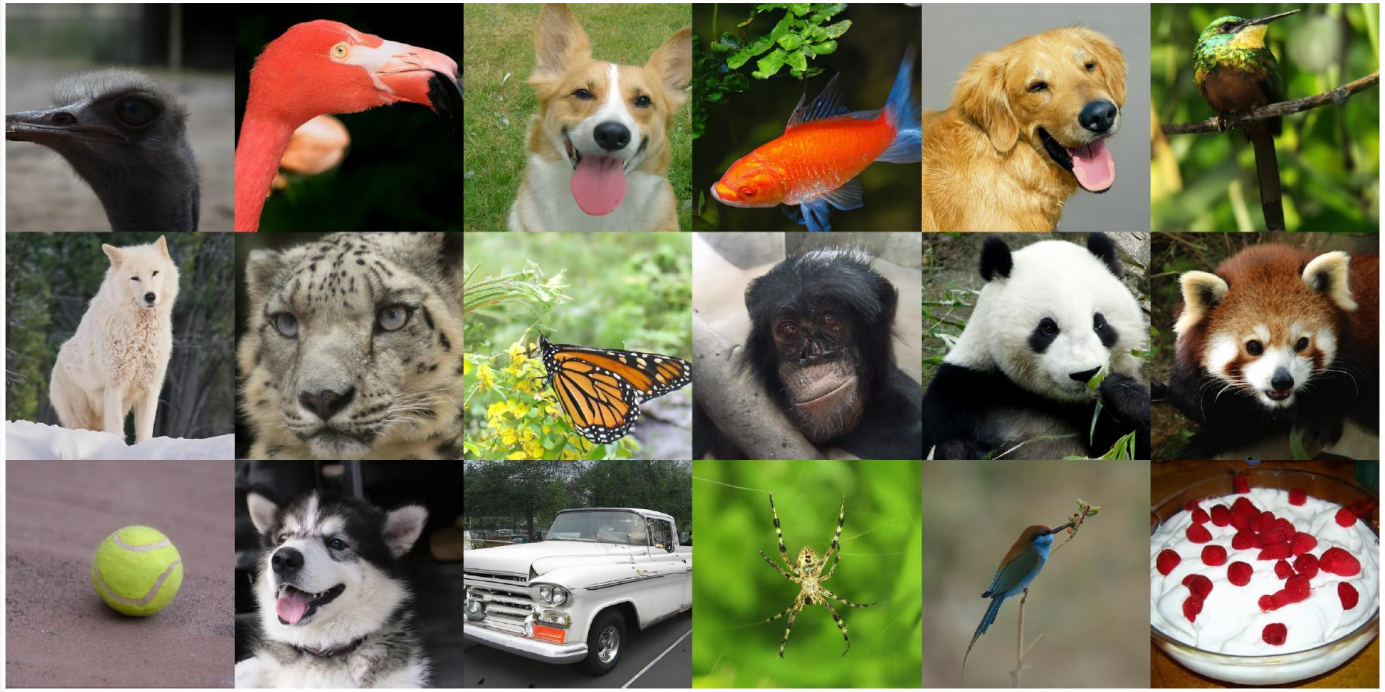
- Controllable Generation

$$\mathrm{d}\mathbf{x} = \{\mathbf{f}(\mathbf{x}, t) - g(t)^2[\nabla_{\mathbf{x}} \log p_t(\mathbf{x}) + \nabla_{\mathbf{x}} \log p_t(\mathbf{y} \mid \mathbf{x})]\}\mathrm{d}t + g(t)\mathrm{d}\bar{\mathbf{w}}$$

Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021.

ADM: Diffusion Models Beat GANs

- Combining classifier guidance $p_{\theta,\phi}(x_t|x_{t+1}, y) = Z p_\theta(x_t|x_{t+1}) p_\phi(y|x_t)$
- ADM: ablated diffusion model

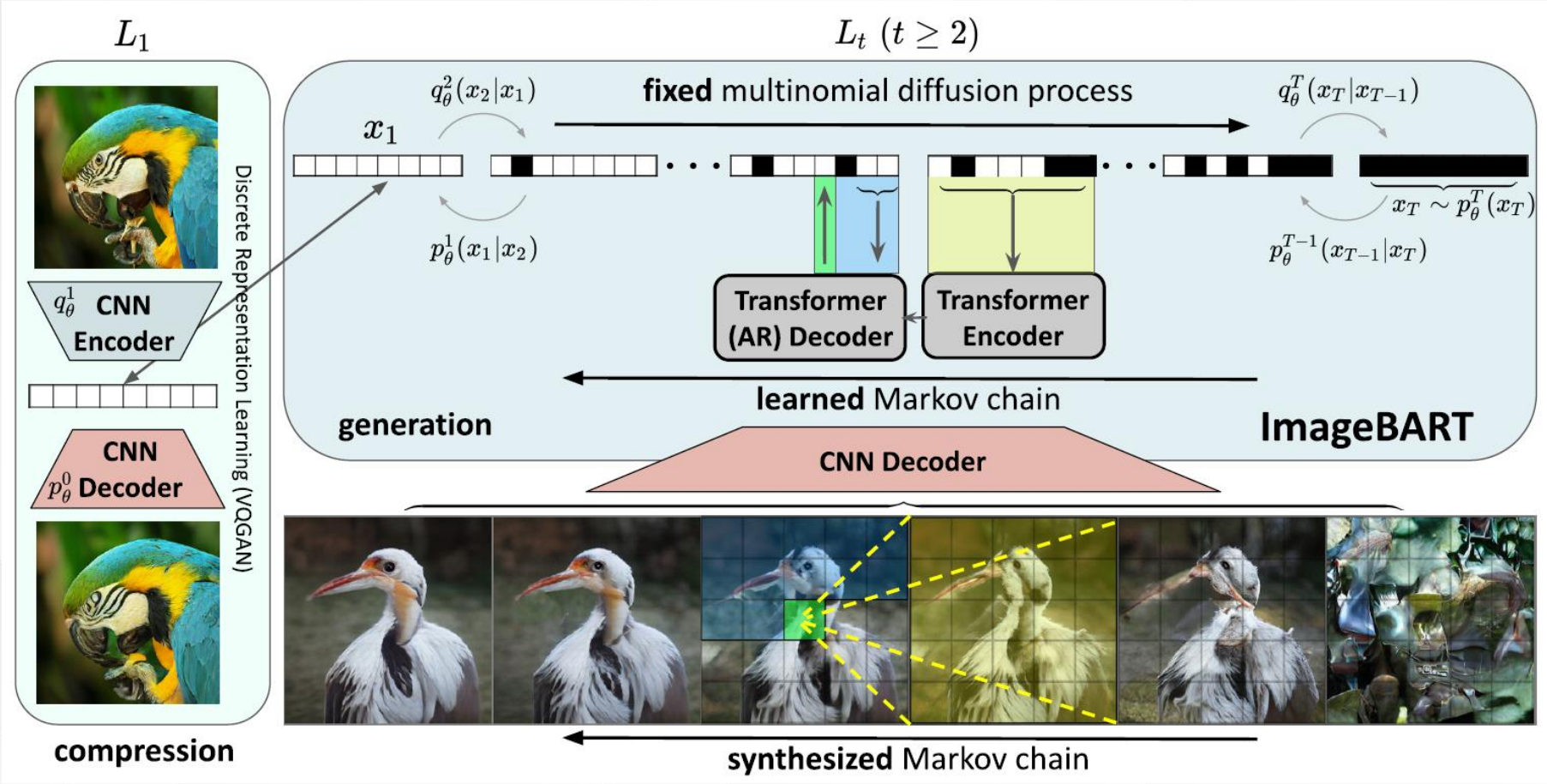


Model	FID	sFID	Prec	Rec
LSUN Bedrooms 256×256				
DCTransformer† [42]	6.40	6.66	0.44	**0.56**
DDPM [25]	4.89	9.07	0.60	0.45
IDDPM [43]	4.24	8.21	0.62	0.46
StyleGAN [27]	2.35	6.62	0.59	0.48
ADM (dropout)	**1.90**	**5.59**	**0.66**	0.51
LSUN Horses 256×256				
StyleGAN2 [28]	3.84	6.46	0.63	0.48
ADM	2.95	**5.94**	0.69	**0.55**
ADM (dropout)	**2.57**	6.81	**0.71**	**0.55**
LSUN Cats 256×256				
DDPM [25]	17.1	12.4	0.53	0.48
StyleGAN2 [28]	7.25	**6.33**	0.58	0.43
ADM (dropout)	**5.57**	6.69	**0.63**	**0.52**
ImageNet 64×64				
BigGAN-deep* [5]	4.06	3.96	**0.79**	0.48
IDDPM [43]	2.92	**3.79**	0.74	0.62
ADM	2.61	**3.77**	0.73	0.63
ADM (dropout)	**2.07**	4.29	0.74	**0.63**

Model	FID	sFID	Prec	Rec
ImageNet 128×128				
BigGAN-deep [5]	6.02	7.18	**0.86**	0.35
LOGAN† [68]	3.36			
ADM	5.91	**5.09**	0.70	**0.65**
ADM-G (25 steps)	5.98	7.04	0.78	0.51
ADM-G	**2.97**	**5.09**	0.78	0.59
ImageNet 256×256				
DCTransformer† [42]	36.51	8.24	0.36	**0.67**
VQ-VAE-2†‡ [51]	31.11	17.38	0.36	0.57
IDDPM‡ [43]	12.26	5.42	0.70	0.62
SR3†‡ [53]	11.30			
BigGAN-deep [5]	6.95	7.36	**0.87**	0.28
ADM	10.94	6.02	0.69	0.63
ADM-G (25 steps)	5.44	5.32	0.81	0.49
ADM-G	**4.59**	**5.25**	0.82	0.52
ImageNet 512×512				
BigGAN-deep [5]	8.43	8.13	**0.88**	0.29
ADM	23.24	10.19	0.73	**0.60**
ADM-G (25 steps)	8.41	9.67	0.83	0.47
ADM-G	**7.72**	**6.57**	0.87	0.42

Diffusion Models Beat GANs on Image Synthesis, Arxiv 2021.

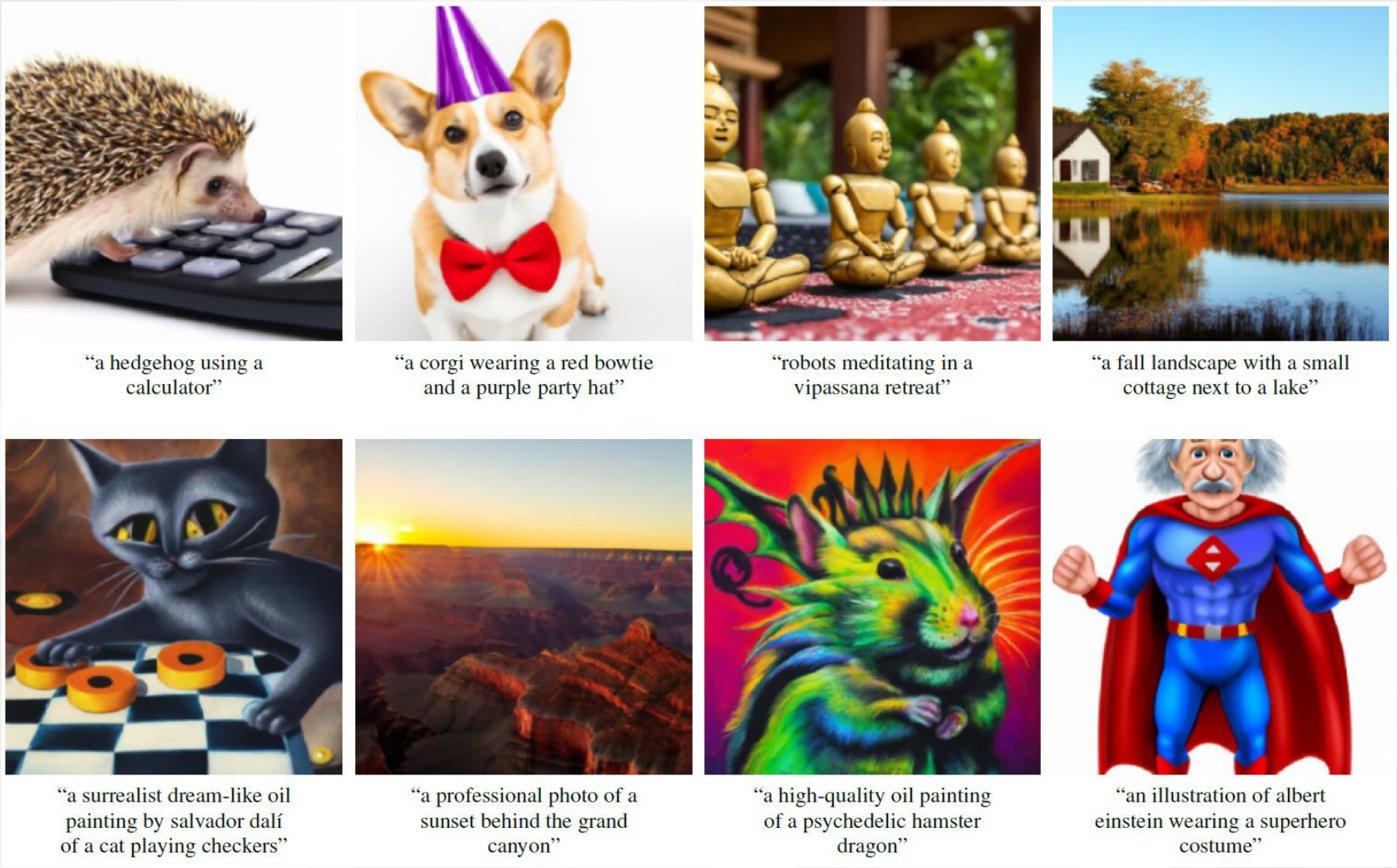
ImageBART



Patrick Esser, Robin Rombach, Andreas Blattmann, Björn Ommer, ImageBART: Bidirectional Context with Multinomial Diffusion for Autoregressive Image Synthesis, Arxiv 2021

GLIDE

- VQVAE
- Transformer
- Diffusion model



GLIDE: Towards Photorealistic Image Generation and Editing with Text-Guided Diffusion Models, Arxiv 2021.

GLIDE: Language-guided Image Inpainting

"a man with red hair"

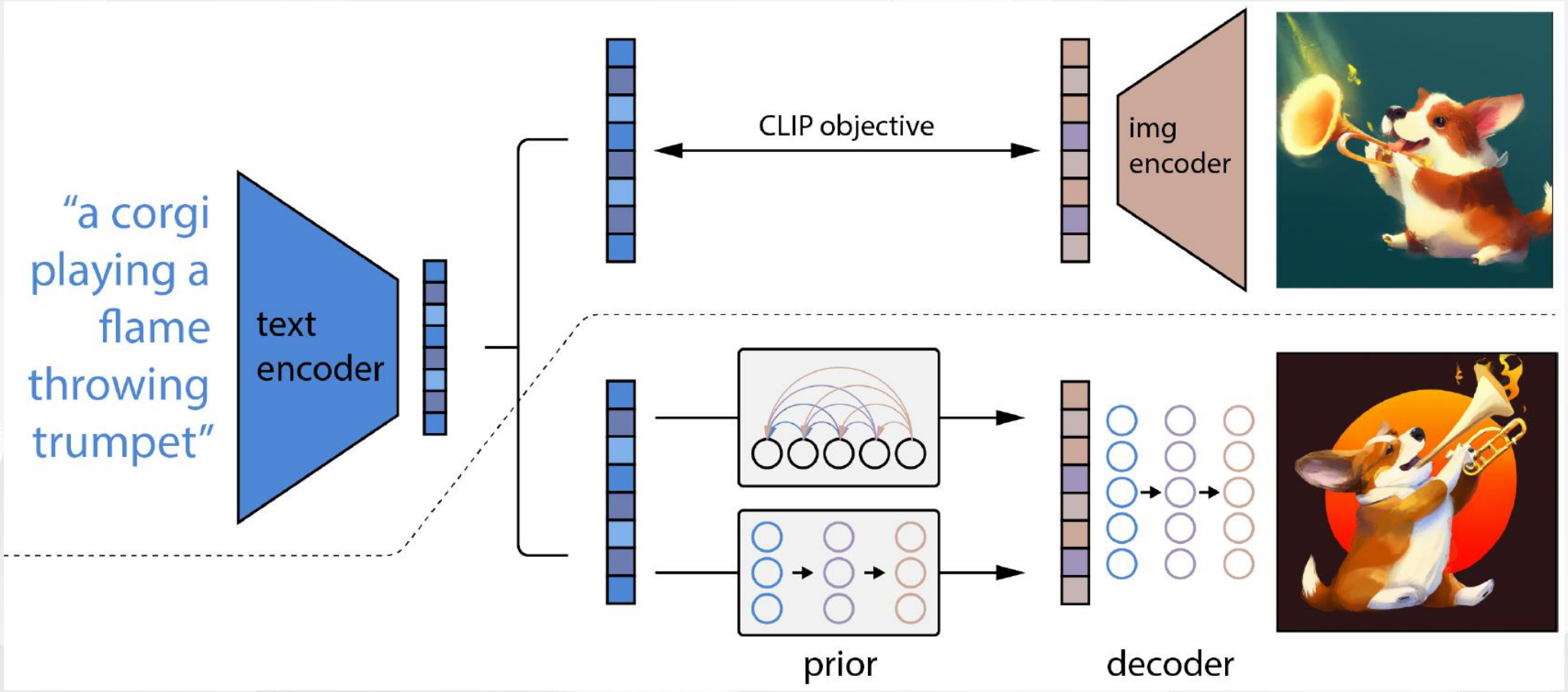
"a vase of flowers"

"an old car in a snowy forest"

"a man wearing a white hat"

DALL.E-2: unCLIP

- High quality 1024 × 1024 iImages



Hierarchical Text-Conditional Image Generation with CLIP Latents, Arxiv 2022

DALL.E-2: unCLIP

an espresso machine that makes coffee from human souls, artstation

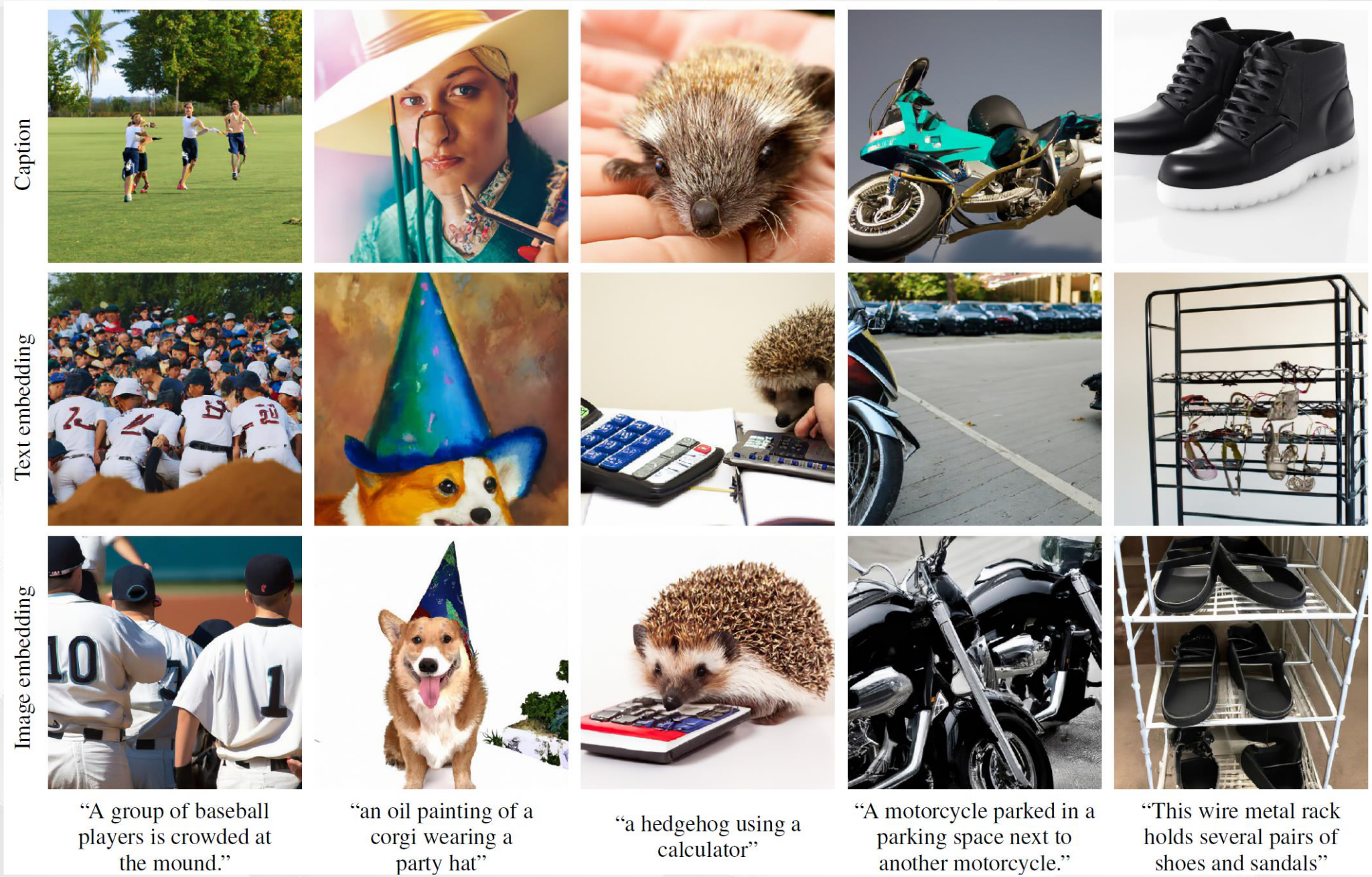
panda mad scientist mixing sparkling chemicals, artstation

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

a dolphin in an astronaut suit on saturn, artstation

a propaganda poster depicting a cat dressed as french emperor napoleon holding a piece of cheese

a teddybear on a skateboard in times square


Caption
Text embedding
Image embedding
"A group of baseball players is crowded at the mound."
"an oil painting of a corgi wearing a party hat"
"a hedgehog using a calculator"
"A motorcycle parked in a parking space next to another motorcycle."
"This wire metal rack holds several pairs of shoes and sandals"

Samples on MS-COCO Prompts

Imagen

- Abstract
  - Generic large language model, eg. T5, pretrained on text only corpora.
  - Text-guided super-res model

