AI Painting

A Survey of Multimodal Image Generation

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2022.11.02

Introduction

Begin
2012

DALL.E
2021.02

Disco Diffusion
2022.02

MidJourney
2022.05

Noval AI
2022.10

Deep Dream
2015

GLIDE
2021.12

DALL.E2
2022.04

Stable diffusion
2022.08

CNN
2012

GAN
2014

VQ-VAE
2017

DDPM
2020

Begin

Deep Dream

GAN

(b) an illustration of a baby hedgehog in a christmas sweater walking a dog

DALL.E

作者：末知

关键词："Cyberpunk city in the night seen from below,cityscape,mist,rain,artstation,Greg Rutkowski

Disco Diffusion

a shiba inu wearing a beret and black turtleneck

DALL.E2

MidJourney

Noval AI

AI Generation

AI Painting

Contents

Preliminaries of Deep Generative Model

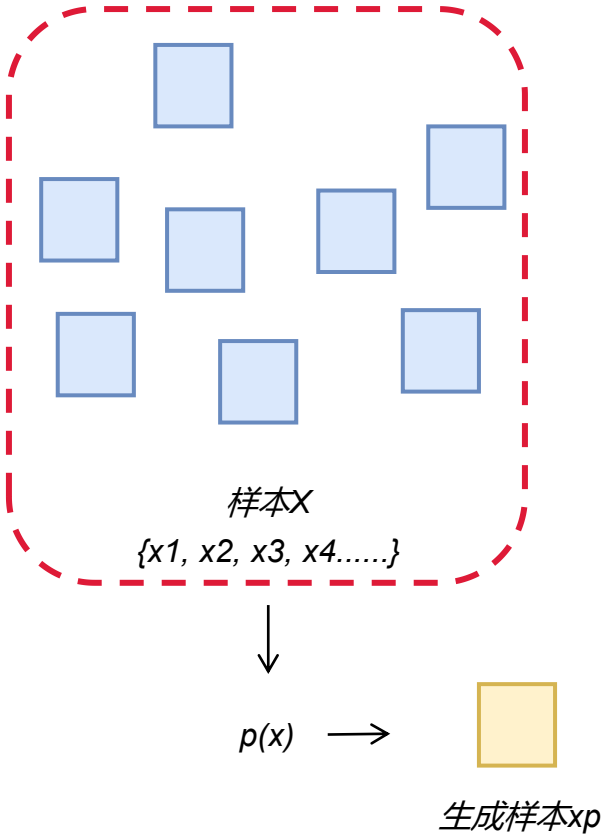
00 VAE

01 VQVAE

02 VQGAN

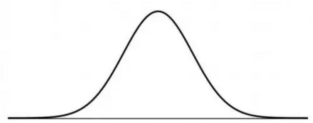
03 DDPM

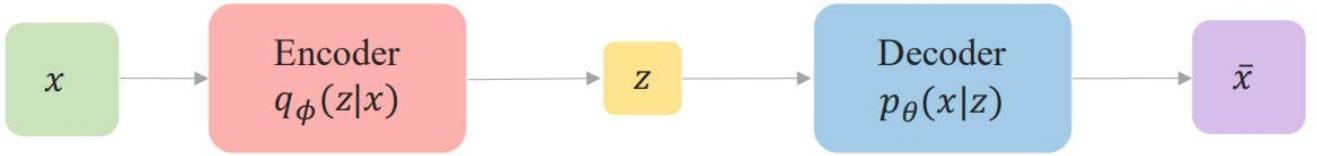
04 DDIM



VAE & VQVAE & VQGAN

p(x) = Σ p(x|z) p(z) → p(z) →

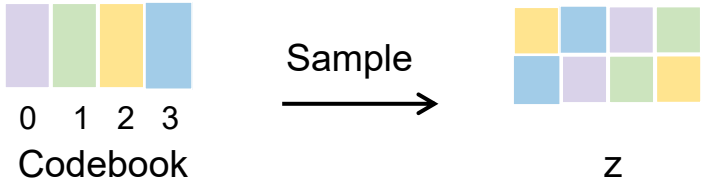


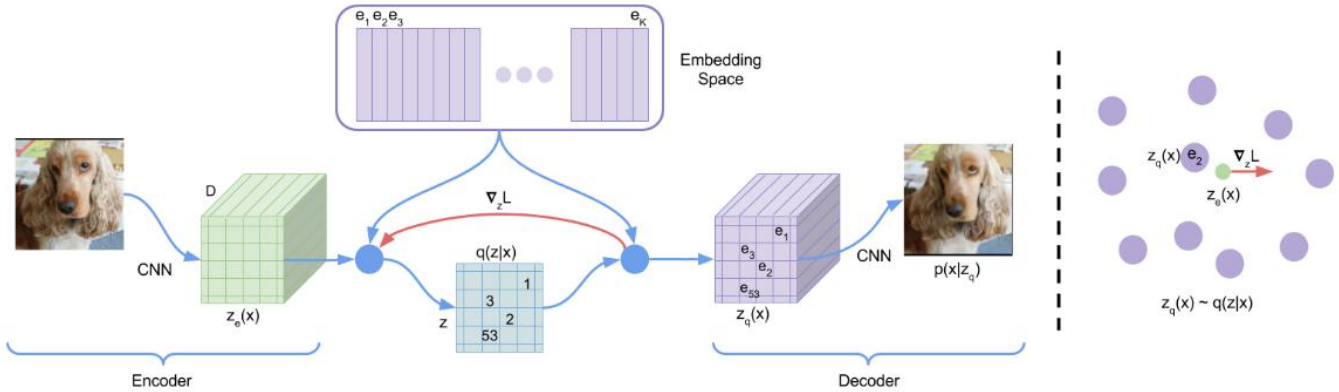


Auto-Encoding Variational Bayes

将p(z)定义为连续的均值为0方差为1的正态分布N(0, 1)

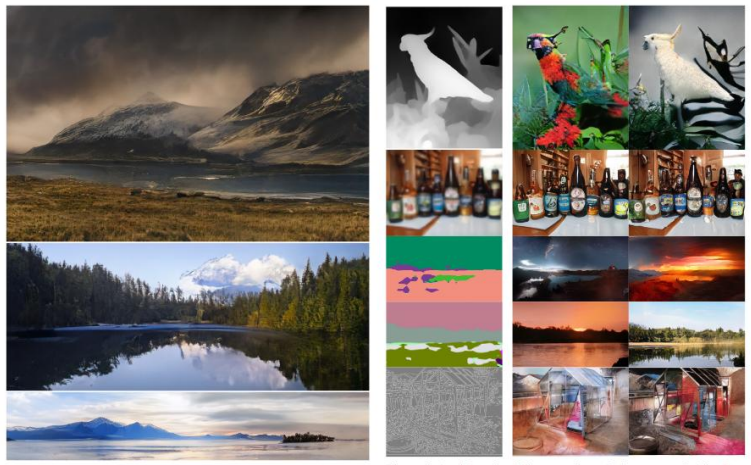
p(z) → z(cd1)z(cd2|cd1)z(cd3|cd1, cd2) .....





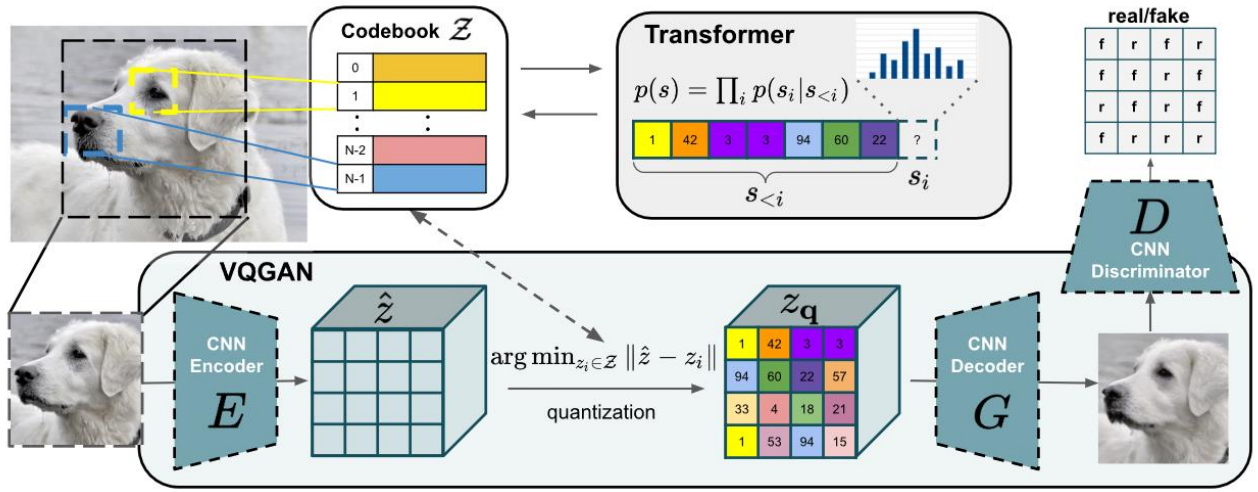
Neural Discrete Representation Learning

将p(z)定义为表示codebook中离散向量c的分布z(cb)