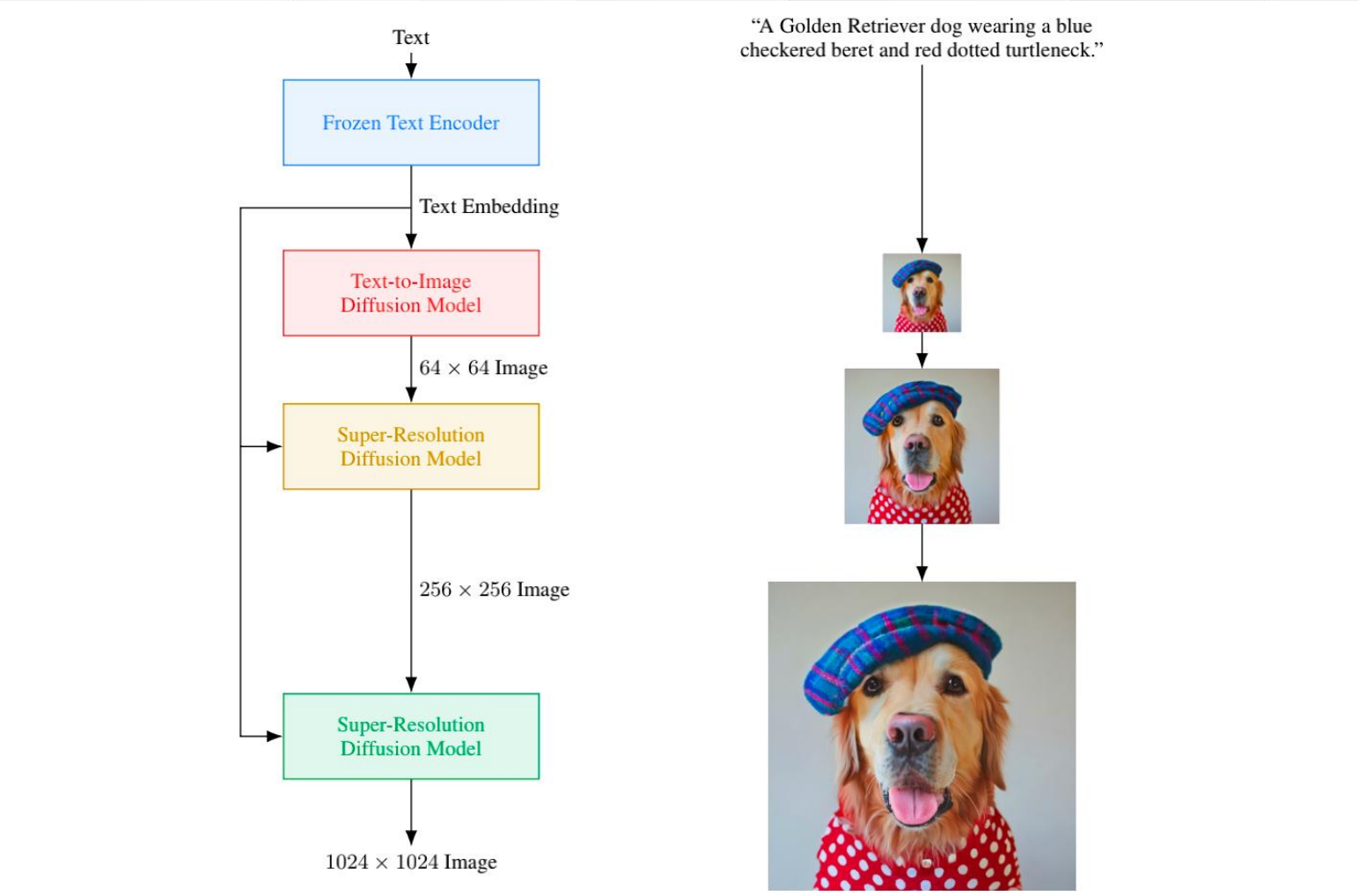
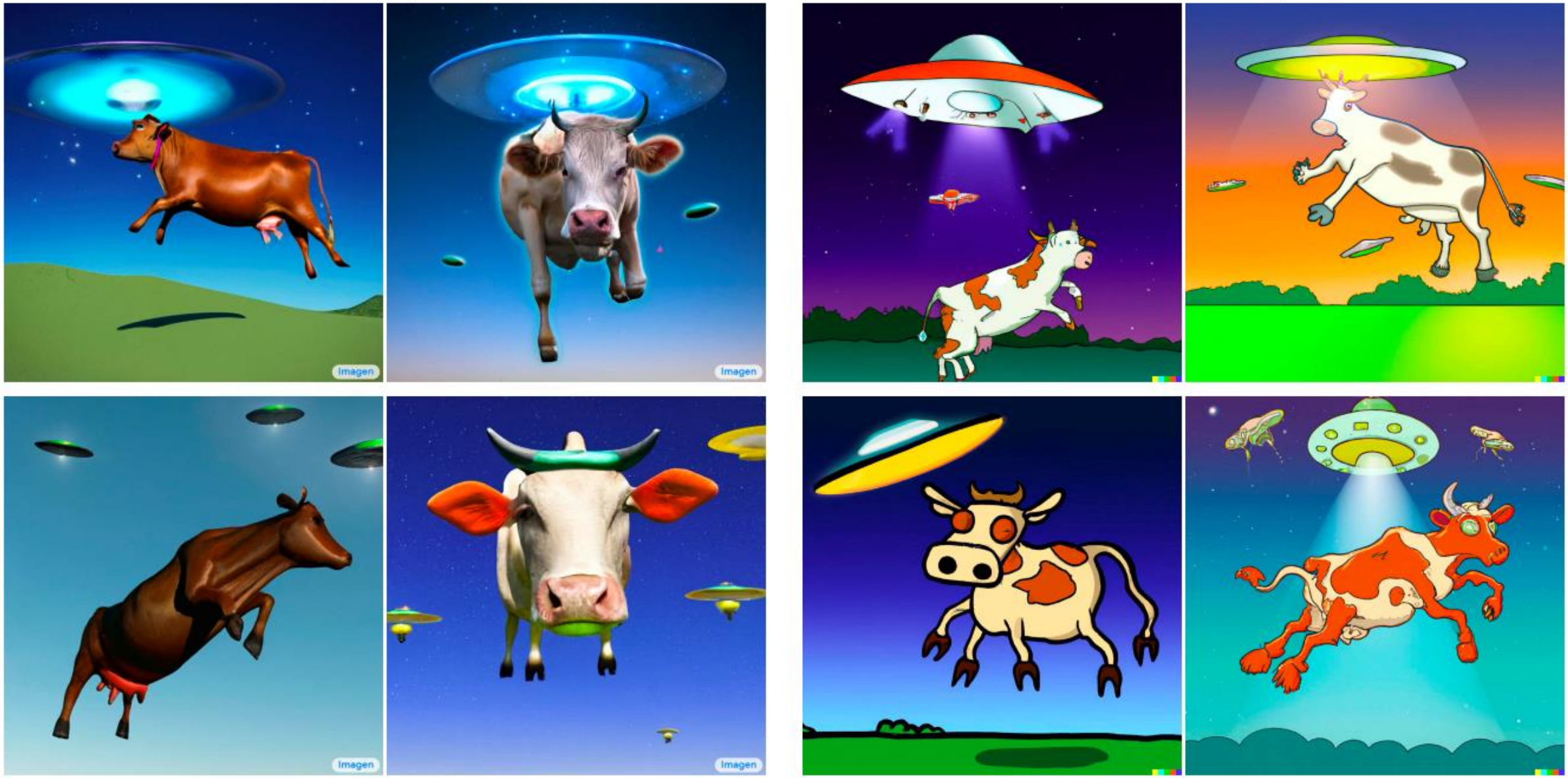


Figure A.4: Visualization of Imagen. Imagen uses a frozen text encoder to encode the input text into text embeddings. A conditional diffusion model maps the text embedding into a 64×64 image. Imagen further utilizes text-conditional super-resolution diffusion models to upsample the image, first $64 \times 64 \rightarrow 256 \times 256$, and then $256 \times 256 \rightarrow 1024 \times 1024$.

Imagen (Ours)

DALL-E 2 [54]



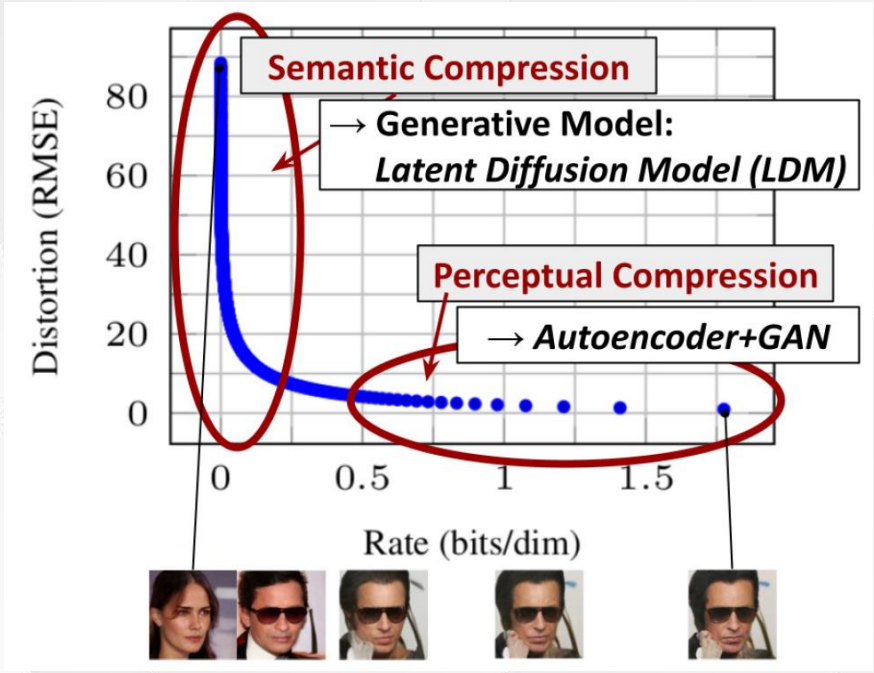
Hovering cow abducting aliens.

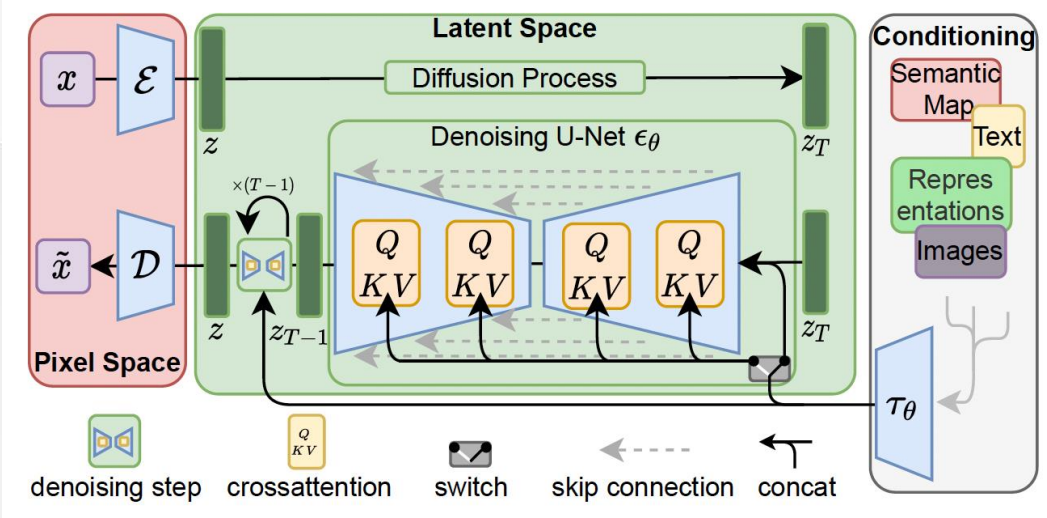
Imagen (Ours)

DALL-E 2 [54]

New York Skyline with Hello World written with fireworks on the sky.

LDM (Latent Diffusion Models)



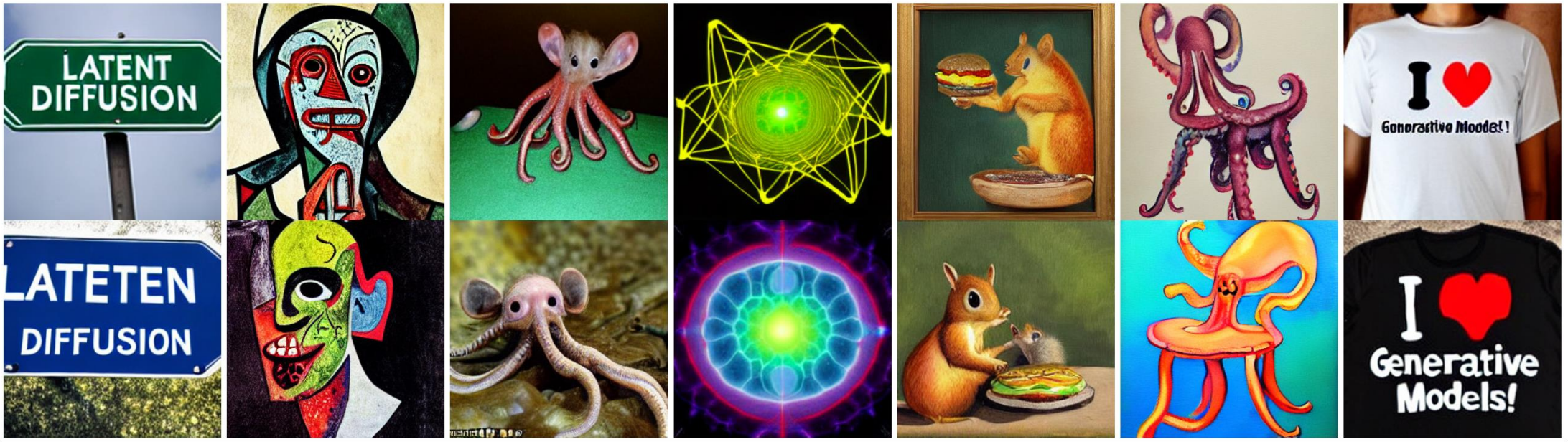


Convert an image into latent space to reduce computational resources

LDM: Results

Text-to-Image Synthesis on LAION. 1.45B Model.

'A street sign that reads "Latent Diffusion" '	*'A zombie in the style of Picasso'*	*'An image of an animal half mouse half octopus'*	*'An illustration of a slightly conscious neural network'*	*'A painting of a squirrel eating a burger'*	*'A watercolor painting of a chair that looks like an octopus'*	*'A shirt with the inscription: "I love generative models!" '*



Stable Diffusion

Stable Diffusion

Fork 4.6k | Starred 31k

Stable Diffusion was made possible thanks to a collaboration with Stability AI and Runway and builds upon our previous work:

High-Resolution Image Synthesis with Latent Diffusion Models
Robin Rombach*, Andreas Blattmann*, Dominik Lorenz, Patrick Esser, Björn Ommer
CVPR '22 Oral | GitHub | arXiv | Project page

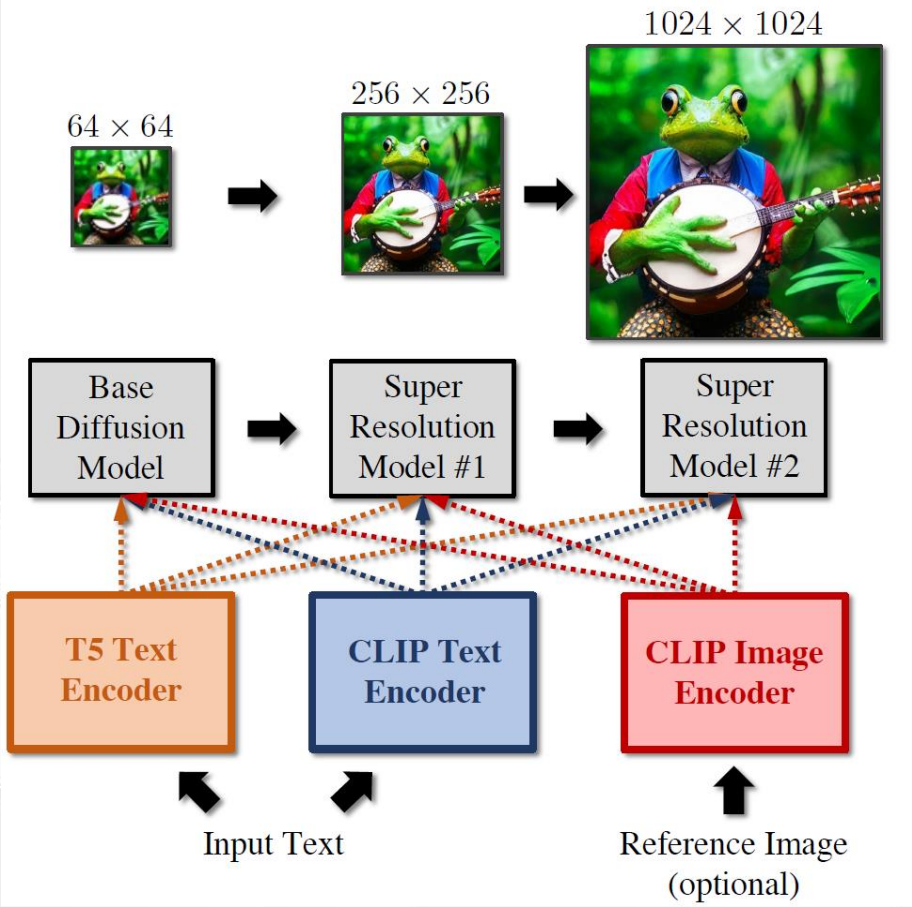
Stable Diffusion is a latent text-to-image diffusion model. Thanks to a generous compute donation from Stability AI and support from LAION, we were able to train a Latent Diffusion Model on 512x512 images from a subset of the LAION-5B database. Similar to Google's Imagen, this model uses a frozen CLIP ViT-L/14 text encoder to condition the model on text prompts. With its 860M UNet and 123M text encoder, the model is relatively lightweight and runs on a GPU with at least 10GB VRAM. See this section below and the model card.

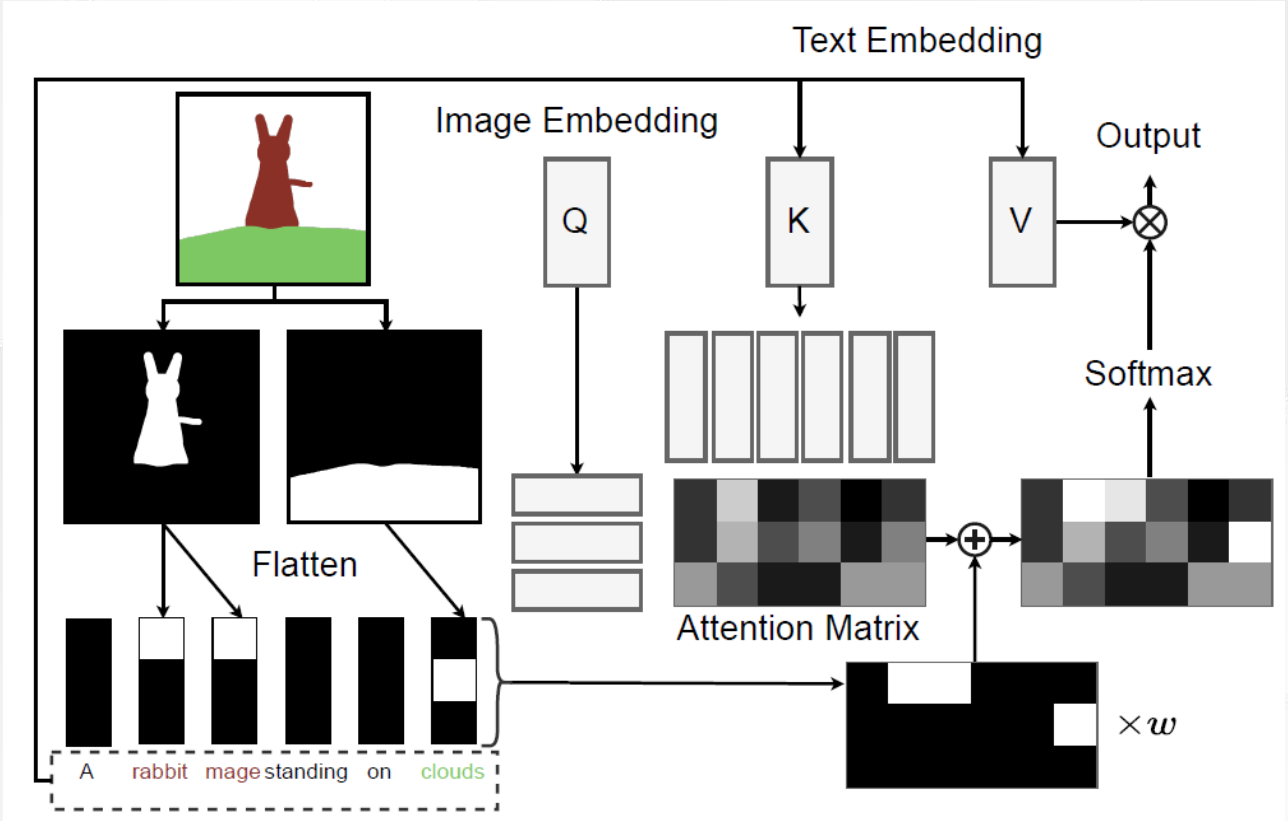
Diffusers

GitHub release v0.6.0 Contributor Covenant 2.0

集成现有Diffusion模型，直接调用

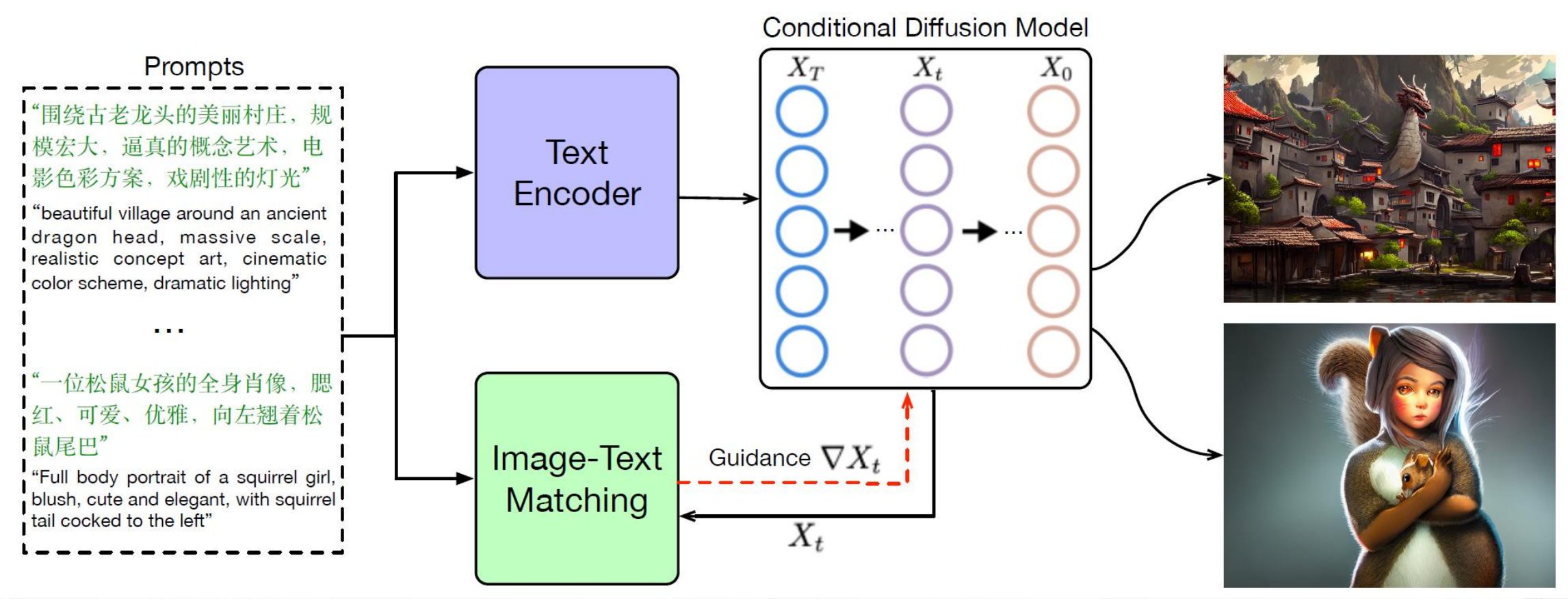
eDiffi (Nvidea)





eDiffi: Text-to-Image Diffusion Models with an Ensemble of Expert Denoisers, Arxiv 2022.