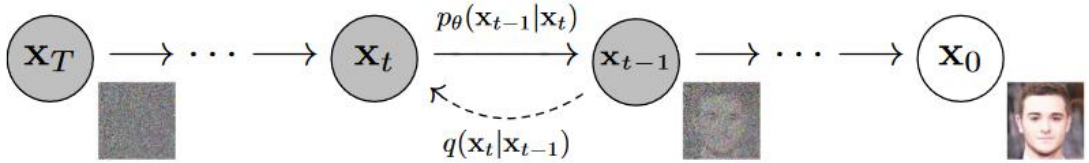
Discriminator

LPIPS



Taming Transformers for High-Resolution Image Synthesis

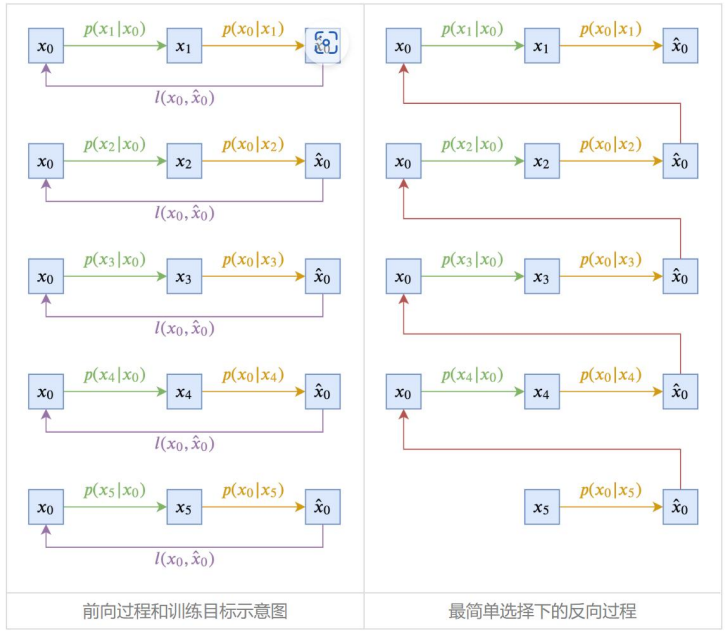
DDPM



$$Add\ Noise:\quad x_0 \;->\; x_1 \;->\; .. \;->\; x_{t-1} \;->\; x_t$$
$$x_t = a_t x_{t-1} + b_t \varepsilon_t\,, \quad \varepsilon_t \sim N(0, I) \quad {a_t}^2 + {b_t}^2 = 1$$

$$Del\ Noise:\quad \bar{x}_0 \;<-\; \bar{x}_1 \;<-\; .. \;<-\; \bar{x}_{t-1} \;<-\; x_t$$
$$x_{t-1} = \mu(x_t)$$

Denoising Diffusion Probabilistic Models



- Predict noise

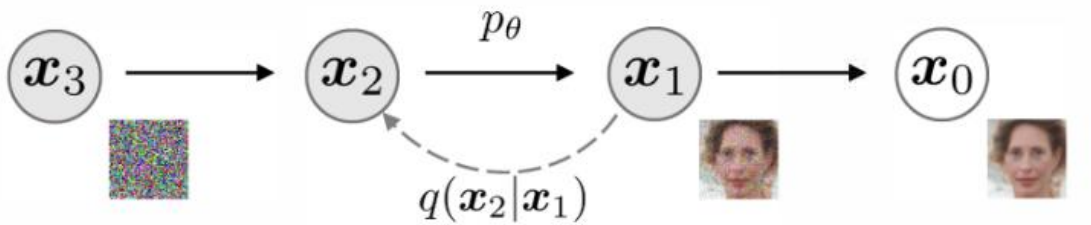
$$min||\mu(\bar{x}_t) - x_{t-1}||^2$$
$$\downarrow$$
$$min||\in_\theta(x_t, t) - \varepsilon_t||^2$$

- Using x_t x_0 to predict x_{t-1}

$$P(x_{t-1}|x_t, x_0) = N(x_{t-1}; \kappa_t x_t + \lambda_t x_0, \sigma^2 I)$$

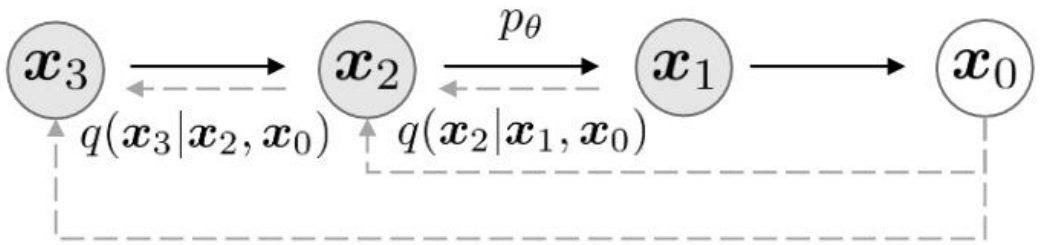
DDIM

$$Suppose:\ P(x_{t-1}|x_t, x_0) = N(x_{t-1}; \kappa_t x_t + \lambda_t x_0, \sigma^2 I)$$
$$= N(x_{t-1}; \frac{\sqrt{{\bar{b}_t}^2 - \sigma^2}}{\bar{b}_t} x_t + (\bar{a}_{t-1} - \frac{\bar{a}_t \sqrt{{\bar{b}_{t-1}}^2 - \sigma^2}}{\bar{b}_t}) x_0, \sigma^2 I)$$



Graphical models for diffusion

$$Sample:\ x_{\tau_{t-1}} = \frac{1}{a_{\tau_t}}(x_{\tau_t} - \frac{{b_{\tau_t}}^2}{{\bar{b}_{\tau_t}}^2} \in_\theta(x_t, \tau_t)) + \frac{\bar{b}_{\tau_{t-1}} {b_{\tau_t}}^2}{\bar{b}_{\tau_t}} \varepsilon$$
$$[\tau_1, \tau_2, ..., \tau_{t-1}\tau_t] \in [1,2, ..., t-1, t]$$



non-Markovain inference models

Denoising Diffusion Implicit Models

Deep Generative Model with Condition

00 Hidden Variables Guidance

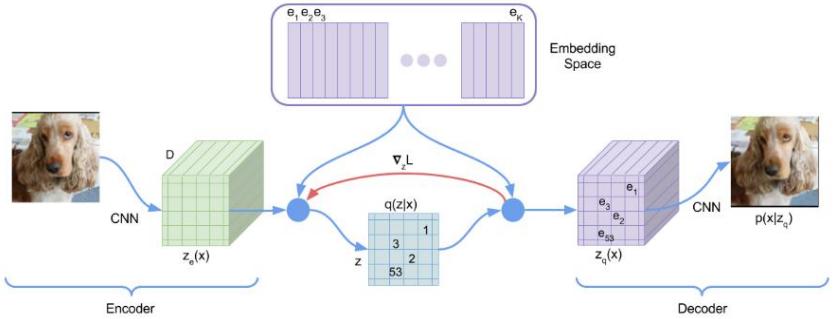
01 Classifier Diffusion Guidance

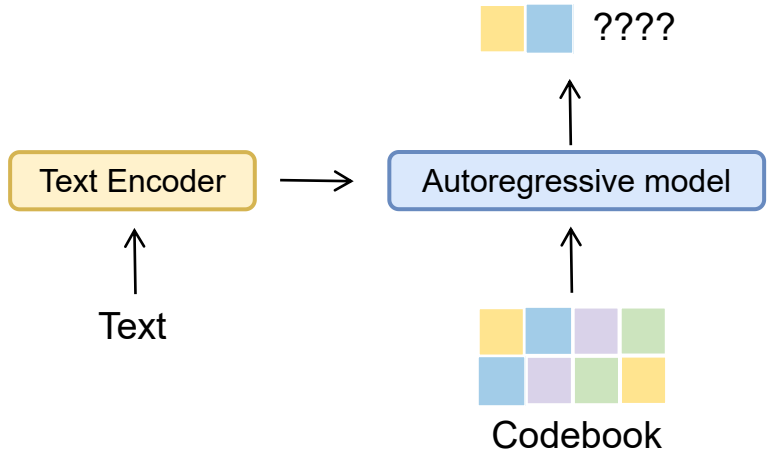
02 Classifier-Free Diffusion Guidance

Hidden Variables Guidance

VQVAE/VQGAN

Transformer-like



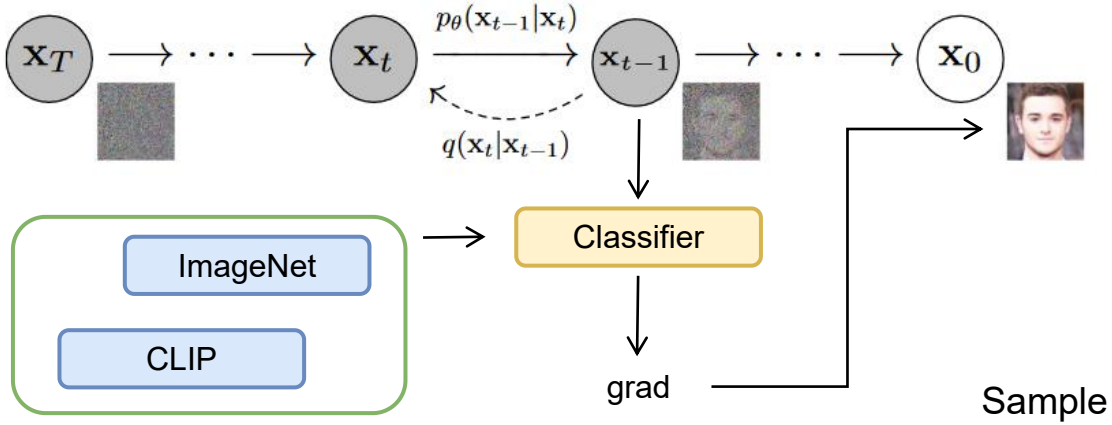


Classifier Diffusion Guidance

Diffusion Models

Sample: $\overline{\epsilon}_\theta(x_t, t) = \epsilon_\theta(x_t, t) - \overline{b}_t \omega \nabla_{x_t} log P(y|x_t)$

Diffusion Models Beat GANs on Image Synthesis

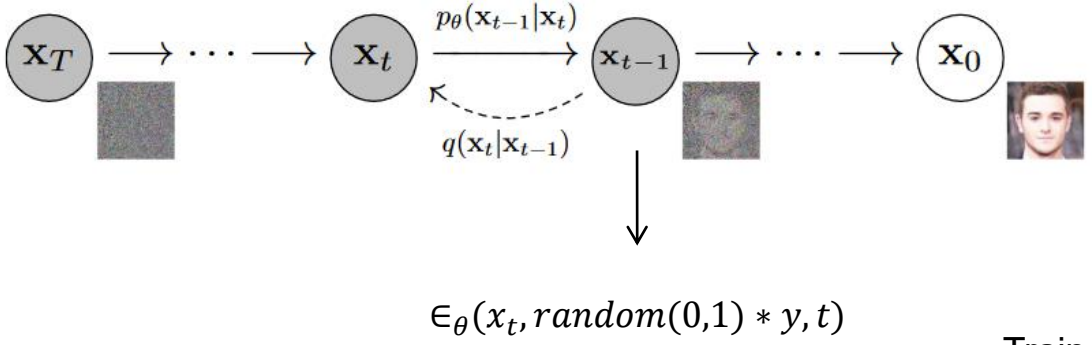


Classifier-Free Diffusion Guidance

Diffusion Models

Train: $\overline{\epsilon}_\theta(x_t, y, t) = \epsilon_\theta(x_t, y, t) + \omega(\overline{\epsilon}_\theta(x_t, y, t) - \overline{\epsilon}_\theta(x_t, t))$