Upainting (Baidu)



UPainting: Unified Text-to-Image Diffusion Generation with Cross-modal Guidance, Arxiv 2022.

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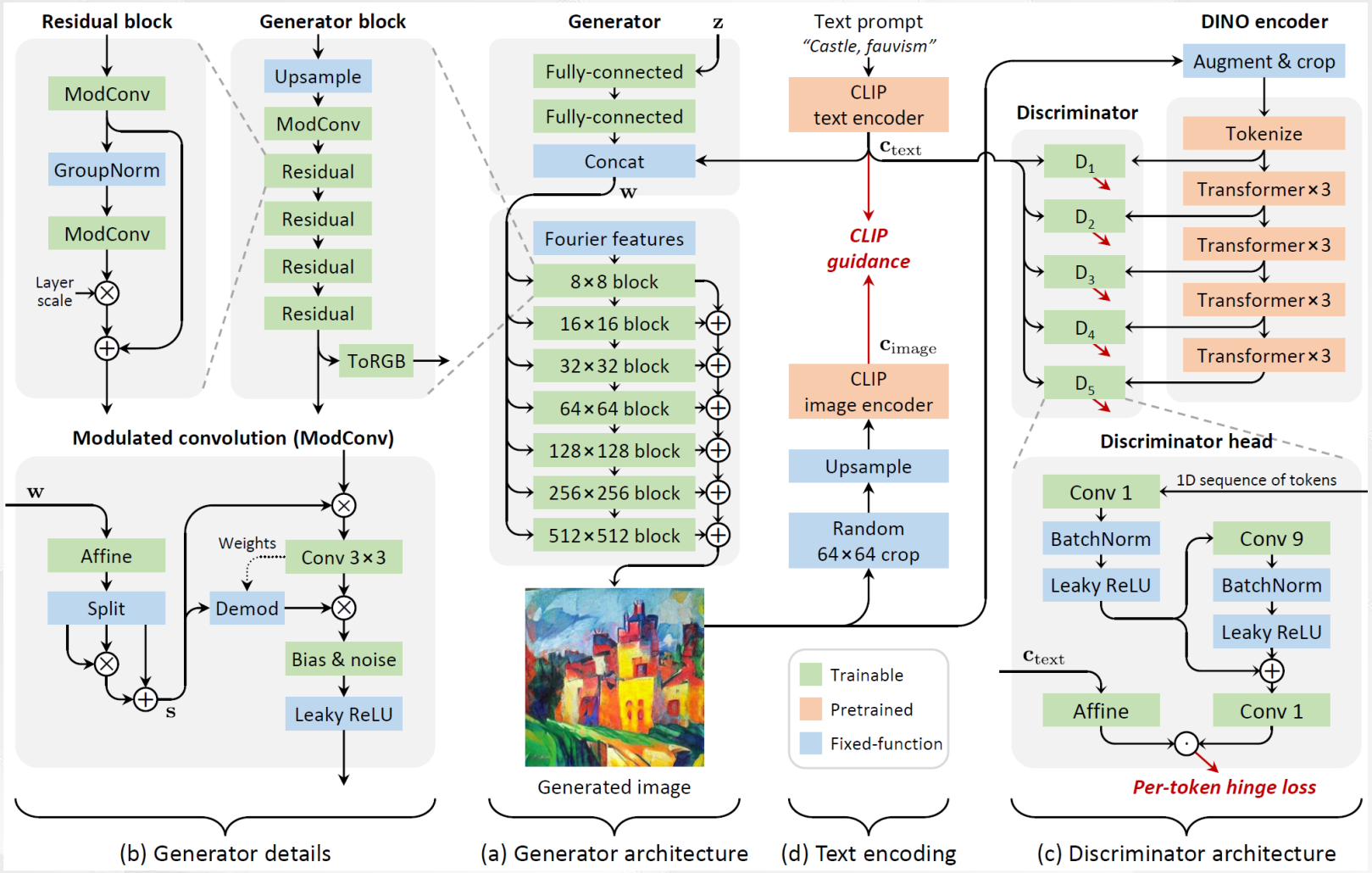
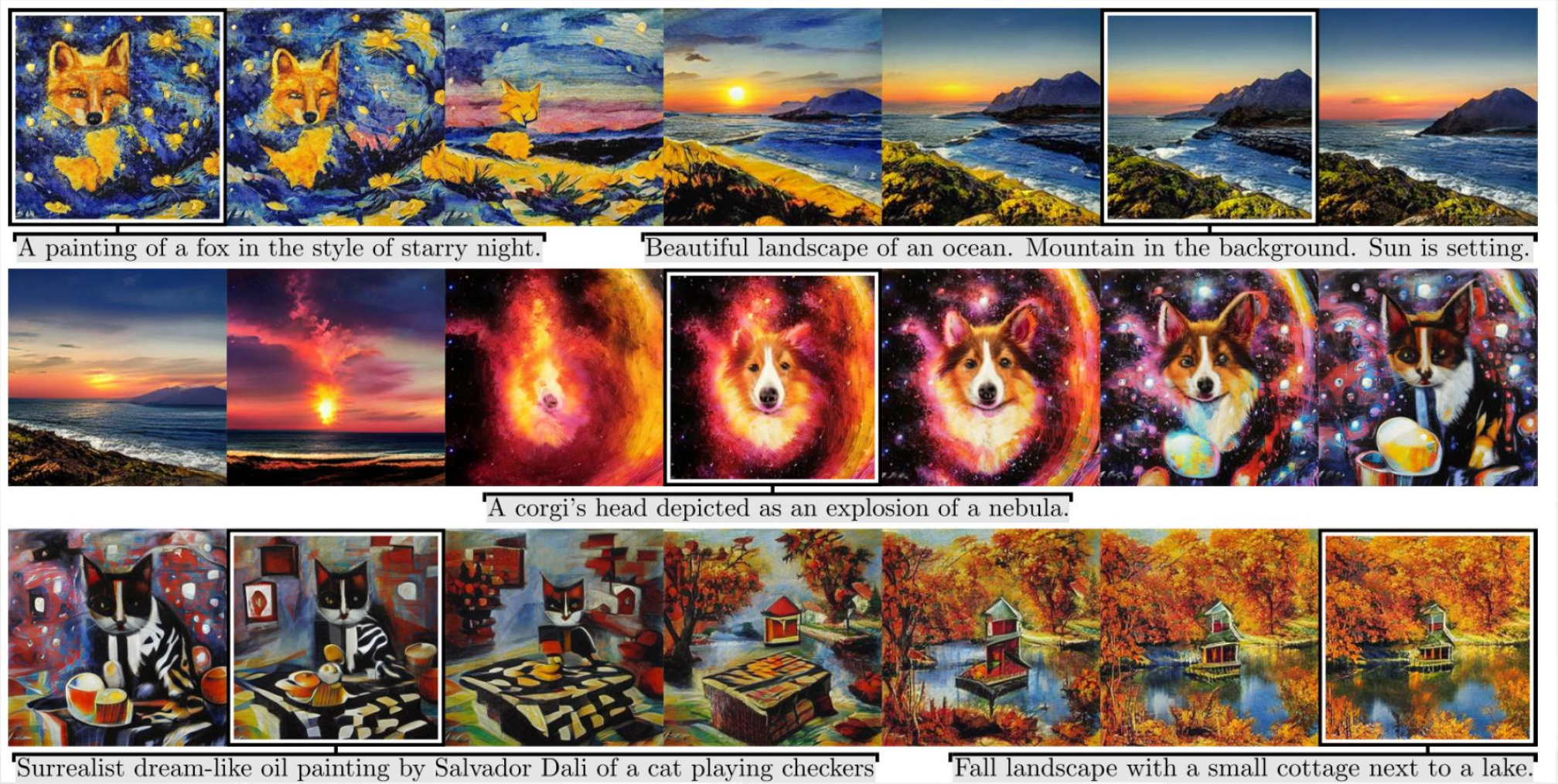
StyleGAN-T (Arxiv 2023)



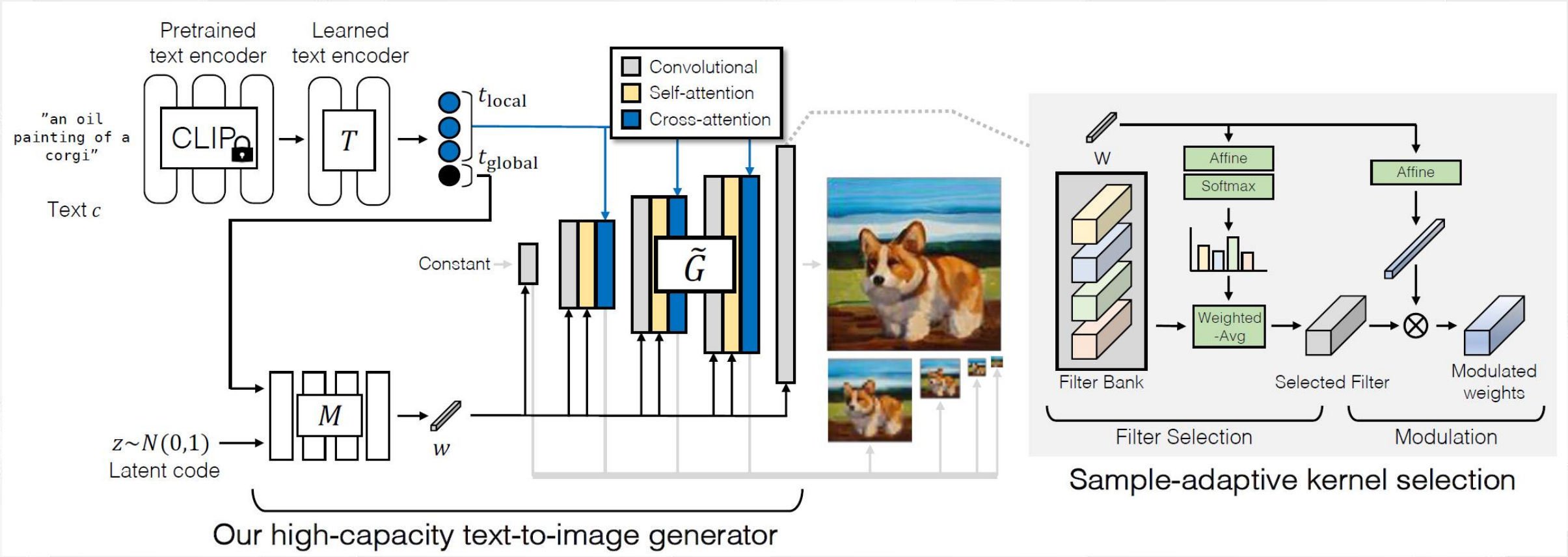
StyleGAN-T: Unlocking the Power of GANs for Fast Large-Scale Text-to-Image Synthesis, Arxiv 2023.

StyleGAN-T (Arxiv 2023)



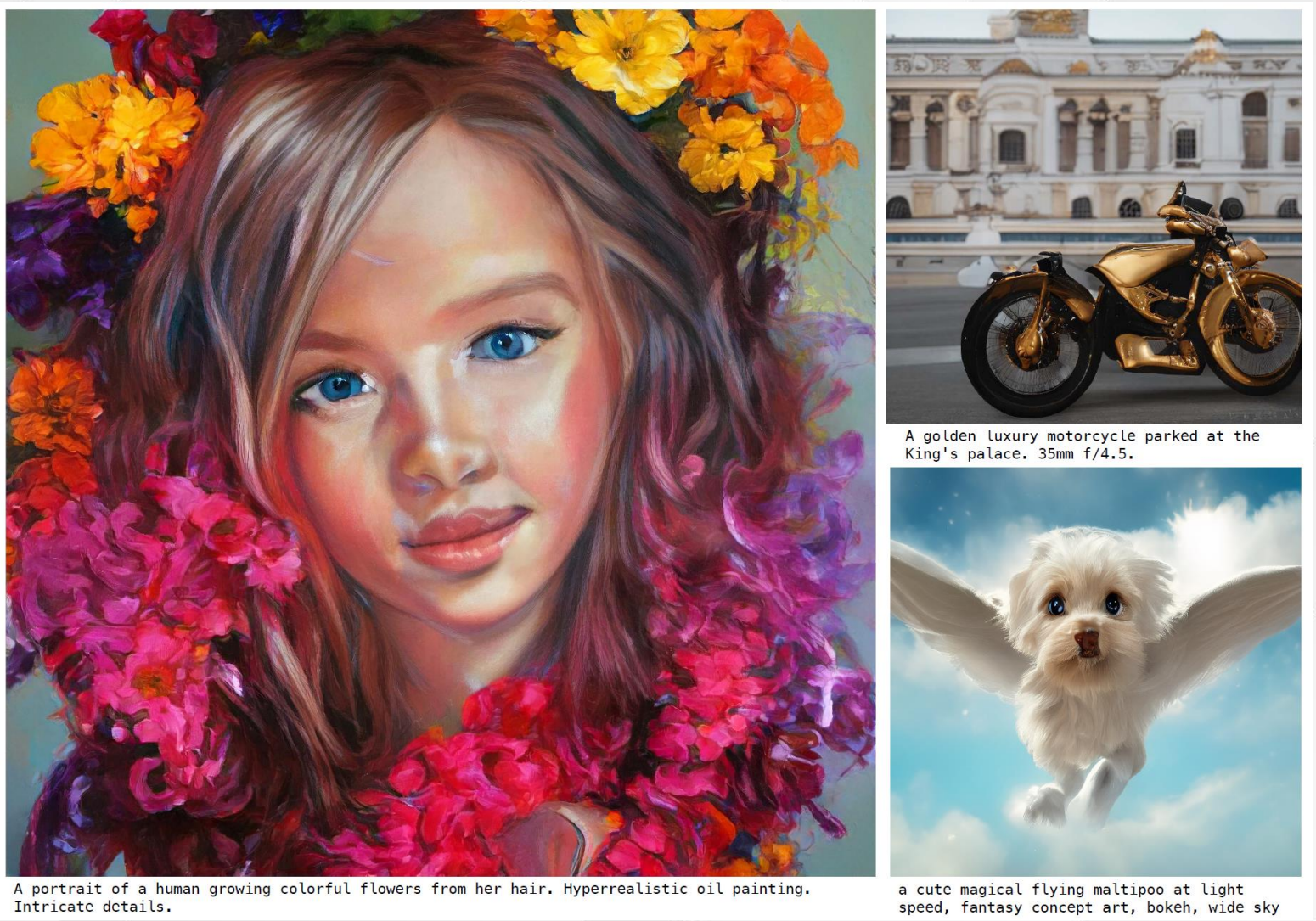
StyleGAN-T: Unlocking the Power of GANs for Fast Large-Scale Text-to-Image Synthesis, Arxiv 2023.

GigaGAN (Arxiv 2023)

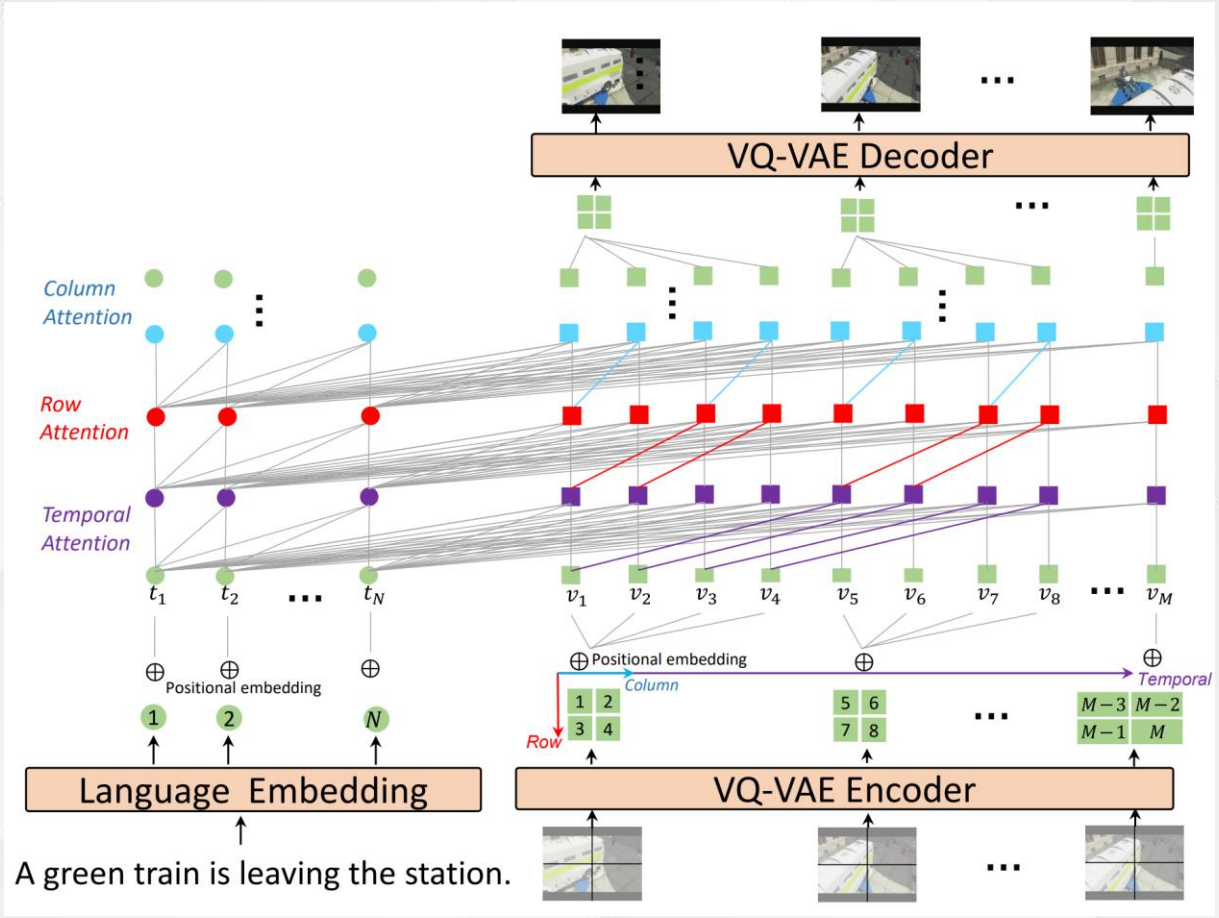


Scaling up GANs for Text-to-Image Synthesis, Arxiv 2023.