Classifier-Free Diffusion Guidance



Multimodal Deep Generative Model

00 DALL.E & DALL.E mini

01 Parti

02 GLIDE & DALL.E 2

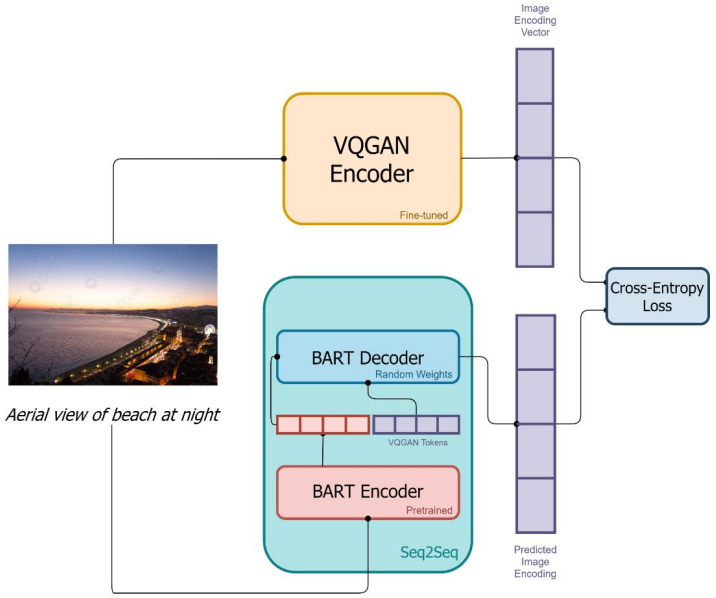
03 Imagen

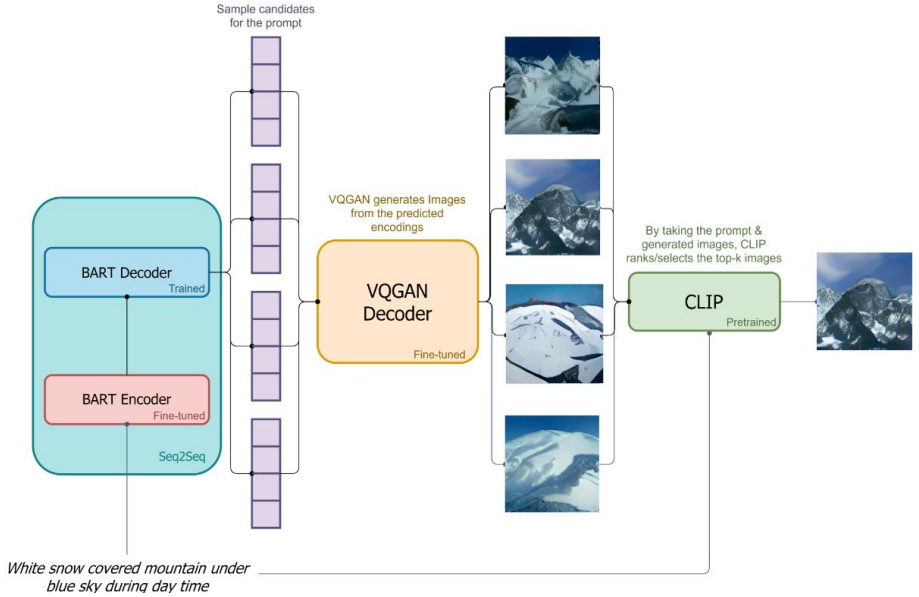
04 文心

DALL.E & DALL.E mini

(a) a tapir made of accordion. a tapir with the texture of an accordion.

(b) an illustration of a baby hedgehog in a christmas sweater walking a dog





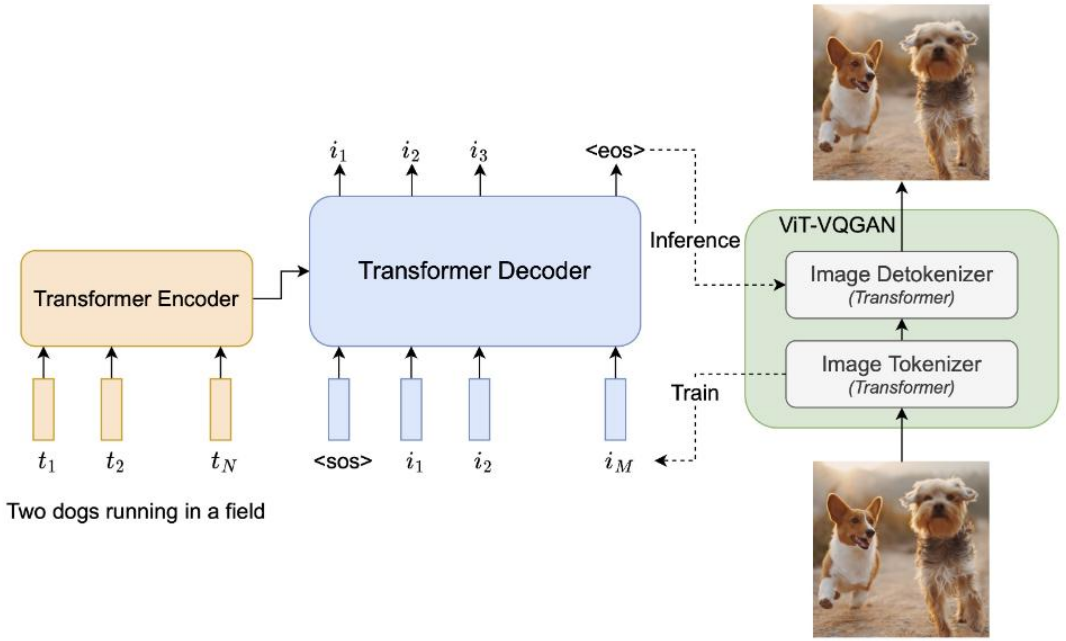
Zero-Shot Text-to-Image Generation

Parti

A. *A photo of a frog reading the newspaper named "Toaday" written on it. There is a frog printed on the newspaper too.*

B. *A portrait of a statue of the Egyptian god Anubis wearing aviator goggles, white t-shirt and leather jacket. The city of Los Angeles is in the background. Hi-res DSLR photograph.*

C. *A high-contrast photo of a panda riding a horse. The panda is wearing a wizard hat and is reading a book. The horse is standing on a street against a gray concrete wall. Colorful flowers and the word "PEACE" are painted on the wall. Green grass grows from cracks in the street. DSLR photograph. daytime lighting.*

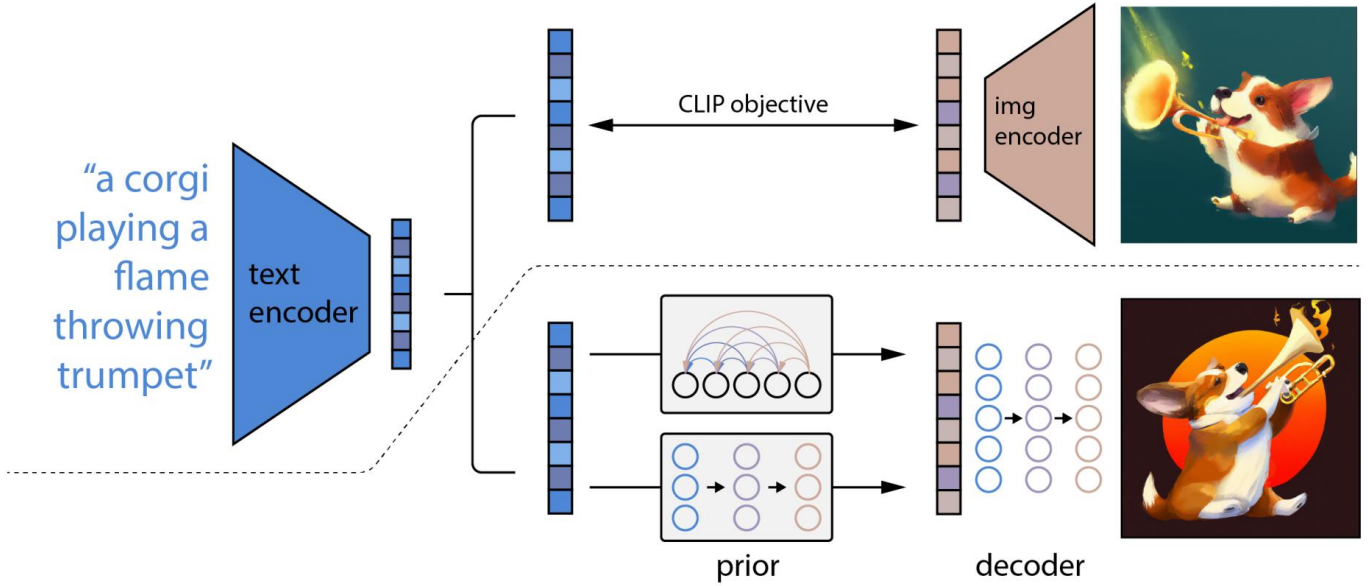


Scaling Autoregressive Models for Content-Rich Text-to-Image Generation

GLIDE & DALL.E 2

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

a teddy bear on a skateboard in times square



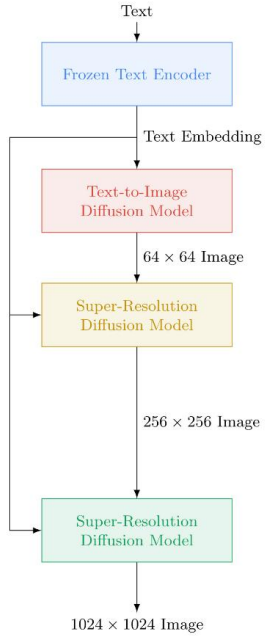
Hierarchical Text-Conditional Image Generation with CLIP Latents

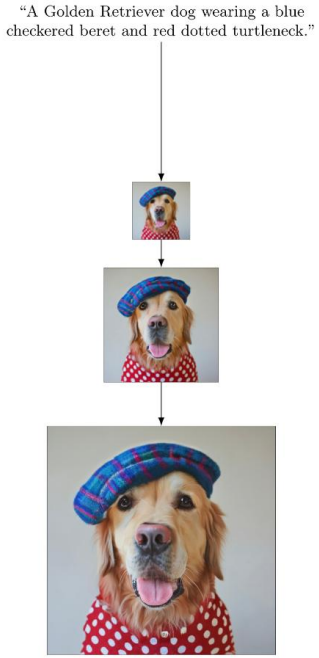
Imagen

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

A photo of a Shiba Inu dog with a backpack riding a bike. It is wearing sunglasses and a beach hat.