GigaGAN (Arxiv 2023)

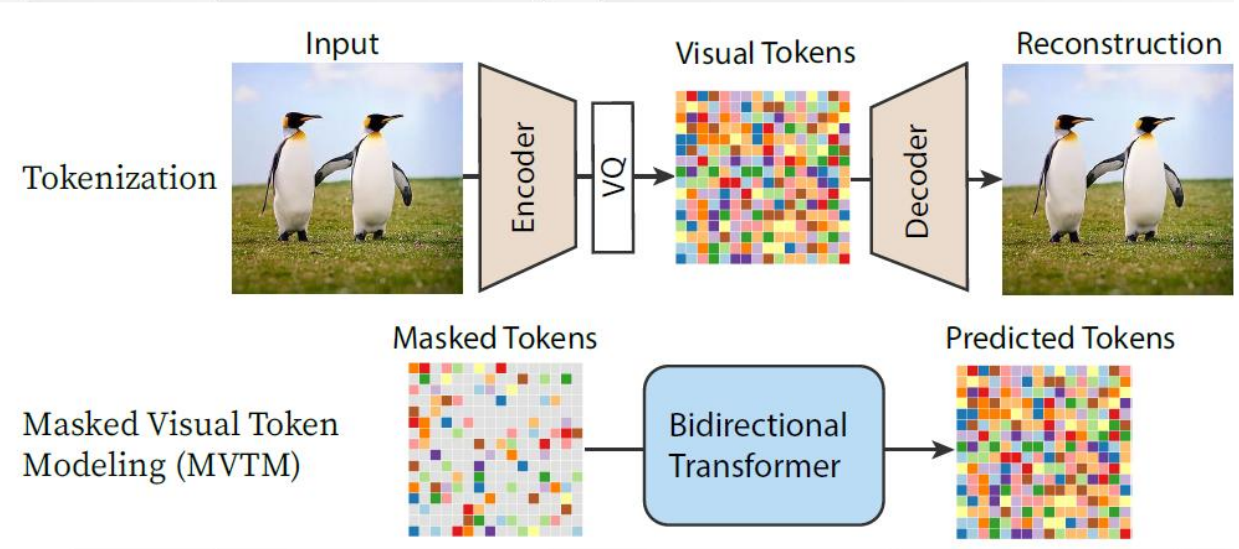


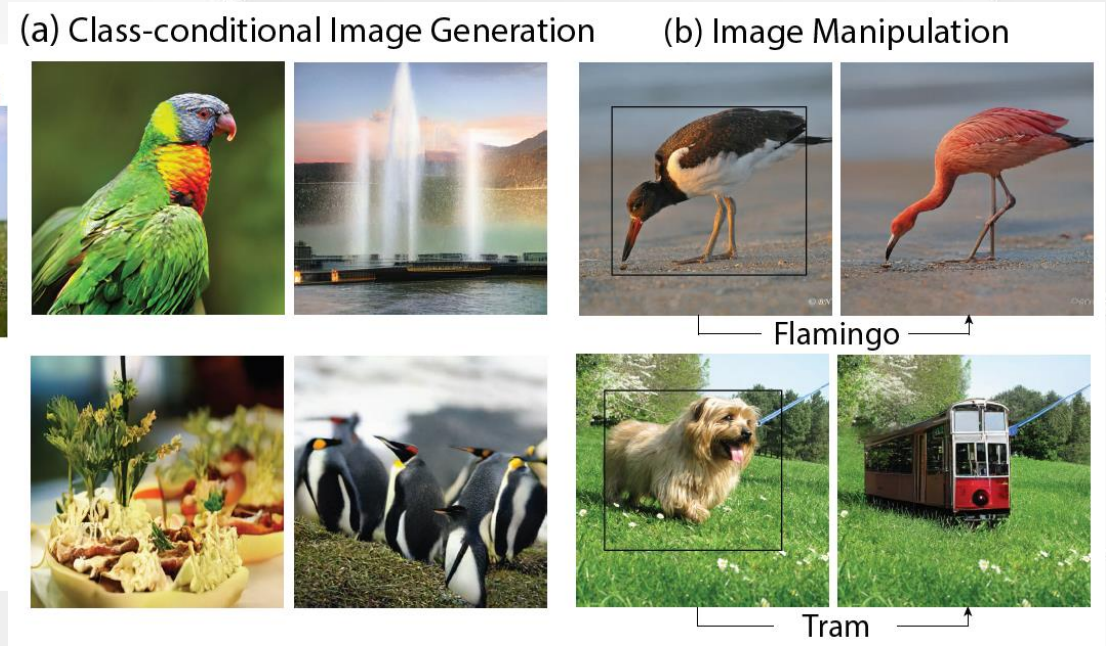
Autoregressive Model



GODIVA: Generating Open-DomaIn Videos from nAtural Descriptions, arXiv 2021

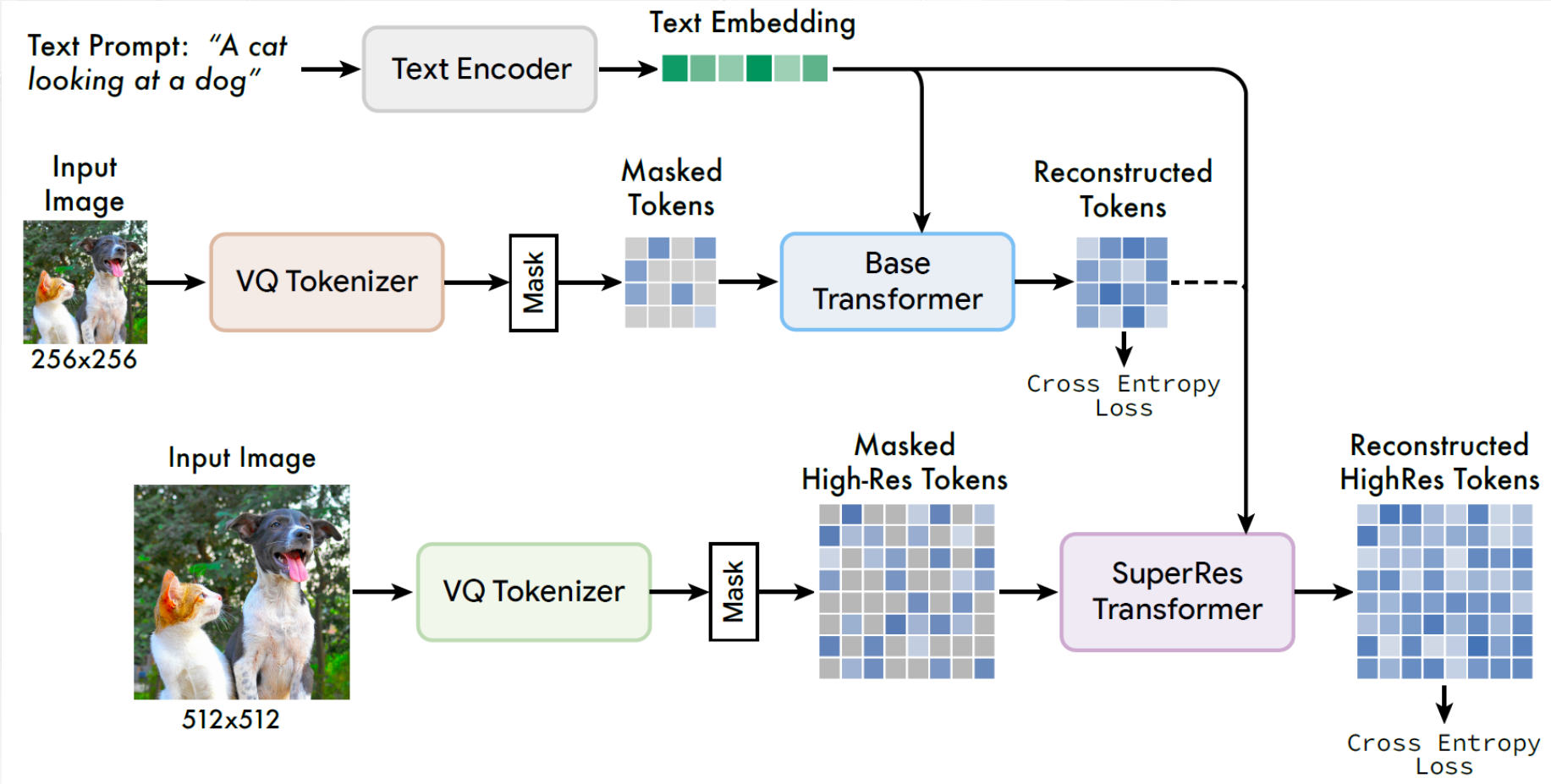
MaskGIT (CVPR 2022)





MaskGIT: Masked Generative Image Transformer, CVPR 2022.

MUSE (Arxiv 2023)



Muse: Text-To-Image Generation via Masked Generative Transformers, Arxiv 2023.

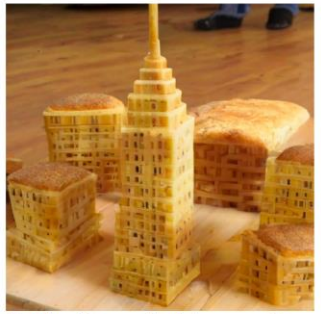
MUSE (Arxiv 2023)


A fluffy baby sloth with a knitted hat trying to figure out a laptop, close up.


A sheep in a wine glass.


A futuristic city with flying cars.

A large array of colorful cupcakes, arranged on a maple table to spell MUSE.


Manhattan skyline made of bread.


Astronauts kicking a football in front of Eiffel tower.


Two cats doing research.


3D mesh of Titanic floating on a water lily pond in the style of Monet.

Approach	Model Type	Params	FID-30K	Zero-shot FID-30K
AttnGAN (Xu et al., 2017)	GAN		35.49	-
DM-GAN (Zhu et al., 2019)	GAN		32.64	-
DF-GAN (Tao et al., 2020)	GAN		21.42	-
DM-GAN + CL (Ye et al., 2021)	GAN		20.79	-
XMC-GAN (Zhang et al., 2021)	GAN		9.33	-
LAFITE (Zhou et al., 2021)	GAN		8.12	-
Make-A-Scene (Gafni et al., 2022)	Autoregressive		7.55	-
DALL-E (Ramesh et al., 2021)	Autoregressive		-	17.89
LAFITE (Zhou et al., 2021)	GAN		-	26.94
LDM (Rombach et al., 2022)	Diffusion		-	12.63
GLIDE (Nichol et al., 2021)	Diffusion		-	12.24
DALL-E 2 (Ramesh et al., 2022)	Diffusion		-	10.39
Imagen-3.4B (Saharia et al., 2022)	Diffusion		-	7.27
Parti-3B (Yu et al., 2022)	Autoregressive		-	8.10
Parti-20B (Yu et al., 2022)	Autoregressive		3.22	7.23
Muse-3B	Non-Autoregressive		-	7.88

Muse: Text-To-Image Generation via Masked Generative Transformers, Arxiv 2023.

Content

- Large Scale Pretraining Models
  - GAN
  - Auto-autoregressive models
  - Diffusion models
  - Return of GAN and AR Models
  - From T2I to 3D/Video Generation
- Applications

Generative Process

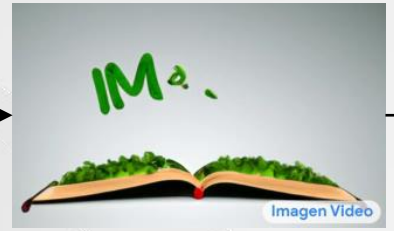
Sprouts in the shape of text 'Imagen' coming out of a fairytale book.

Base 16×24×48 3fps

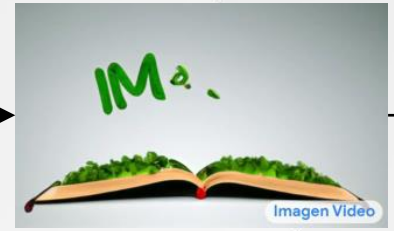
TSR 32×24×48 6fps

SSR 32×48×96 6fps

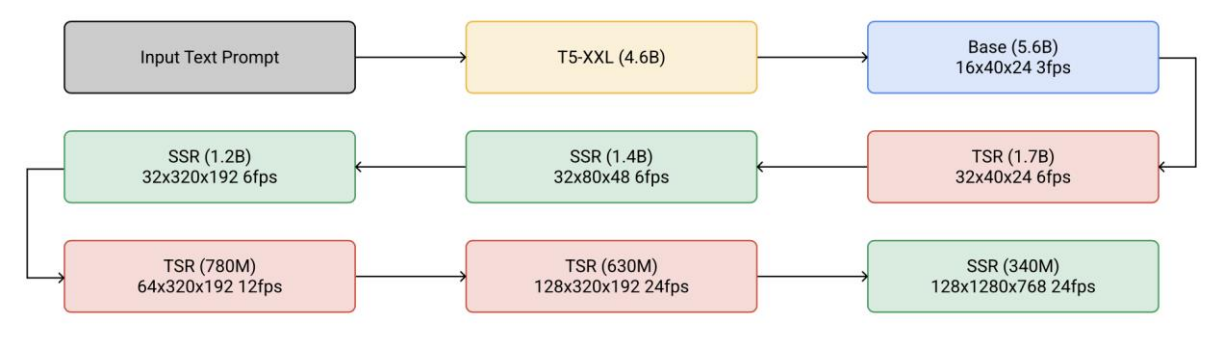
TSR 64×192×320 12fps



TSR 128×192×320 24fps



TSR 128×1280×768 24fps



SSR 128×1280×768 24fps

Imagen Video: High-Definition Video Generation with Diffusion Models, Arxiv 2022.

Imagen Video Results

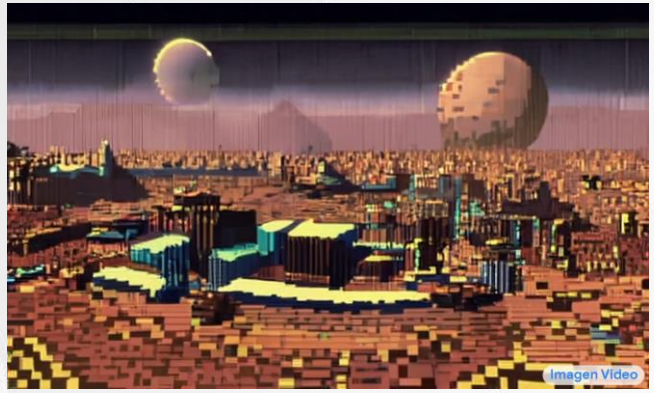
A goldendoodle playing in a park by a lake.

A giraffe underneath a microwave.

Tiny plant sprout coming out of the ground.

Flying through an intense battle between pirate ships in a stormy ocean.

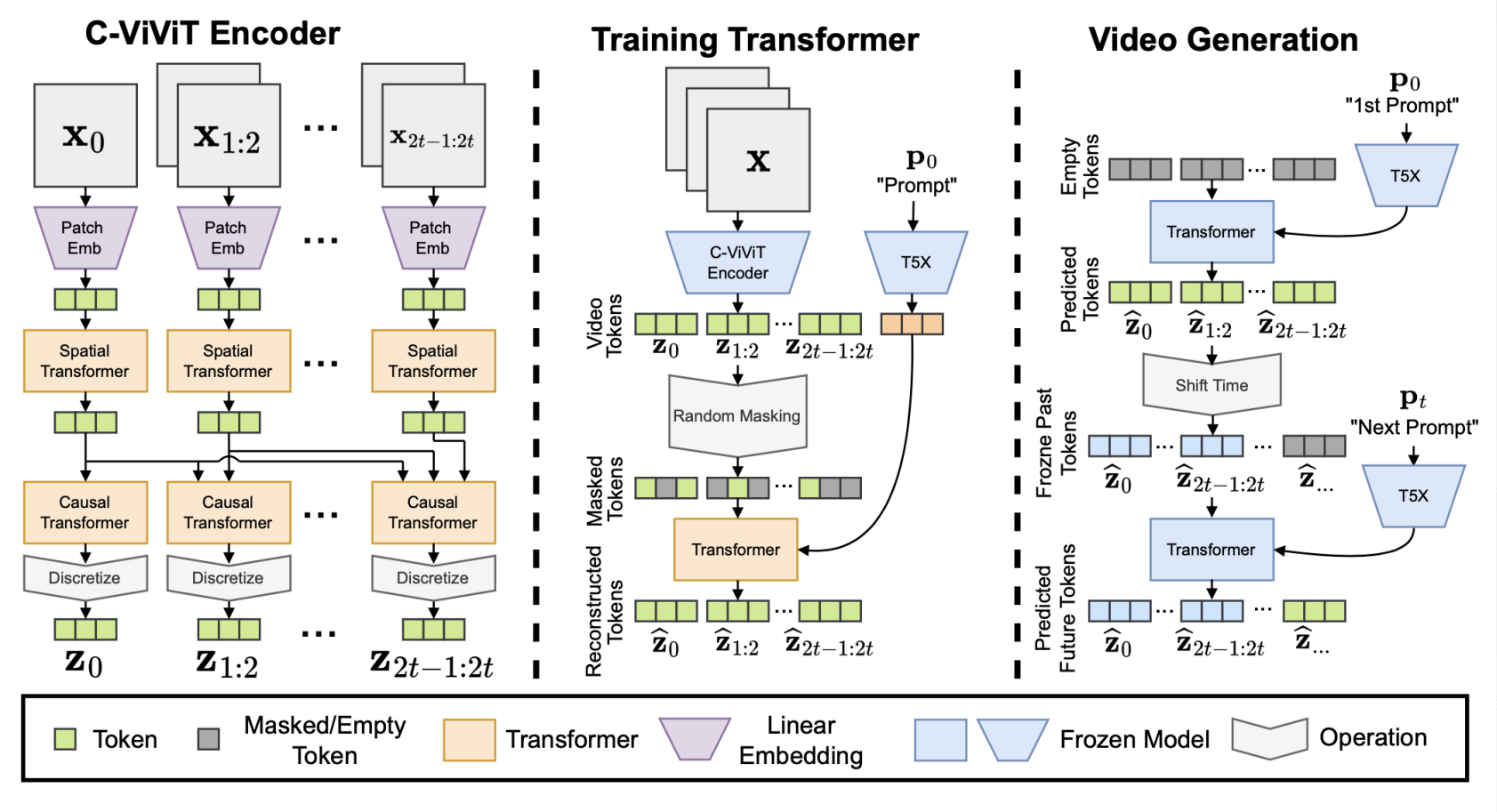
Studio shot of minimal kinetic sculpture made from thin wire shaped like a bird on white background.



Incredibly detailed science fiction scene set on an alien planet, view of a marketplace. Pixel art.

Imagen Video: High-Definition Video Generation with Diffusion Models, Arxiv 2022.

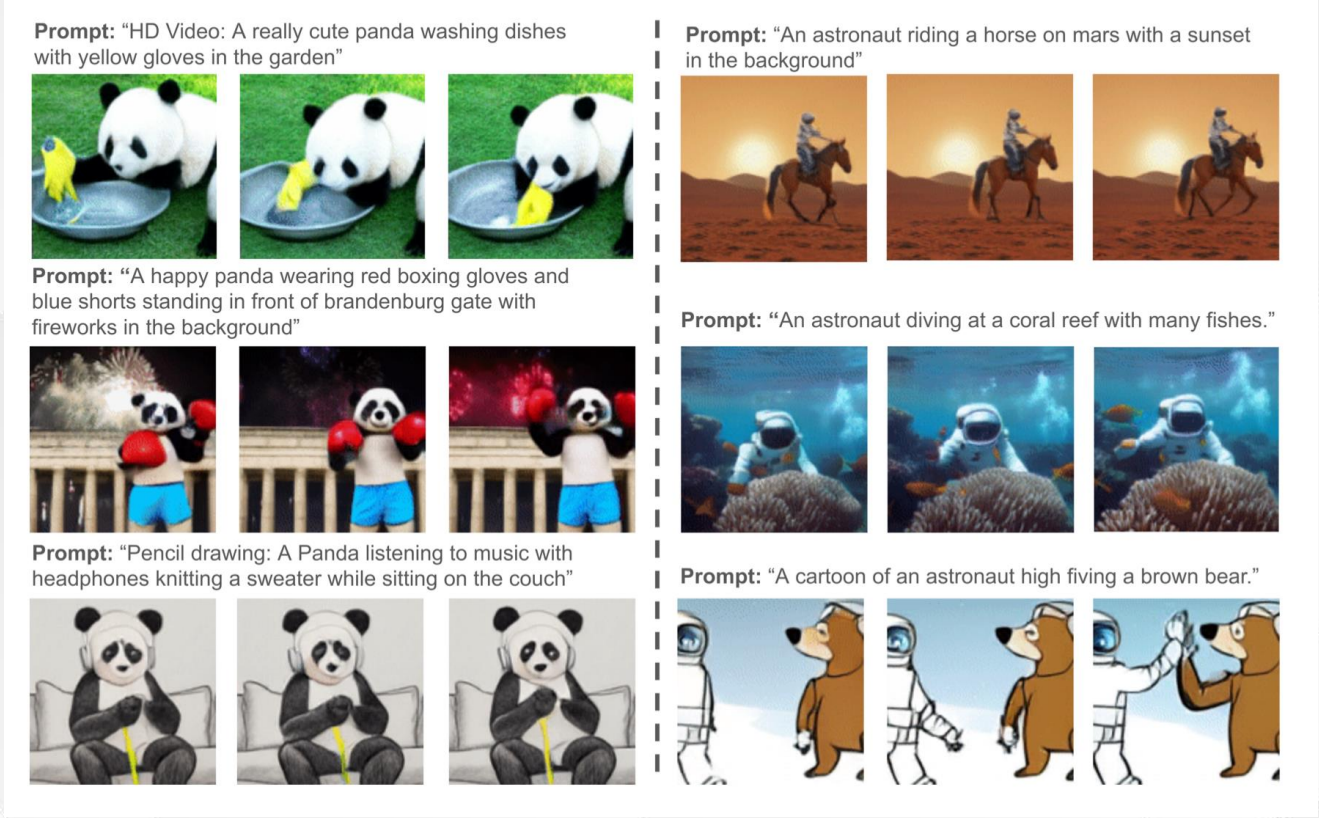
PHENAKI



PHENAKI: Variable Length Video Generation from Open Domain Textual Descriptions, Arxiv 2022.

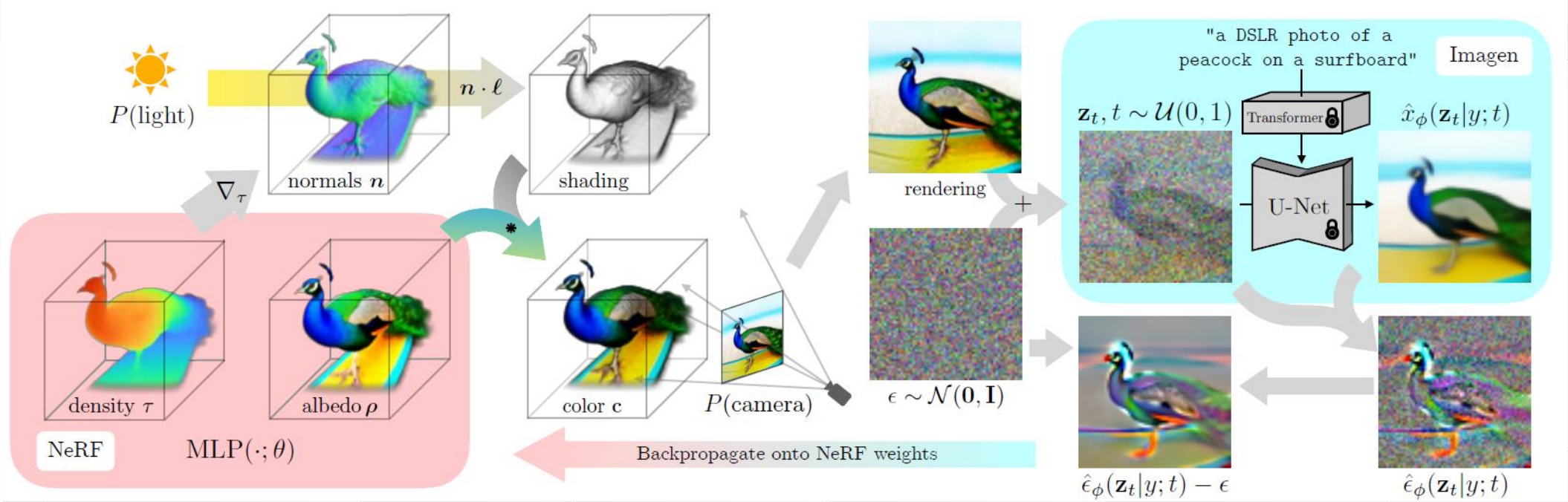
Text-to-video Results

Method	FID Image ↓	FID Video ↓
T2V [25]	82.13	14.65
SC [5]	33.51	7.34
TFGAN [5]	31.76	7.19
NUWA	28.46	7.05
Phenaki [0-Shot]	37.74	3.84



PHENAKI: Variable Length Video Generation from Open Domain Textual Descriptions, Arxiv 2022.

DreamFusion (ICLR 2023)



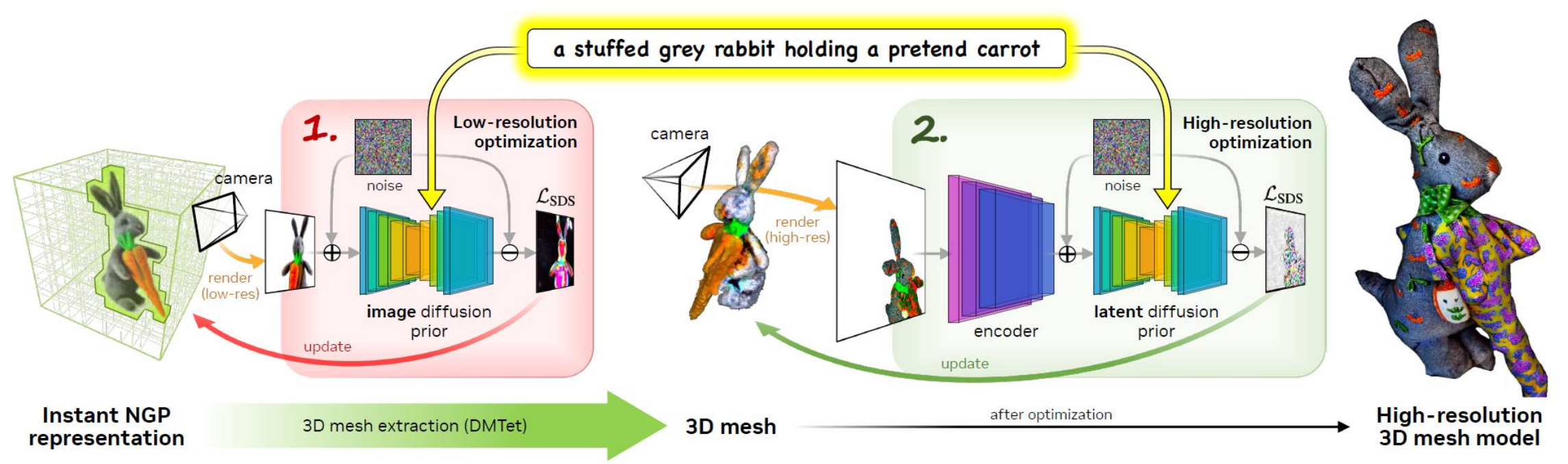
$$\nabla_\theta \mathcal{L}_{\text{SDS}}(\phi, \mathbf{x} = g(\theta)) \triangleq \mathbb{E}_{t,\epsilon}\left[w(t)\left(\hat{\epsilon}_\phi(\mathbf{z}_t; y, t) - \epsilon\right) \frac{\partial \mathbf{x}}{\partial \theta} \right]$$

Dreamfusion: Text-to-3d using 2d diffusion, ICLR 2023.

DreamFusion (ICLR 2023)

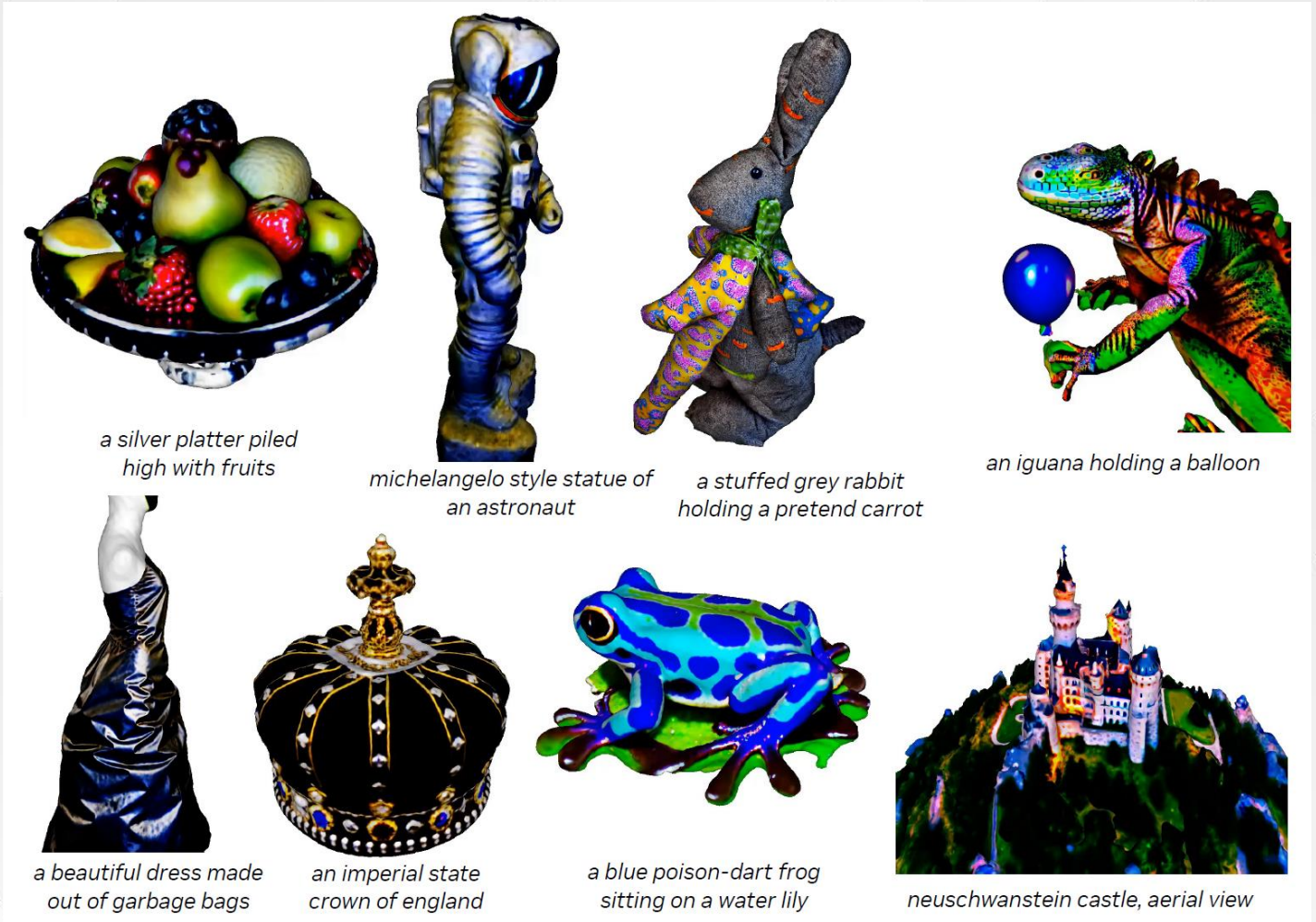
Dreamfusion: Text-to-3d using 2d diffusion, ICLR 2023.

Magic3D



Magic3D: High-Resolution Text-to-3D Content Creation, Arxiv 2022

Magic3D



Magic3D: High-Resolution Text-to-3D Content Creation, Arxiv 2022

Content

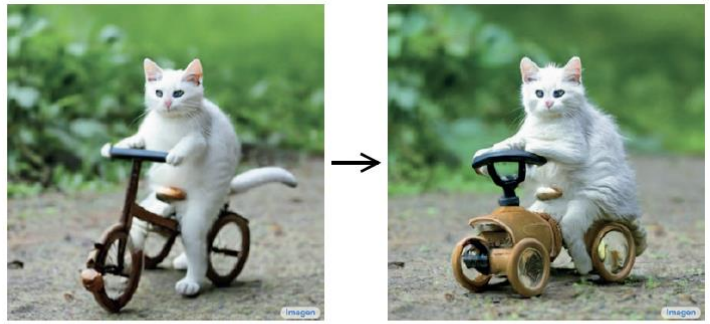
- Large Scale Pretraining Models
- Applications
  - Image Editing (Prompt-to-Prompt, Imagic, ControlNet)
  - Custom Generation
  - Latent Space

Prompt-to-Prompt Image Editing with Cross Attention Control

Amir Hertz*[1,2], Ron Mokady*[1,2], Jay Tenenbaum[1], Kfir Aberman[1], Yael Pritch[1], and Daniel Cohen-Or*[1,2]

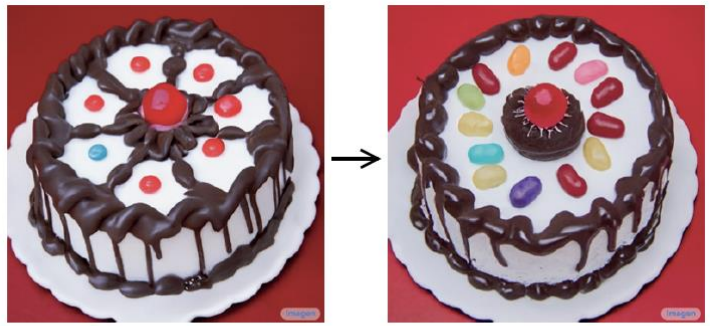
[1] *Google Research*
[2] *The Blavatnik School of Computer Science, Tel Aviv University*

"The boulevards are crowded today."



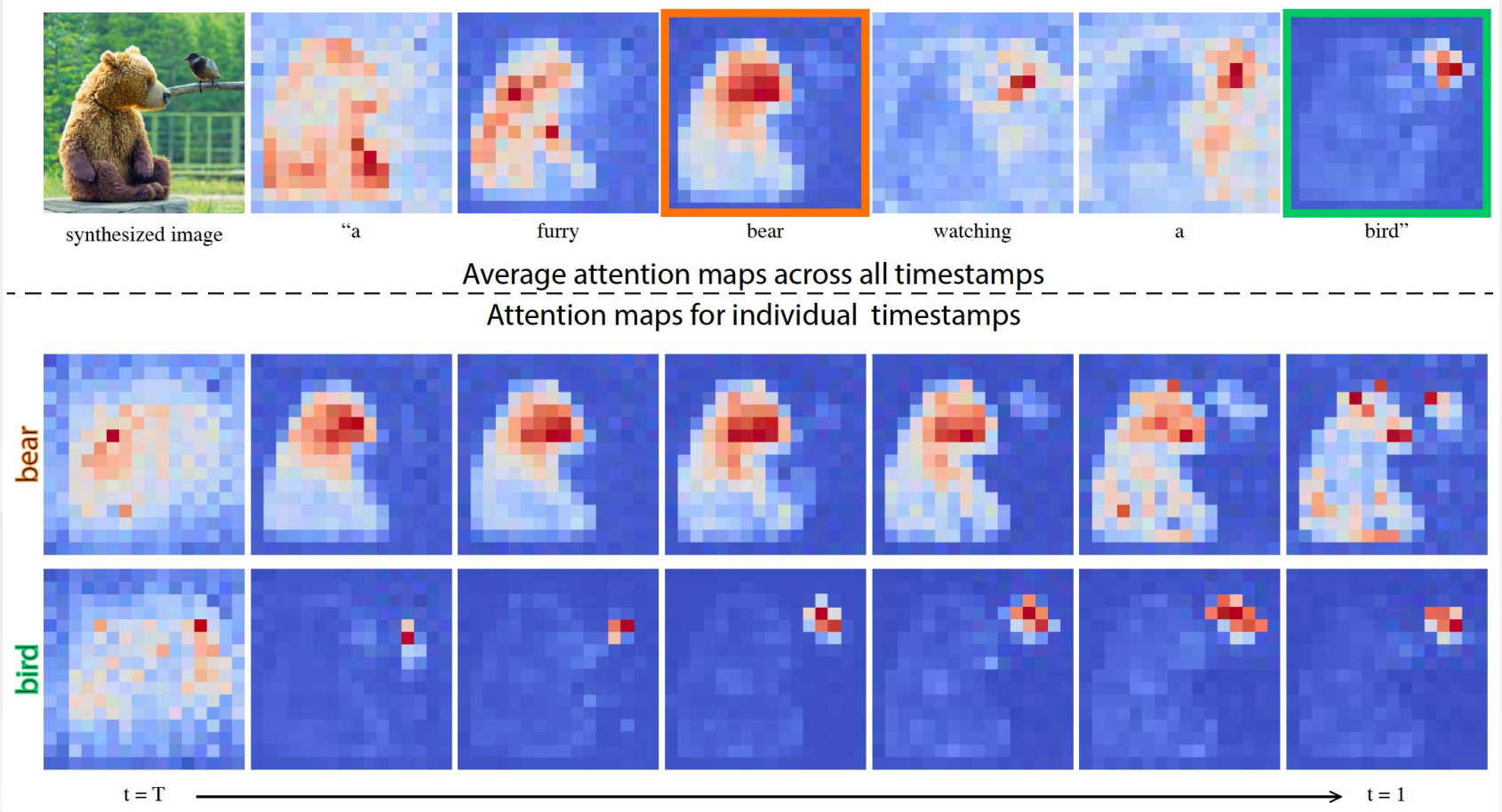
"Photo of a cat riding on a bicycle."

"Children drawing of a castle next to a river."



"a cake with decorations."

Prompt-to-Prompt: Motivation



Prompt-to-Prompt: Method

Algorithm 1: Prompt-to-Prompt image editing

Input: A source prompt $\mathcal{P}$, a target prompt $\mathcal{P}^*$, and a random seed s.
Output: A source image x_{src} and an edited image x_{dst}.
$z_T \sim N(0, I)$ a unit Gaussian random variable with random seed s;
$z_T^* \leftarrow z_T$;
for $t = T, T-1, \ldots, 1$ **do**
  $z_{t-1}, M_t \leftarrow DM(z_t, \mathcal{P}, t, s)$;
  $M_t^* \leftarrow DM(z_t^*, \mathcal{P}^*, t, s)$;
  $\widehat{M}_t \leftarrow Edit(M_t, M_t^*, t)$;
  $z_{t-1}^* \leftarrow DM(z_t^*, \mathcal{P}^*, t, s_t)\{M \leftarrow \widehat{M}_t\}$;
end
Return (z_0, z_0^*)

1. Word Swap

$$Edit(M_t, M_t^*, t) := \begin{cases} M_t^* & \text{if } t < \tau \\ M_t & \text{otherwise.} \end{cases}$$

2. Add a new phase

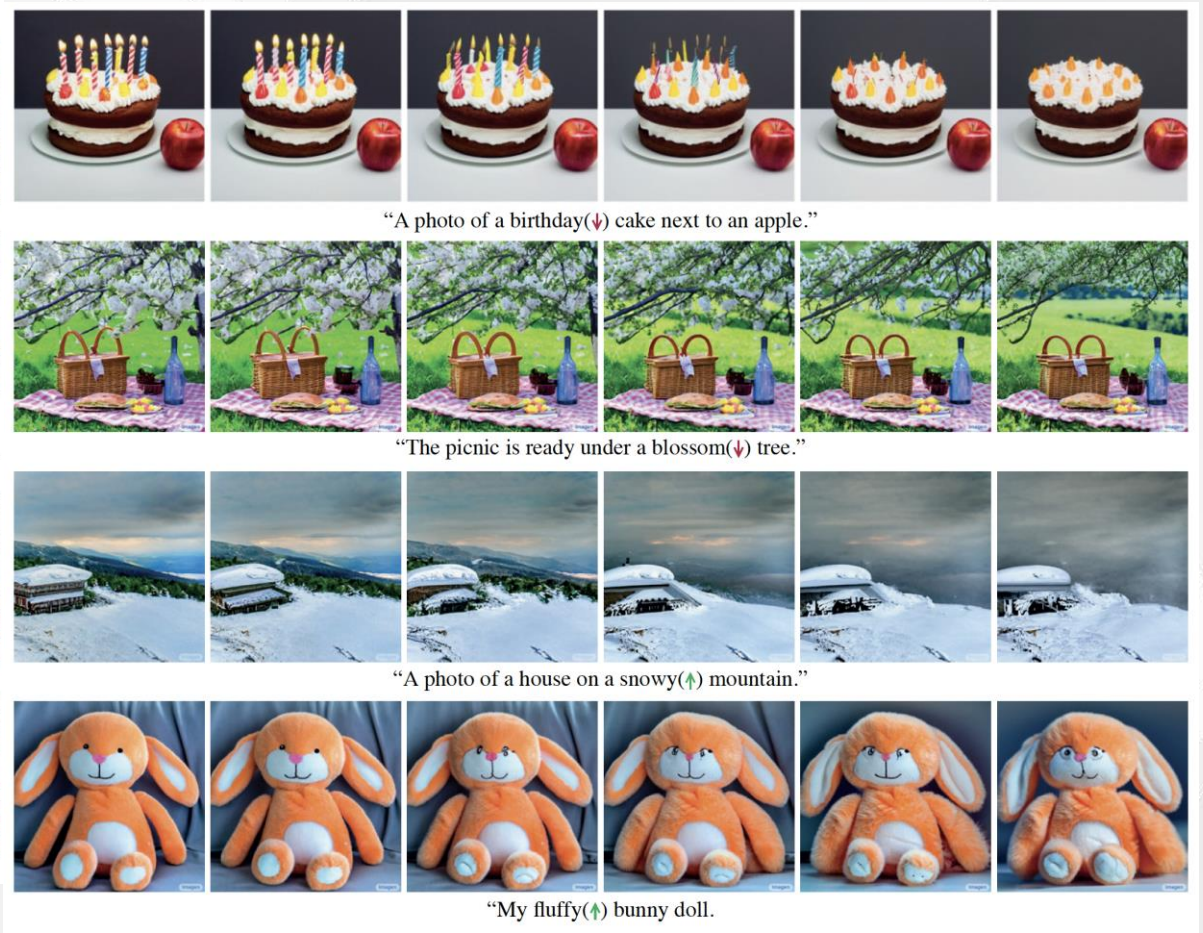
$$(Edit\,(M_t, M_t^*, t))_{i,j} := \begin{cases} (M_t^*)_{i,j} & \text{if } A(j) = None \\ (M_t)_{i,A(j)} & \text{otherwise.} \end{cases}$$

3. Attention Re-weighting

$$(Edit\,(M_t, M_t^*, t))_{i,j} := \begin{cases} c \cdot (M_t)_{i,j} & \text{if } j = j^* \\ (M_t)_{i,j} & \text{otherwise.} \end{cases}$$