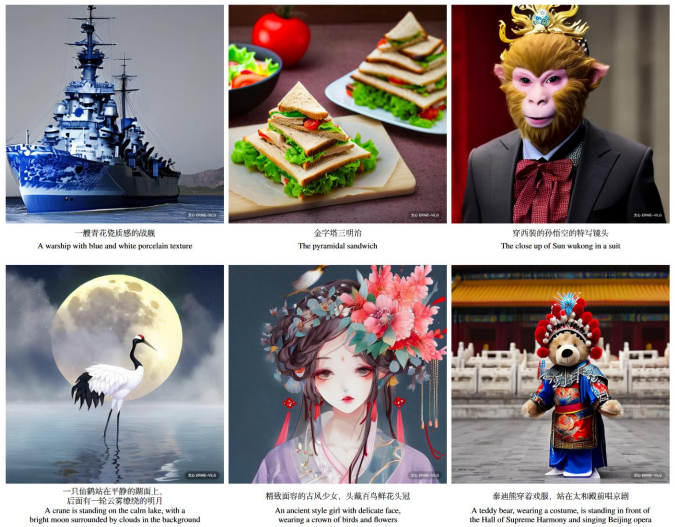
A high contrast portrait of a very happy fuzzy panda dressed as a chef in a high end kitchen making dough. There is a painting of flowers on the wall behind him.

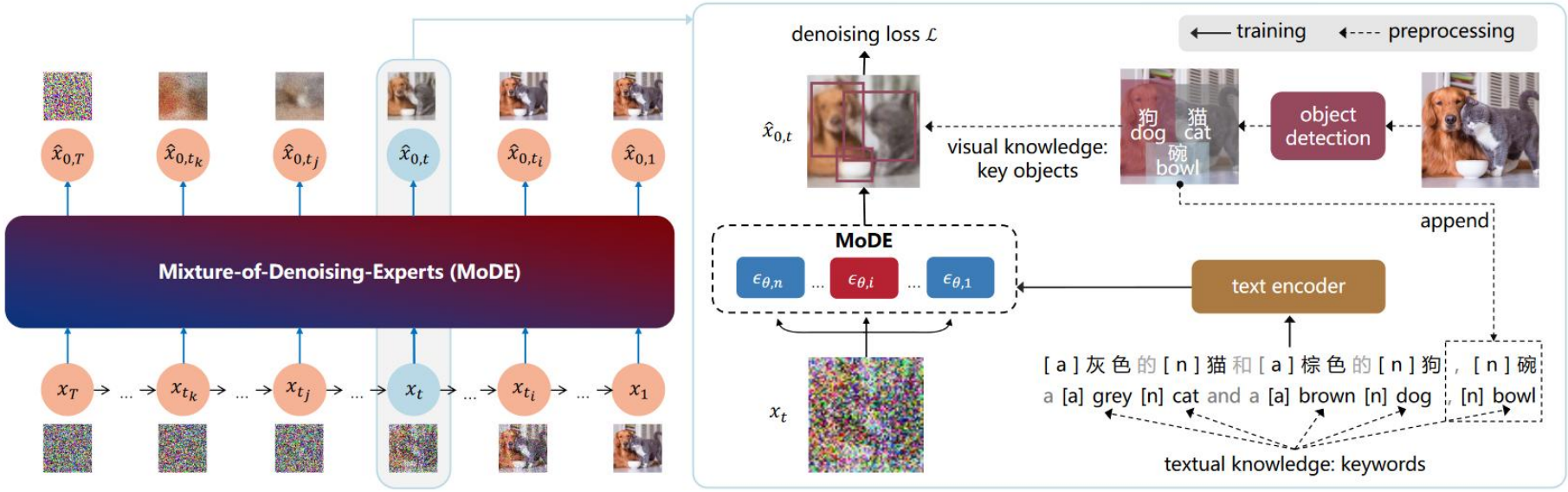




Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding

文心





ERNIE-ViLG 2.0: Improving Text-to-Image Diffusion Model with Knowledge-Enhanced Mixture-of-Denoising-Experts

Knowledge-Enhanced Diffusion Model：

$$\text{Attention}(Q,K,V)' = \text{softmax}\left(\frac{W_a \cdot (QK^\top)}{\sqrt{d}}\right)V,$$

$$\mathcal{L}' = \mathbb{E}_{z,\epsilon\sim\mathcal{N}(0,I),t}\left[W_l \cdot ||\epsilon - \epsilon_\theta(z_t,t)||_2^2\right]$$

Add text prompt from image

Image captioning model

Mixture-of-Denoising-Experts：

$$\epsilon_\theta(x_t,t) = \{\epsilon_{\theta,i}(x_t,t)\}, \quad t \in S_i,$$

Knowledge-Enhanced Diffusion Model

Mixture-of-Denoising-Experts

Model	Zero-Shot FID-30k ↓
DALL-E (Ramesh et al., 2021)	27.50
CogView (Ding et al., 2021)	27.10
LAFITE (Zhou et al., 2021)	26.94
LDM (Rombach et al., 2021)	12.61
ERNIE-ViLG (Zhang et al., 2021b)	14.70
GLIDE (Nichol et al., 2022)	12.24
Make-A-Scene (Gafni et al., 2022)	11.84
DALL-E 2 (Ramesh et al., 2022)	10.39
CogView2 (Ding et al., 2022)	24.00
Imagen (Saharia et al., 2022)	7.27
Parti (Yu et al., 2022)	7.23
ERNIE-ViLG 2.0	**6.75**