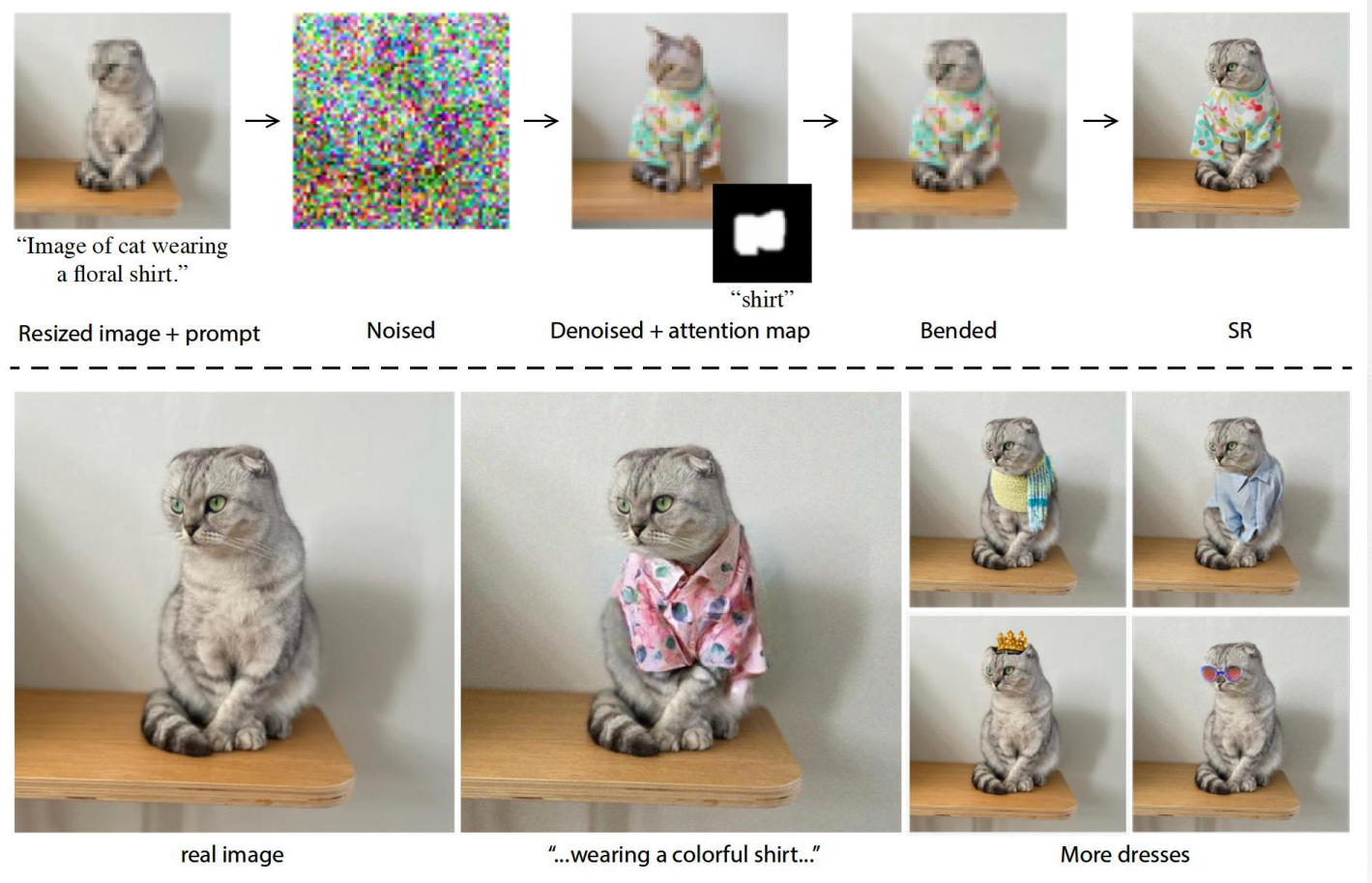
Prompt-to-Prompt: Results

Add new phase



Attention Re-weighting

Prompt-to-Prompt: Results

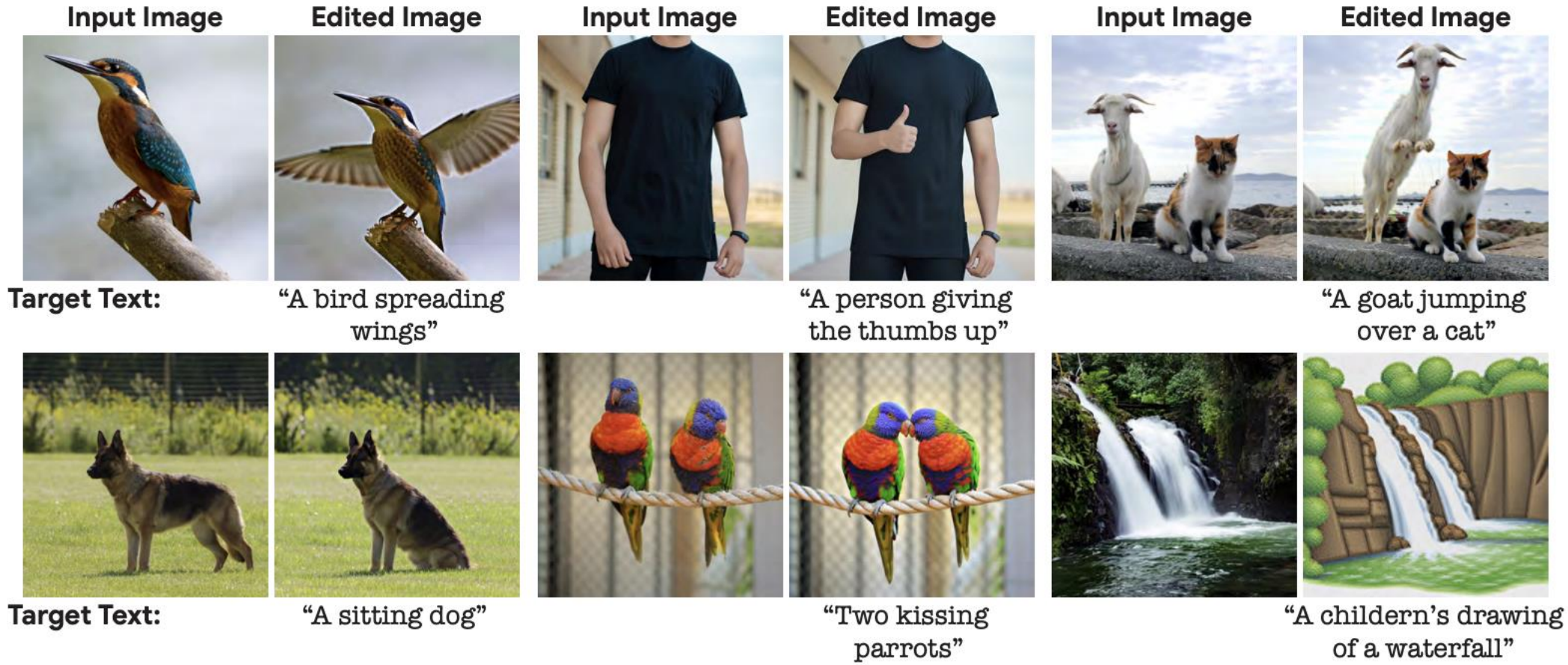


Mask-guided Editing

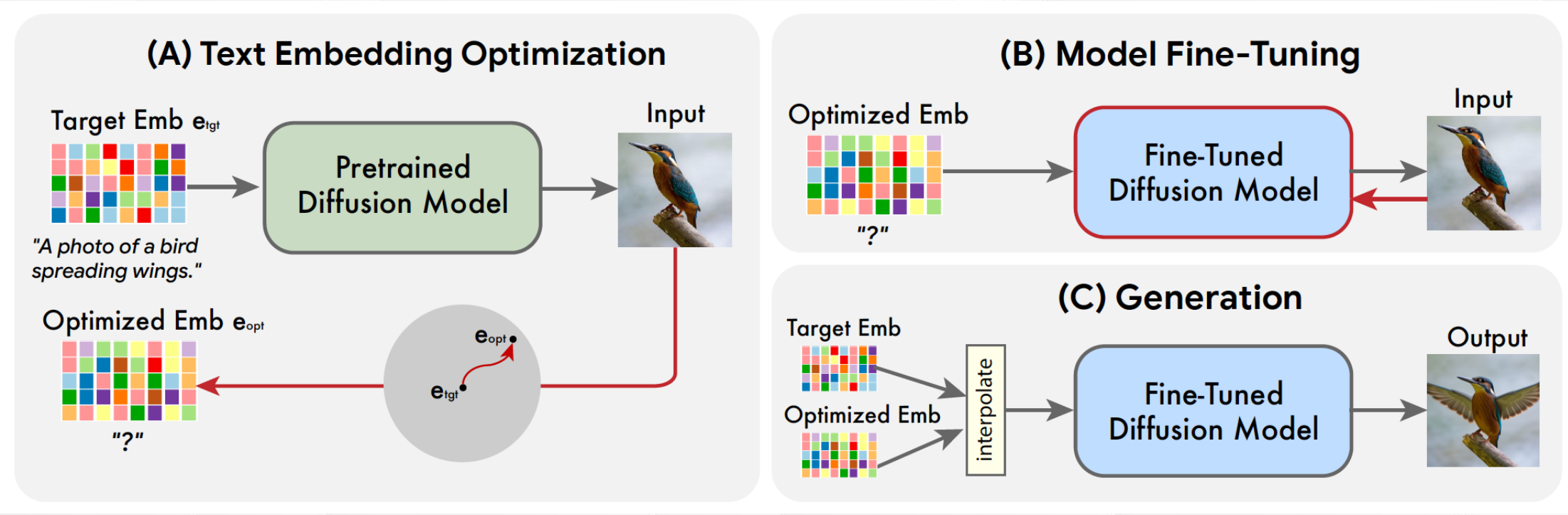
Imagic: Text-Based Real Image Editing with Diffusion Models

Bahjat Kawar* [1,2] Shiran Zada* [1] Oran Lang[1] Omer Tov[1]
Huiwen Chang[1] Tali Dekel[1,3] Inbar Mosseri[1] Michal Irani[1,3]

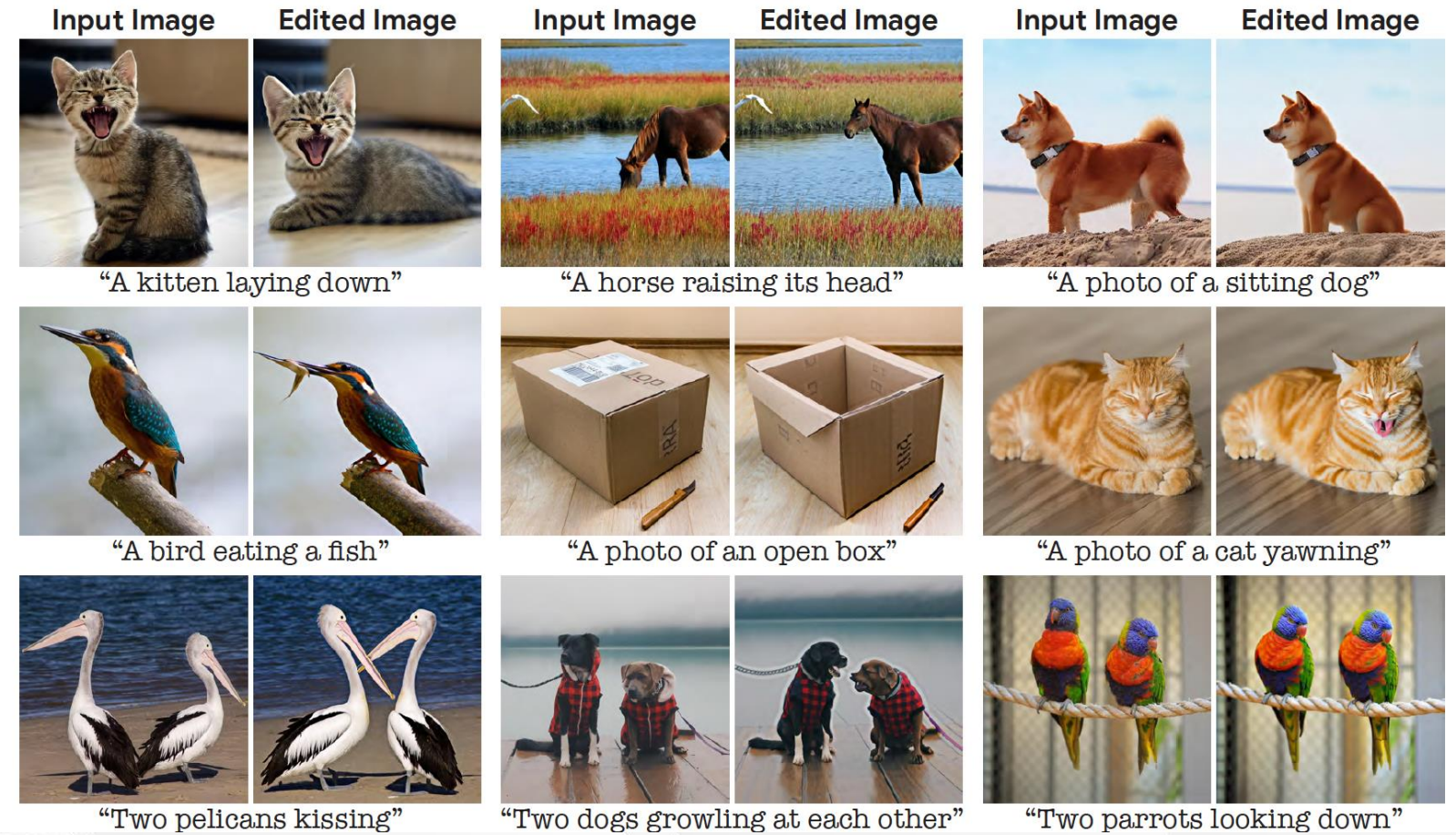
[1]Google Research [2]Technion [3]Weizmann Institute of Science



Imagic: Method



Imagic: Results



Imagic: Results

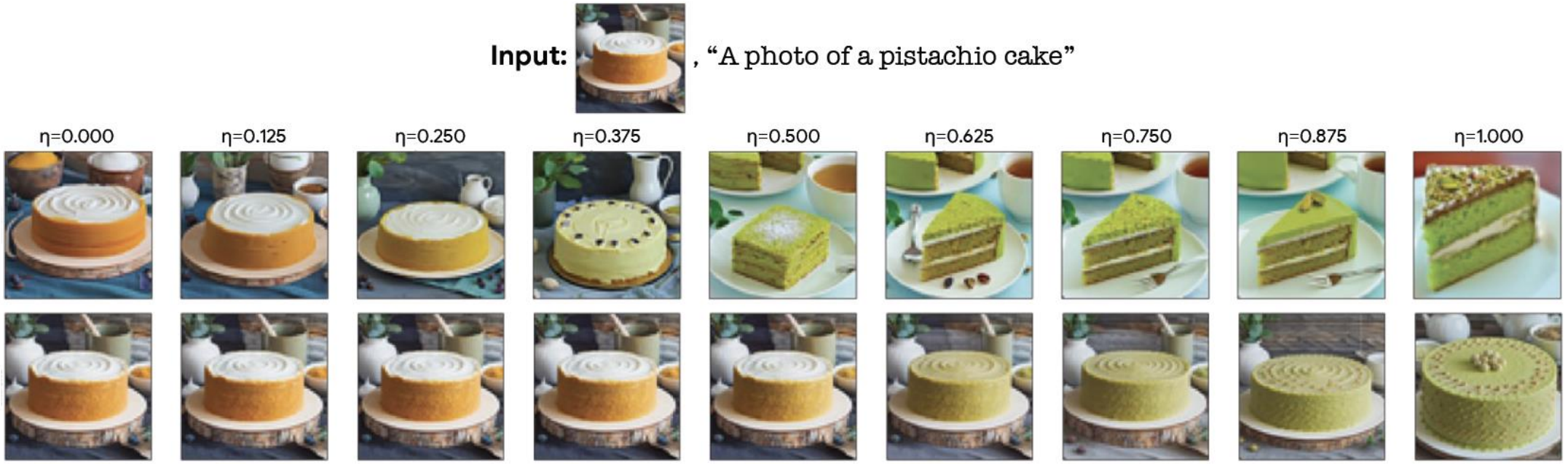
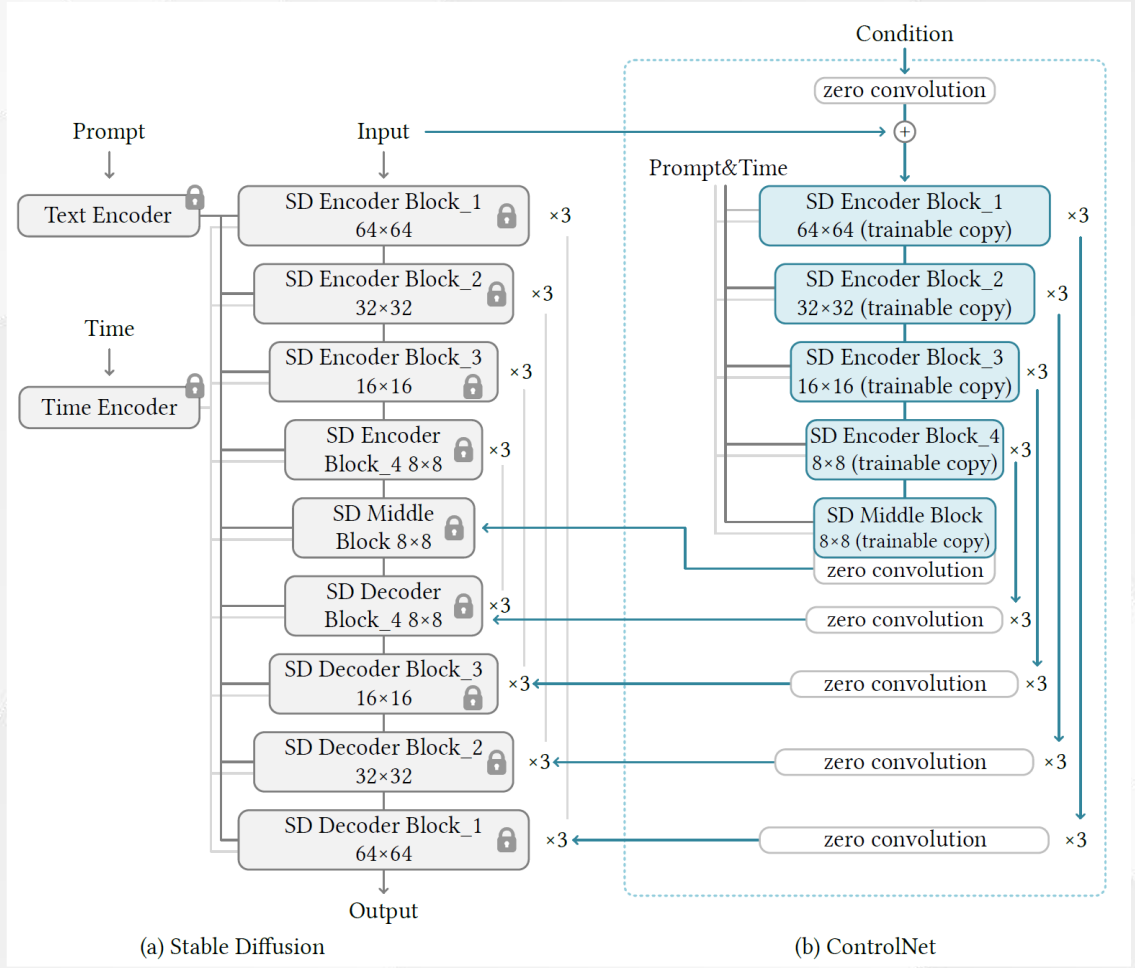


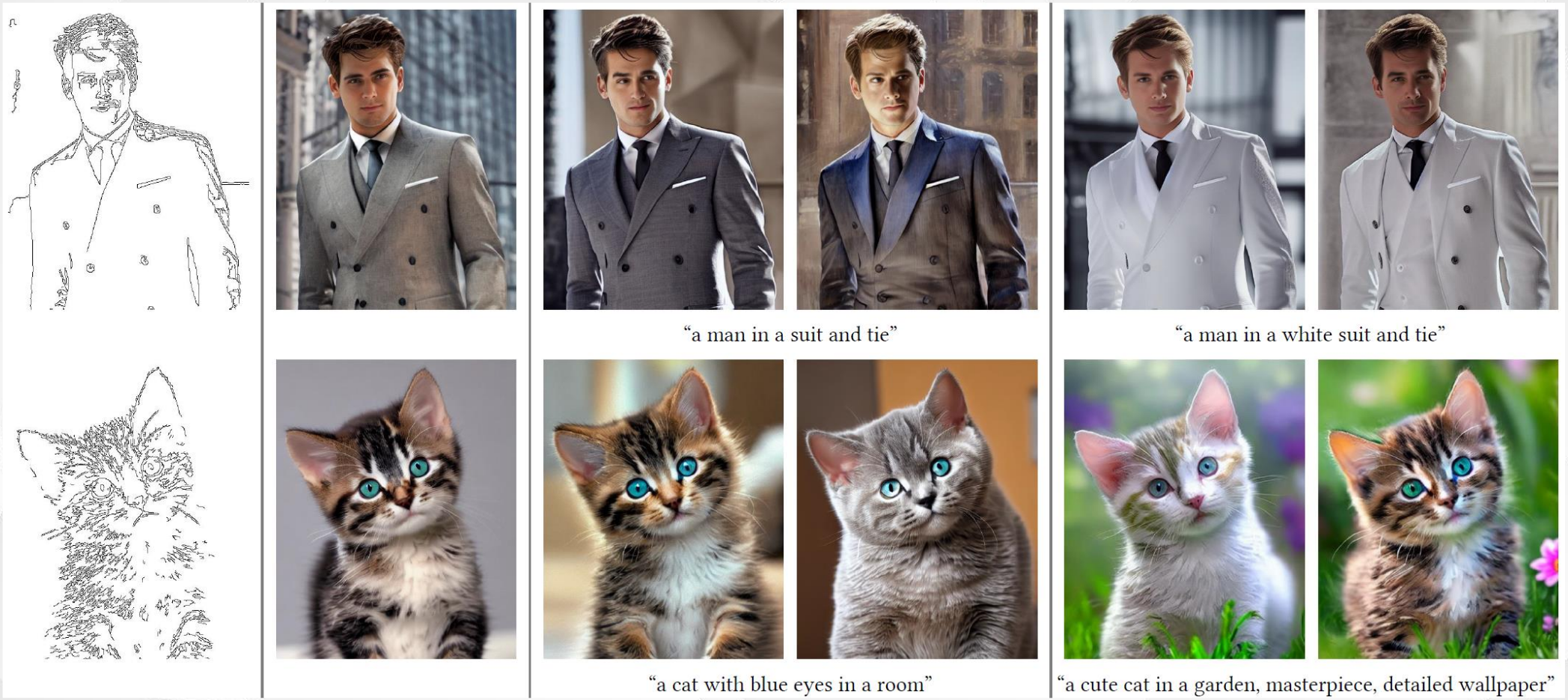
Figure 5. **Embedding interpolation.** Varying η with the same seed, using the pre-trained (top) and fine-tuned (bottom) models.

ControlNet

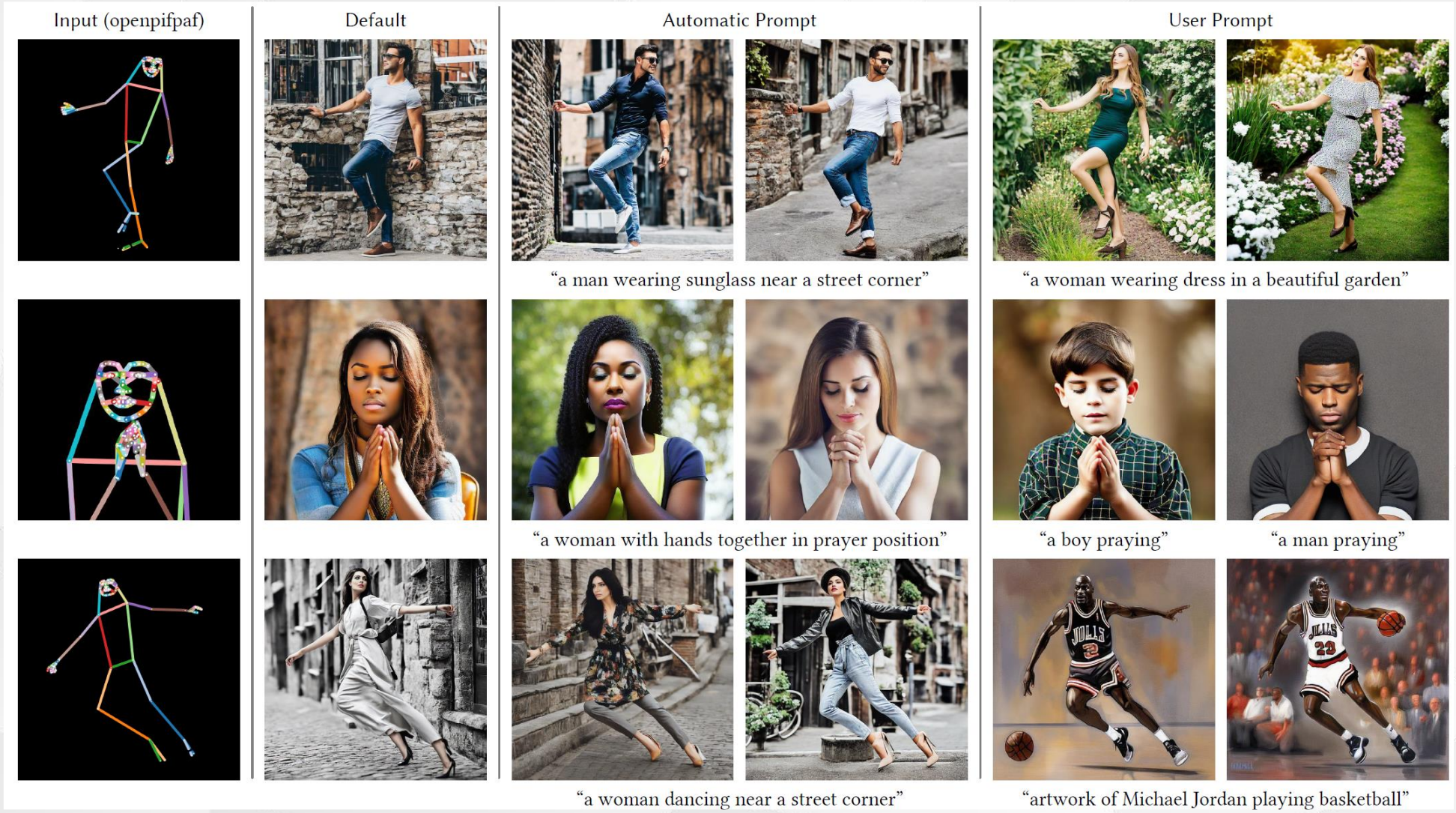


Adding Conditional Control to Text-to-Image Diffusion Models, Arxiv 2023.

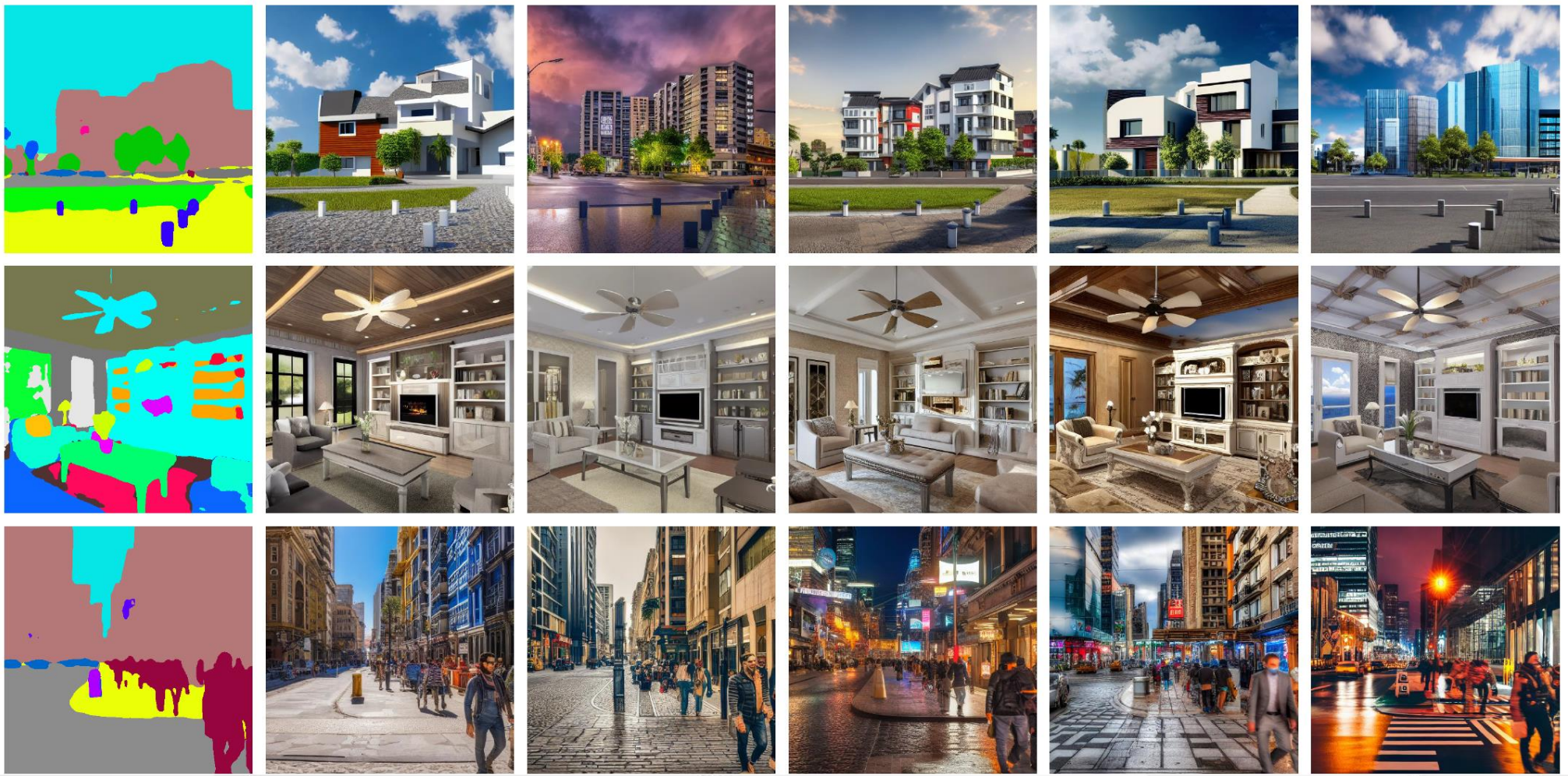
ControlNet


"a man in a suit and tie"
"a man in a white suit and tie"
"a cat with blue eyes in a room"
"a cute cat in a garden, masterpiece, detailed wallpaper"

ControlNet


Input (openpifpaf)
Default
Automatic Prompt
User Prompt
"a man wearing sunglass near a street corner"
"a woman wearing dress in a beautiful garden"
"a woman with hands together in prayer position"
"a boy praying"
"a man praying"
"a woman dancing near a street corner"
"artwork of Michael Jordan playing basketball"

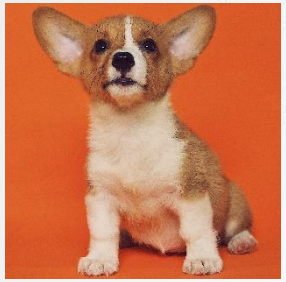
ControlNet



Content

- Large Scale Pretraining Models
- Applications
  - Image Editing
  - Custom Generation (Textual Inversion, Dreambooth, Custom Diffusion, Elite)
  - Latent Space

Customized Generation










Input —*invert*→ S*

S*

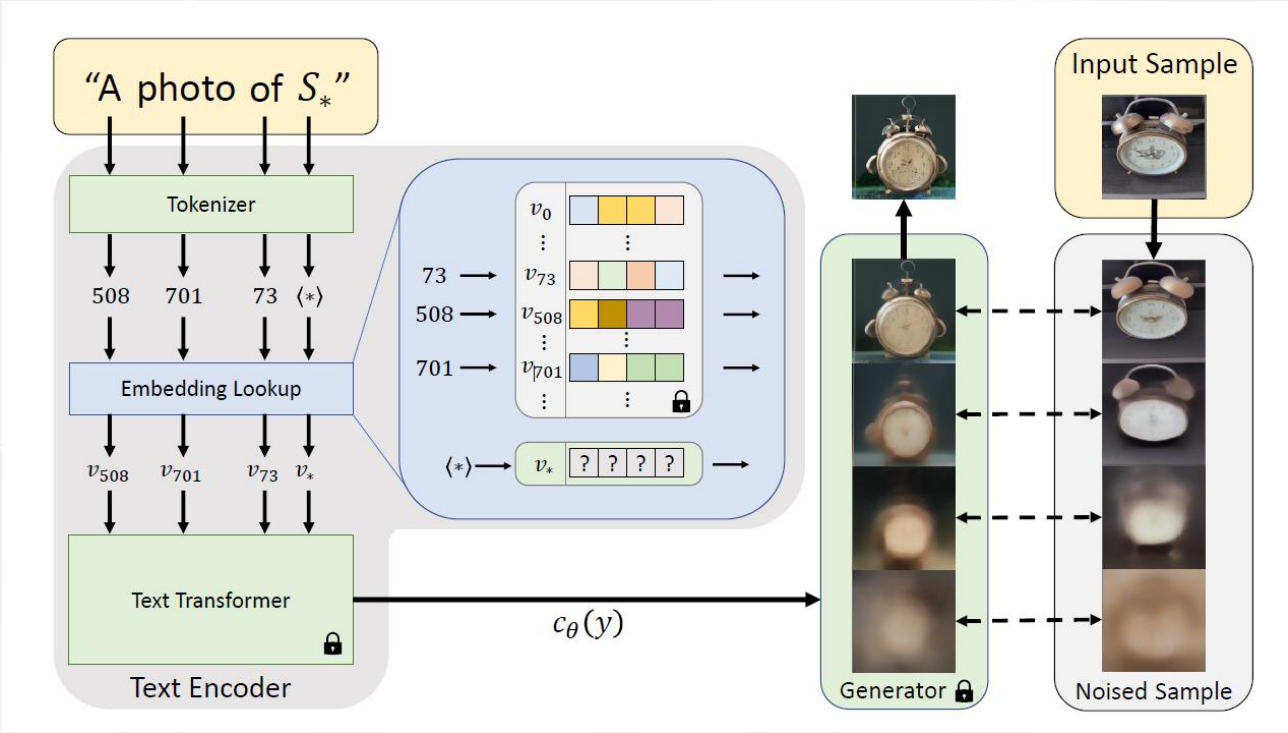
Wearing Sunglasses

In a bucket

Swimming

Textual Inversion

- Encode a visual concept as a word embedding [S*].

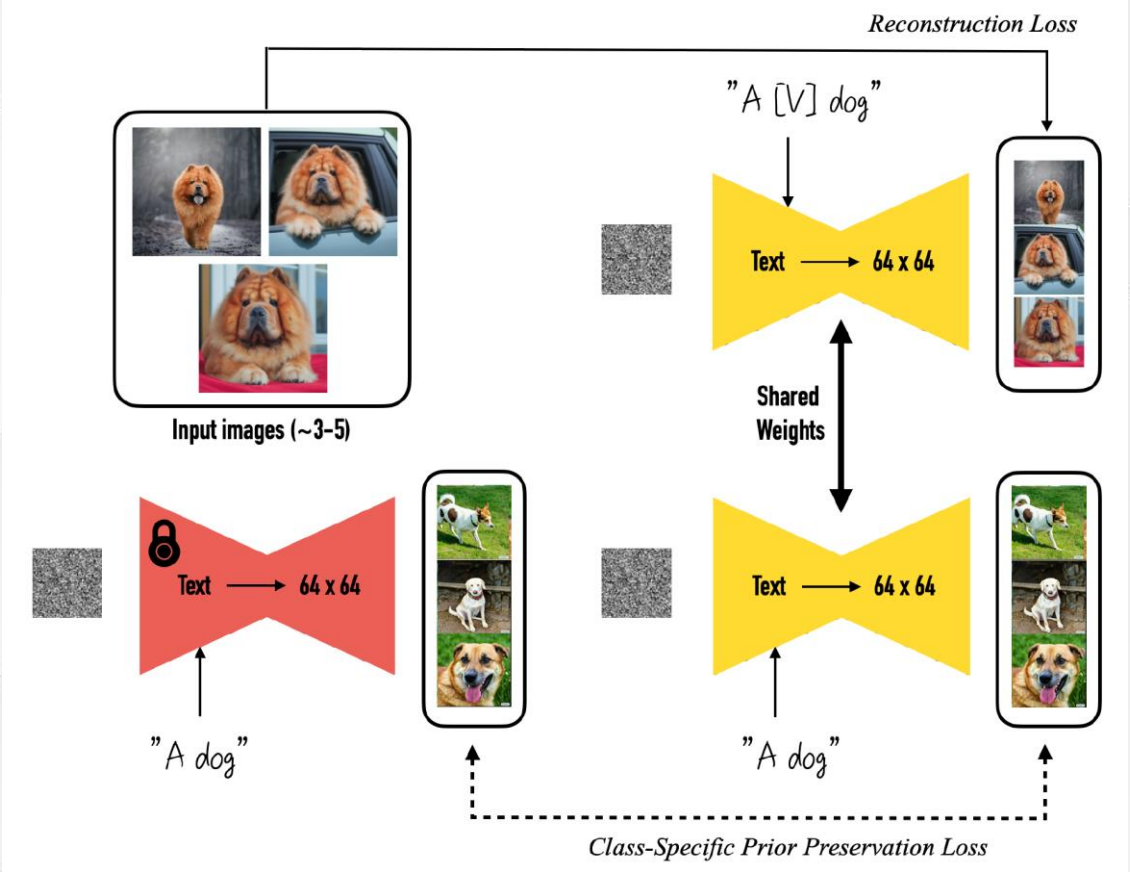


$$v_* = \arg\min_v \mathbb{E}_{z\sim\mathcal{E}(x),y,\epsilon\sim\mathcal{N}(0,1),t}\left[\|\epsilon - \epsilon_\theta(z_t, t, c_\theta(y))\|_2^2\right]$$

Gal, Rinon, et al. "An image is worth one word: Personalizing text-to-image generation using textual inversion." *arXiv preprint arXiv:2208.01618* (2022).

DreamBooth

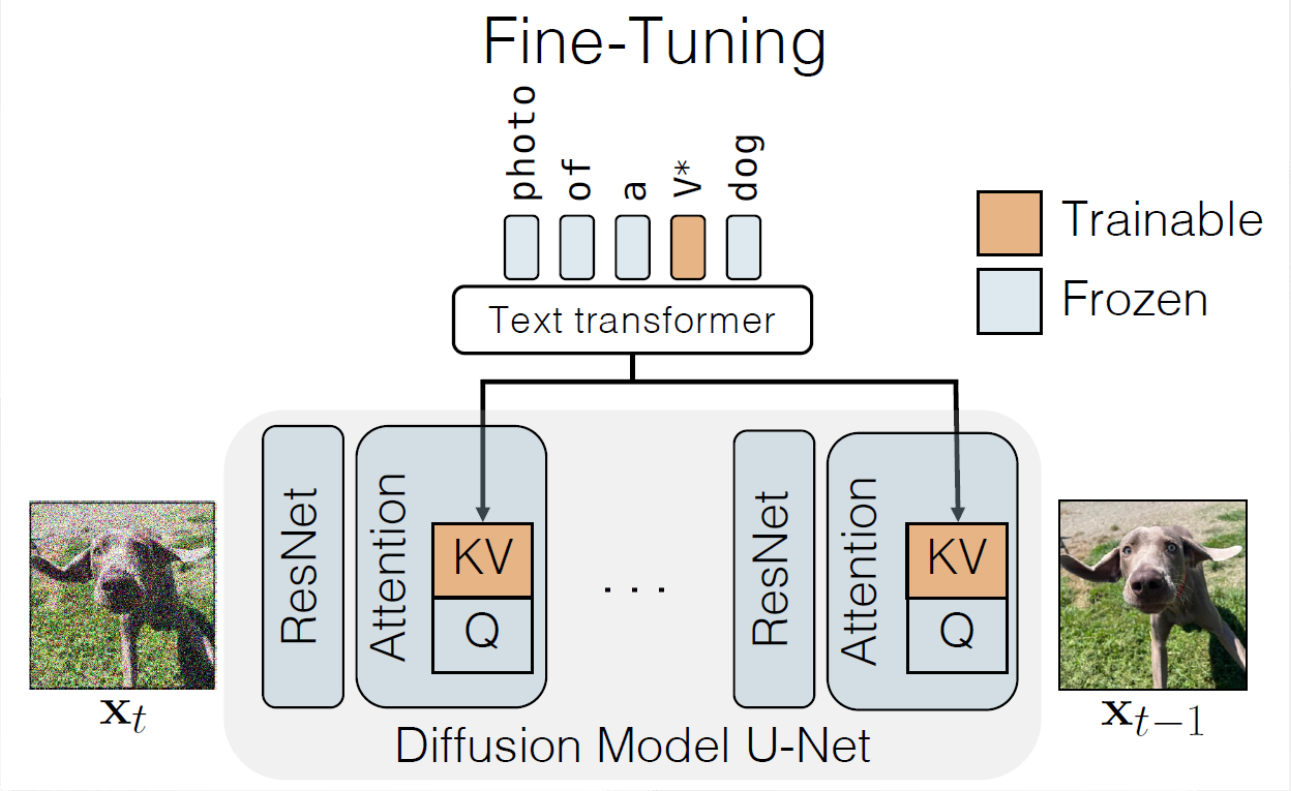
- Align a visual concept with a rare word [v] by finetuning model.



Ruiz, Nataniel, et al. "Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation." *arXiv preprint arXiv:2208.12242* (2022).

Custom Diffusion

- Selectively finetune K, V mapping parameters in cross attention layers.



Kumari, Nupur, et al. "Multi-Concept Customization of Text-to-Image Diffusion." *arXiv preprint arXiv:2212.04488* (2022).

Comparison

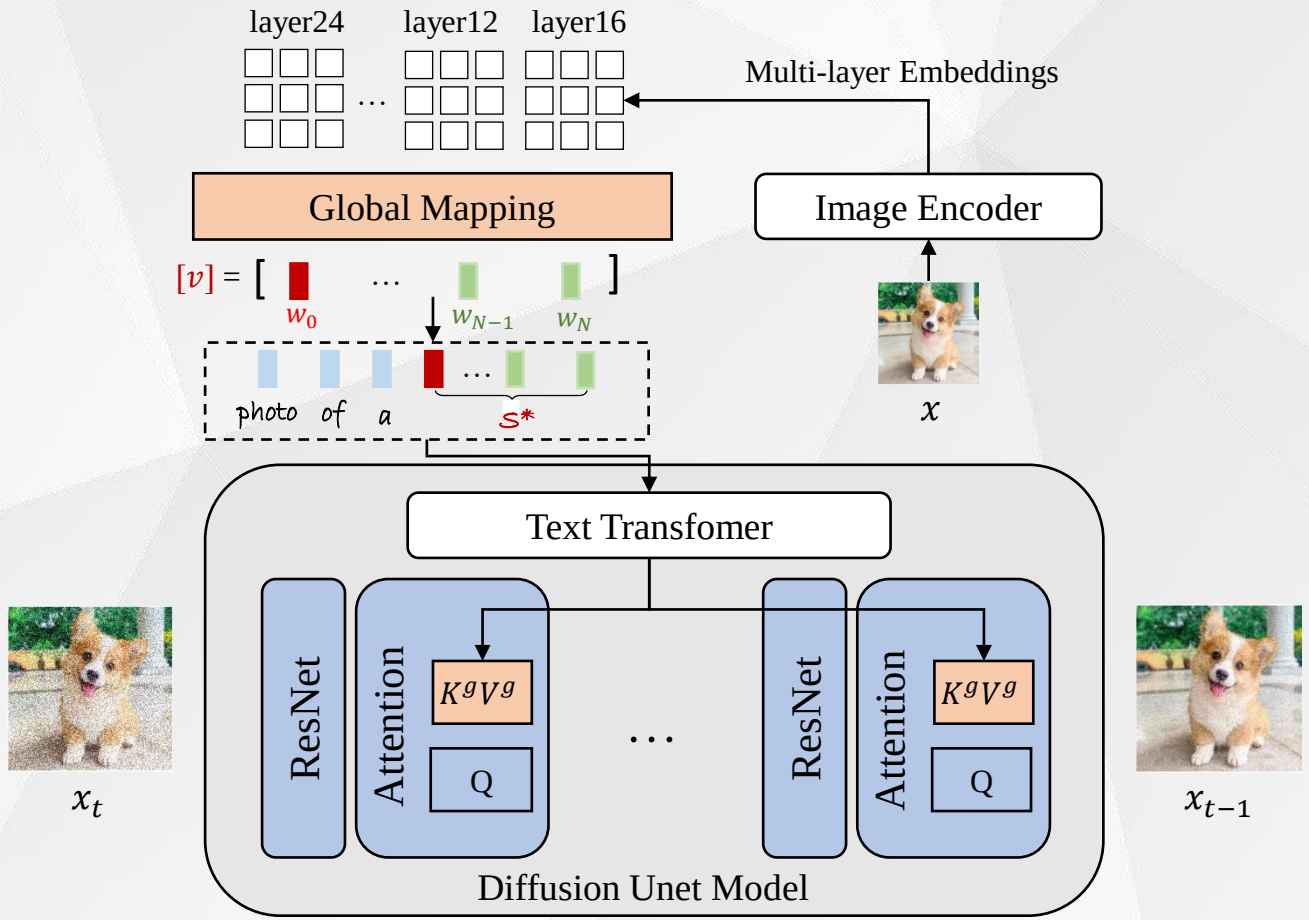
S* wearing sunglasses

Target Images | Custom Diffusion | DreamBooth | Textual Inversion

Method	Text-alignment (↑)	Image-alignment (↑)	KID (×10, ↓)	Time (↓)
Textual Inversion	0.670	0.827	22.27	50 min
DreamBooth	0.781	0.776	32.53	30 min
Custom Diffusion	0.795	0.775	20.96	6 min

Kumari, Nupur, et al. "Multi-Concept Customization of Text-to-Image Diffusion." *arXiv preprint arXiv:2212.04488* (2022).

ELITE: Global



$$L_{global} = L_{LDM} + \lambda_{global}\|v\|_1$$

Generation and Editability

Input

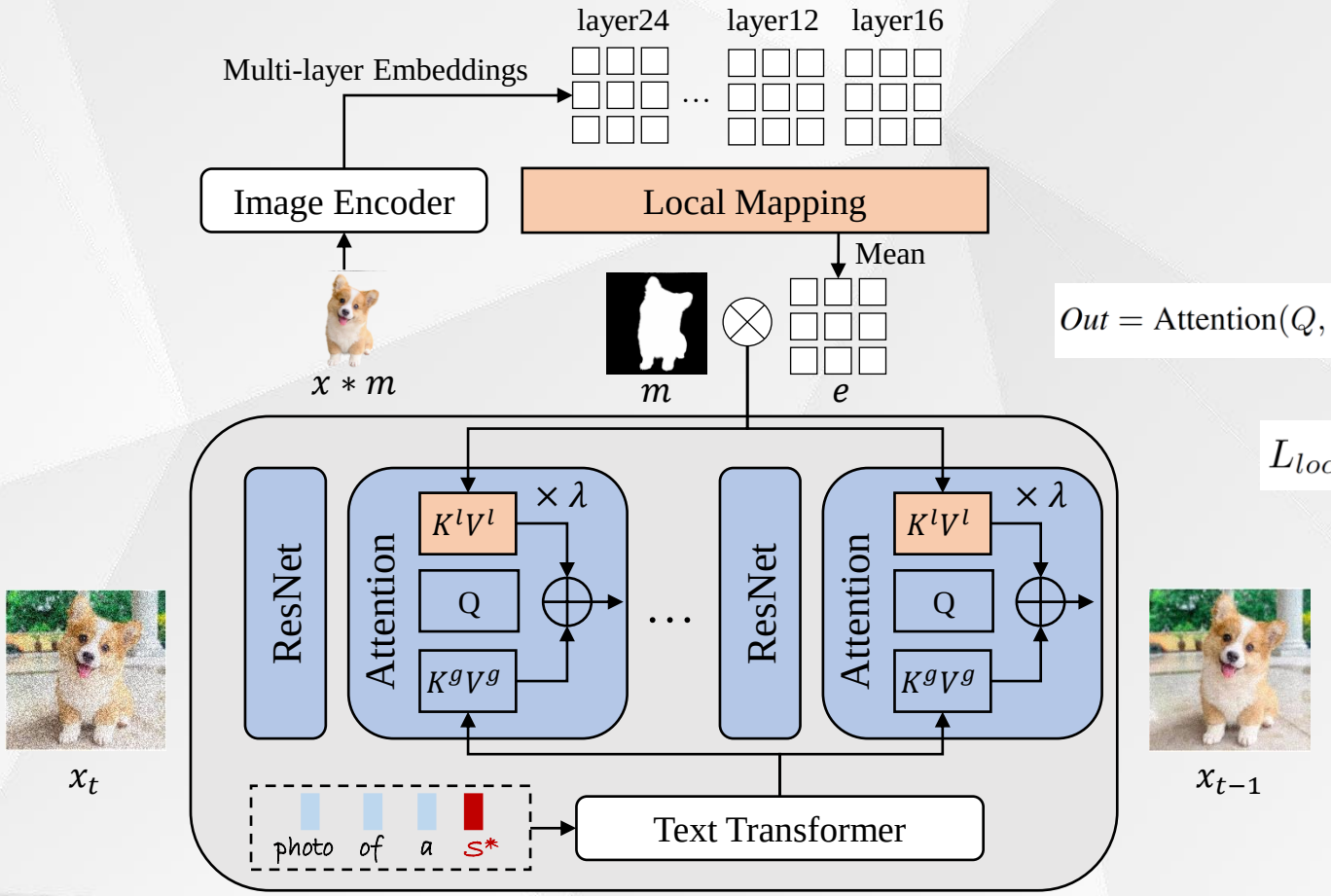
A photo of a S*

A photo of a S* in a bucket

[v]

[w0]

ELITE: Local Mapping



$$Out = \text{Attention}(Q, K^g, V^g) + \lambda \text{Attention}(Q, K^l, V^l)$$

$$L_{local} = L_{LDM} + \lambda_{local} \|V^l\|_1$$

Effect of Local Mapping

Input

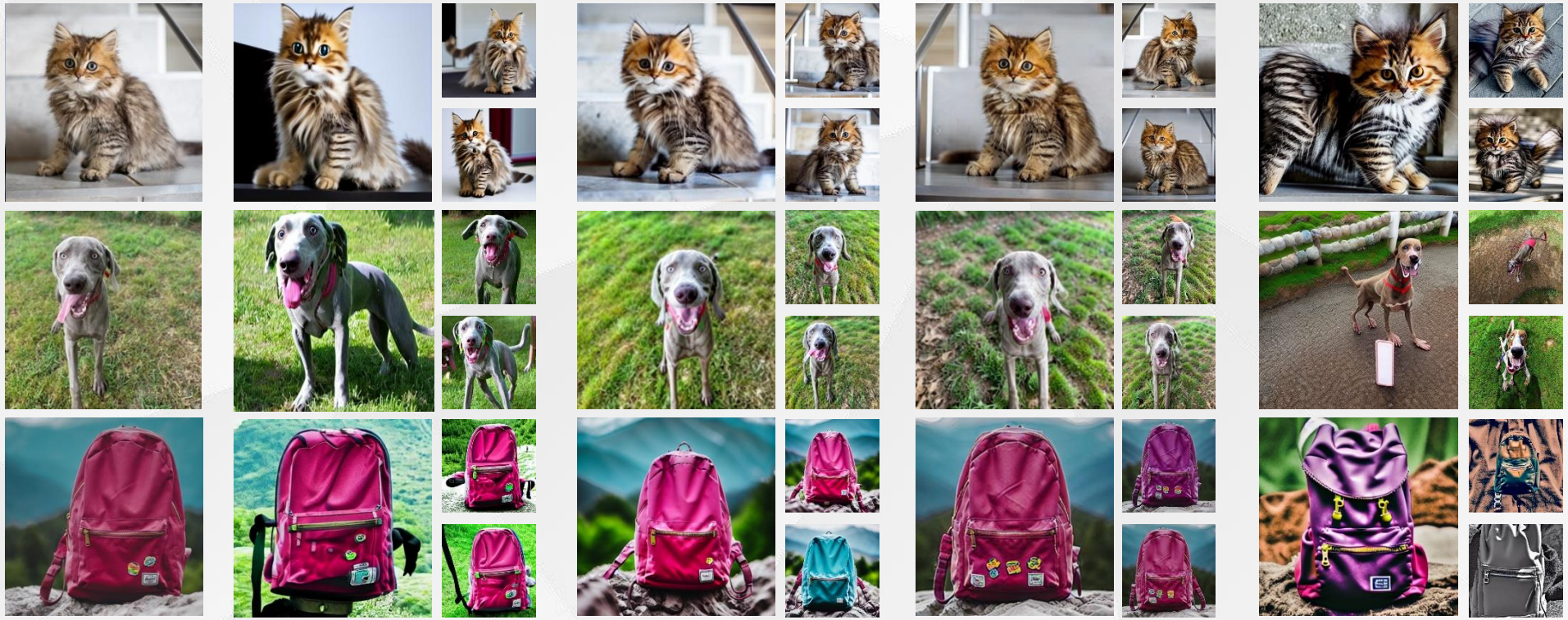
A photo of a S*

A photo of a S* in a bucket

Ours w/o Local

Ours

Inversion Comparison



Input | Ours | Custom Diffusion | Dreambooth | Textual Inversion

Editing Comparison

Content

- Large Scale Pretraining Models

- Applications
  - Image Editing
  - Custom Generation
  - Latent Space

DIFFUSION MODELS ALREADY HAVE A SEMANTIC LATENT SPACE

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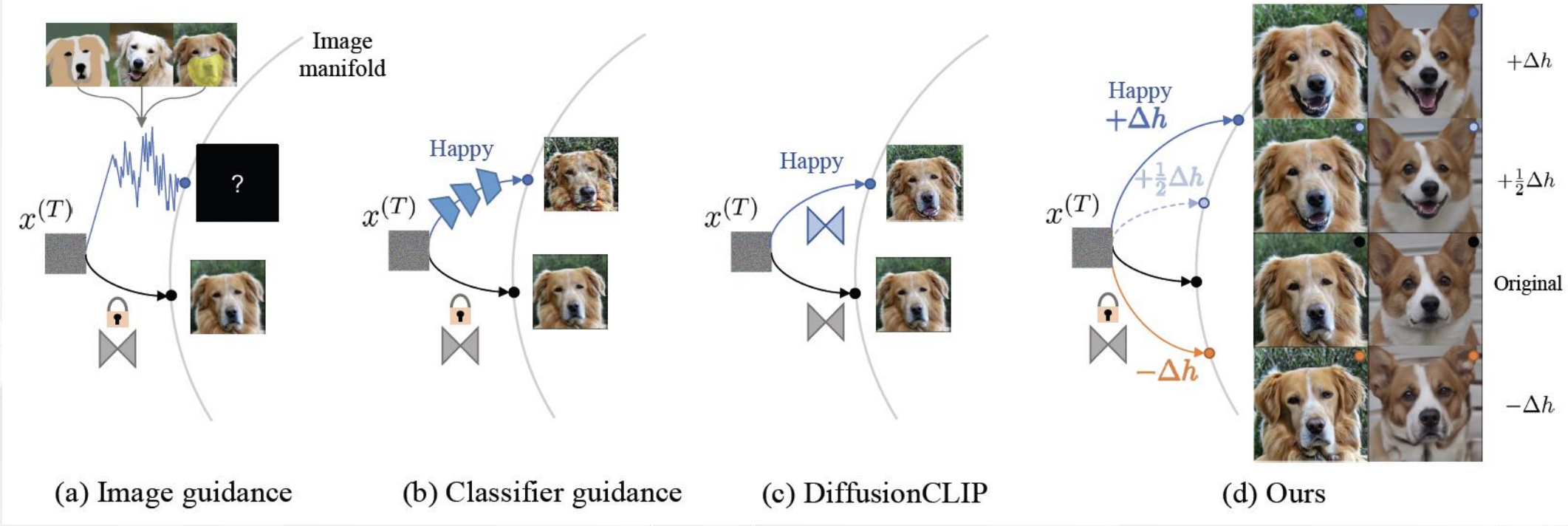
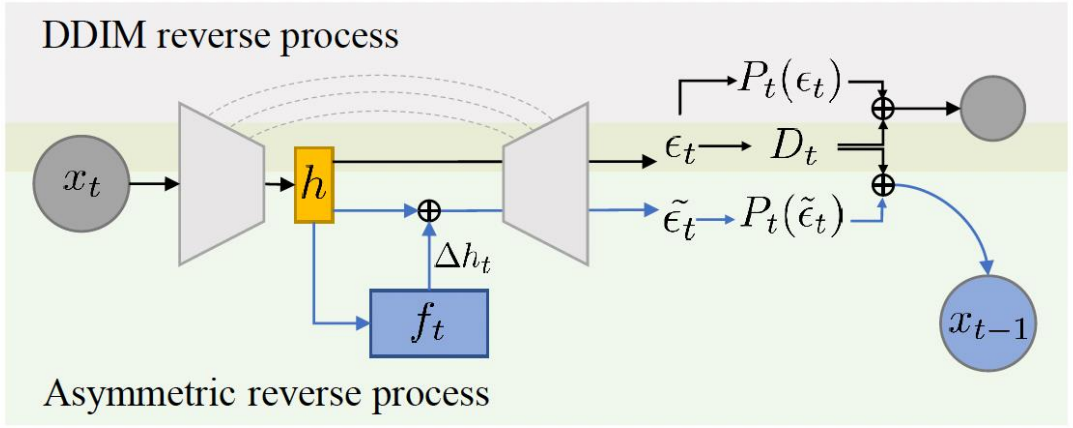
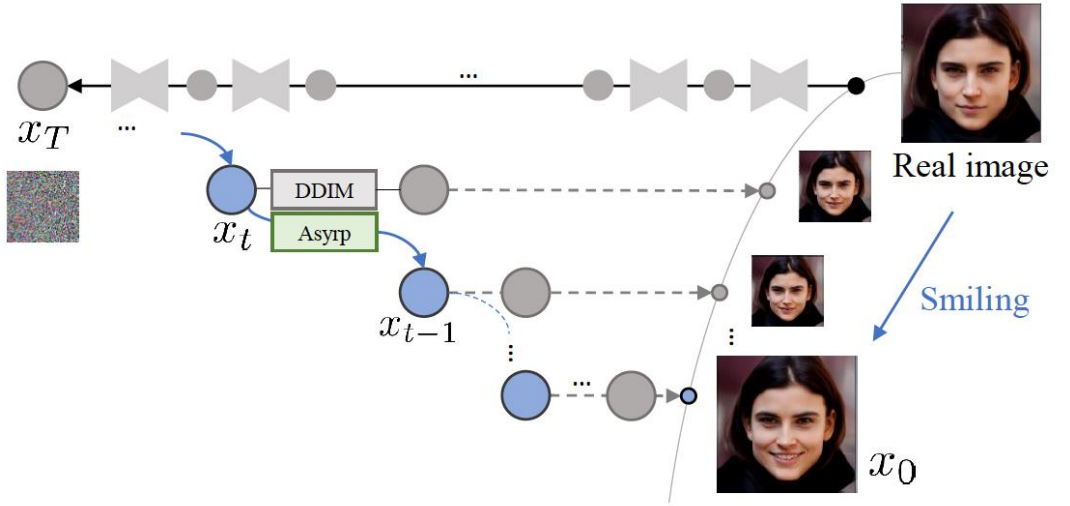


(a) Image guidance (b) Classifier guidance (c) DiffusionCLIP (d) Ours

Latent Space: Method





DDIM Sampling:

$$\boldsymbol{x}_{t-1} = \sqrt{\alpha_{t-1}}\,\mathbf{P}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t)) + \mathbf{D}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t)) + \sigma_t \boldsymbol{z}_t,$$

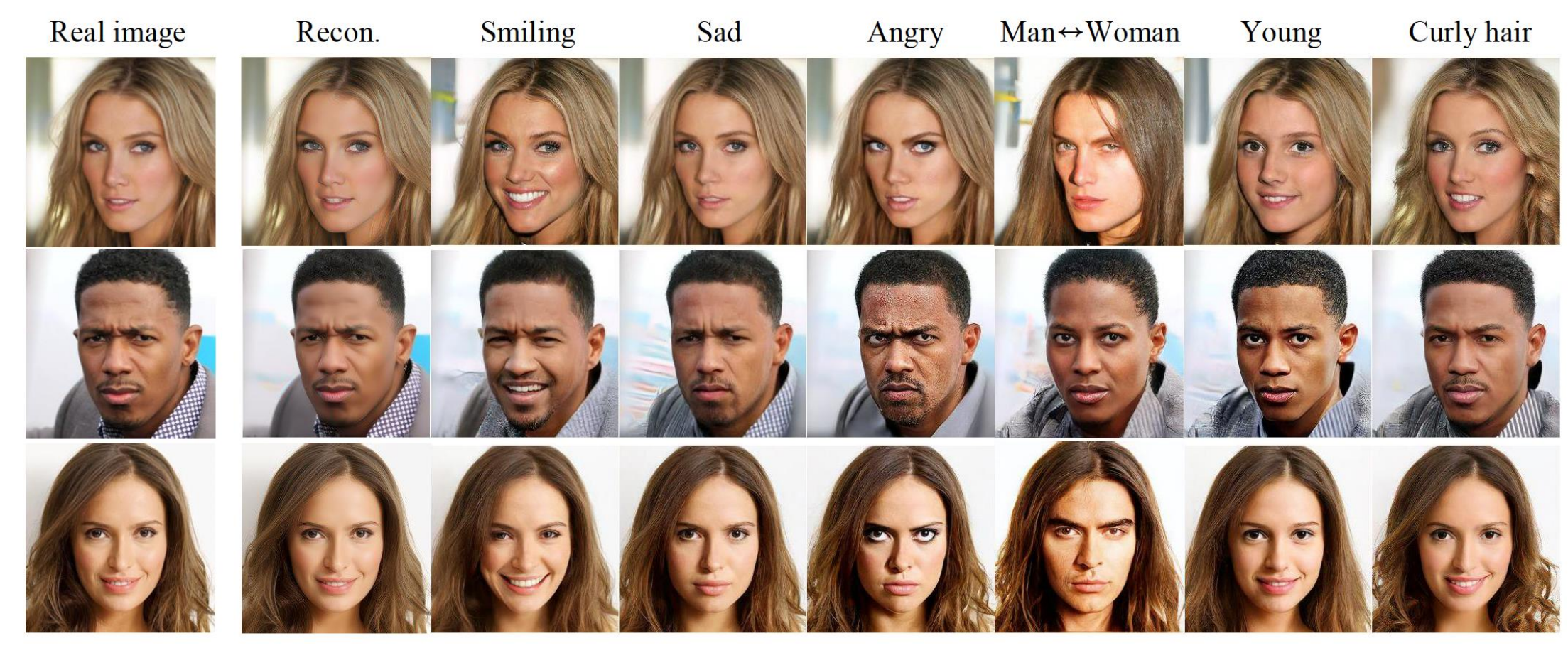
Latent Space Editing:

$$\boldsymbol{x}_{t-1} = \sqrt{\alpha_{t-1}}\,\mathbf{P}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t|\Delta\boldsymbol{h}_t)) + \mathbf{D}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t)) + \sigma_t \boldsymbol{z}_t,$$

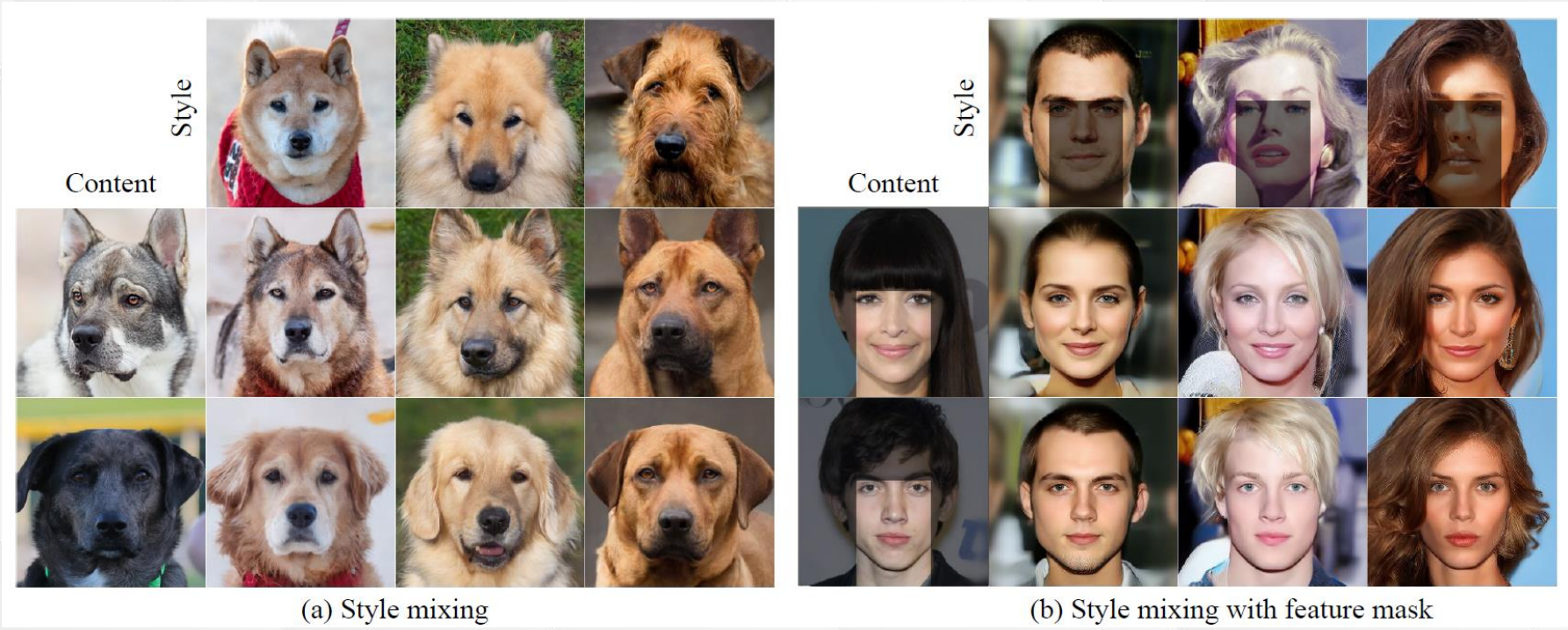
Modified Sampling:

$$p_\theta^{(t)}(\boldsymbol{x}_{t-1} \mid \boldsymbol{x}_t) = \begin{cases} \mathcal{N}\left(\sqrt{\alpha_{t-1}}\,\mathbf{P}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t|\boldsymbol{f}_t)) + \mathbf{D}_t, \sigma_t^2 \boldsymbol{I}\right), \ \eta = 0 & \text{if } T \geq t \geq t_{\text{edit}} \\ \mathcal{N}\left(\sqrt{\alpha_{t-1}}\,\mathbf{P}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t)) + \mathbf{D}_t, \sigma_t^2 \boldsymbol{I}\right), \ \eta = 0 & \text{if } t_{\text{edit}} > t \geq t_{\text{noise}} \\ \mathcal{N}\left(\sqrt{\alpha_{t-1}}\,\mathbf{P}_t(\boldsymbol{\epsilon}_t^\theta(\boldsymbol{x}_t)) + \mathbf{D}_t, \sigma_t^2 \boldsymbol{I}\right), \ \eta = 1 & \text{if } t_{\text{noise}} > t \end{cases}$$

Latent Space: Results



Training-free Style Transfer



(a) Style mixing (b) Style mixing with feature mask

$$\tilde{\boldsymbol{h}}_t \leftarrow f((m \otimes \boldsymbol{h}_t), (m \otimes \boldsymbol{h}_t^{content}), \gamma) \oplus (1 - m) \otimes \boldsymbol{h}_t$$

Training-free Style Transfer Emerges from h-space in Diffusion models, Arxiv 2023

Discovering Interpretable Directions

$$\mathbf{J}_t^{\mathrm{T}} \mathbf{J}_t \mathbf{v} = \frac{\partial}{\partial \mathbf{h}_t} \left\langle \boldsymbol{\epsilon}_t^{\theta}(\mathbf{x}_t, \mathbf{h}_t), \mathbf{J}_t \mathbf{v} \right\rangle$$

Algorithm 1 Jacobian subspace iteration

Input: $\mathbf{f} : \mathbb{R}^{d_{\text{in}}} \to \mathbb{R}^{d_{\text{out}}}$, $\mathbf{h} \in \mathbb{R}^{d_{\text{in}}}$ and $\mathbf{V} \in \mathbb{R}^{d_{\text{in}} \times k}$
Output: $(\mathbf{U}, \mathbf{\Sigma}, \mathbf{V}^{\mathrm{T}})$ – k top singular values and vectors of the Jacobian $\partial \mathbf{f} / \partial \mathbf{h}$

```
y ← f(h)
if V is empty then
    V ← i.i.d. standard Gaussian samples
end if
Q, R ← QR(V)                          ▷ Reduced QR decomposition
V ← Q                                 ▷ Ensures V^T V = I
while stopping criteria do
    U ← ∂f(h + aV)/∂a at a = 0        ▷ Batch forward
    V̂ ← ∂(U^T y)/∂h
    V, Σ², R ← SVD(V̂)                 ▷ Reduced SVD
end while
Orthonormalize U
```

Discovering Interpretable Directions in the Semantic Latent Space of Diffusion Models, Arxiv 2023.

Summary

- Pretraining: From text-to-image to text-to-X
  - 3D
  - Video
- Downstream tasks
  - Generation
  - Editing
  - Understanding
  - Image -> Video
- New Paradigm: Pretraining -> Downstream tasks
  - Network architectures, tasks
  - Self-supervised vision learning
  - Pretraining -> Downstream: VL, GAN, T2I