Quantitative analysis method

Latent Text-to-image Deep Generative Model

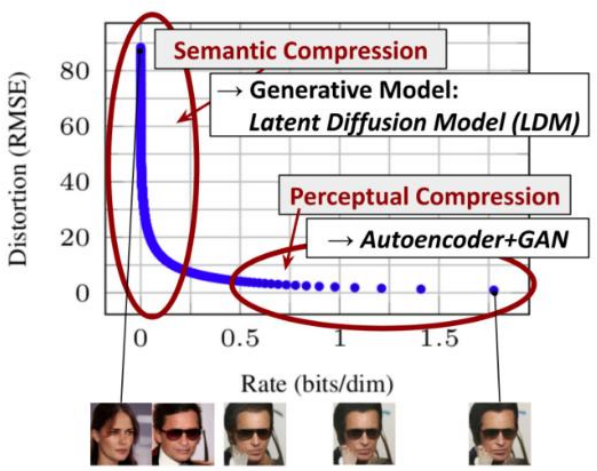
00 High-Resolution Image Synthesis with Latent Diffusion Models

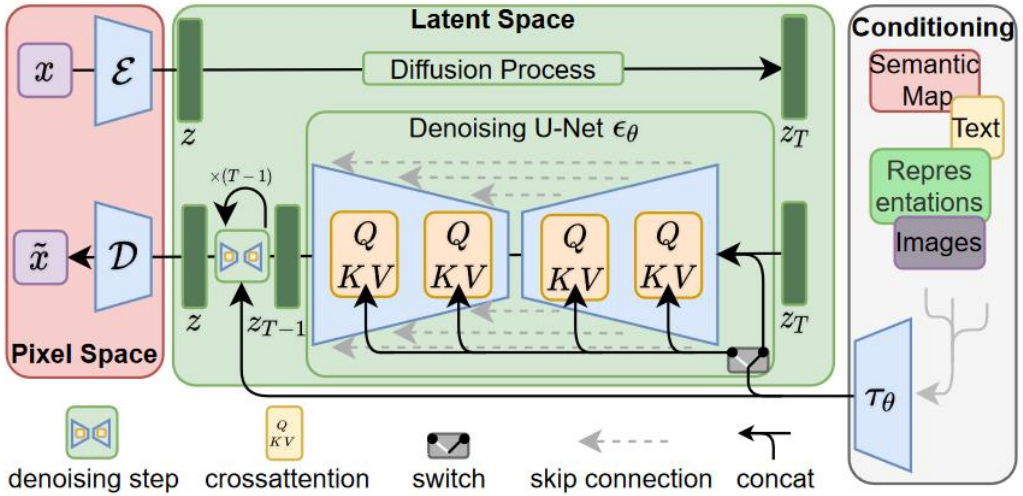
Stable-Diffusion: A latent text-to-image diffusion model

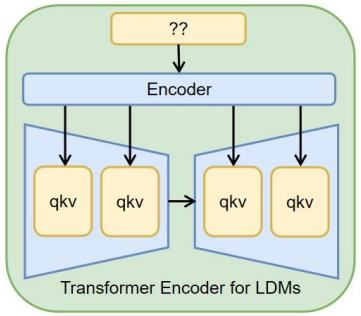
01 Frido: Feature Pyramid Diffusion for Complex Scene Image Synthesis

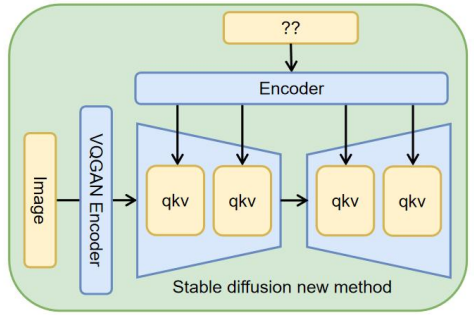
02 Pretraining is All You Need for Image-to-Image Translation

High-Resolution Image Synthesis with Latent Diffusion Models







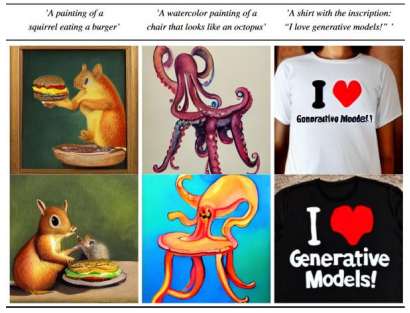


Q
KV

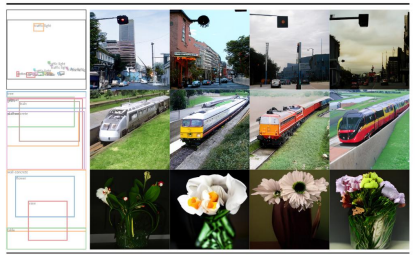
$$K = W_K^{(i)} \cdot \tau_\theta(y), \qquad V = W_V^{(i)} \cdot \tau_\theta(y).$$
$$Q = W_Q^{(i)} \cdot \varphi_i(z_t),$$

cross-attention

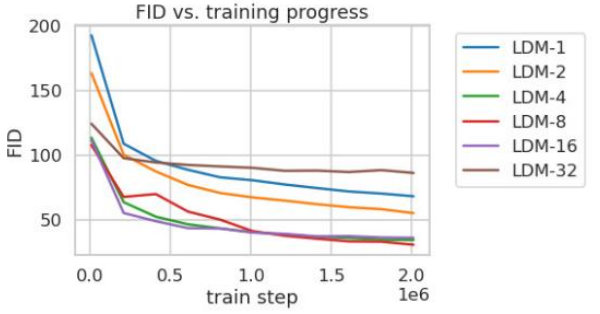
High-Resolution Image Synthesis with Latent Diffusion Models



Test to image



Layout to image

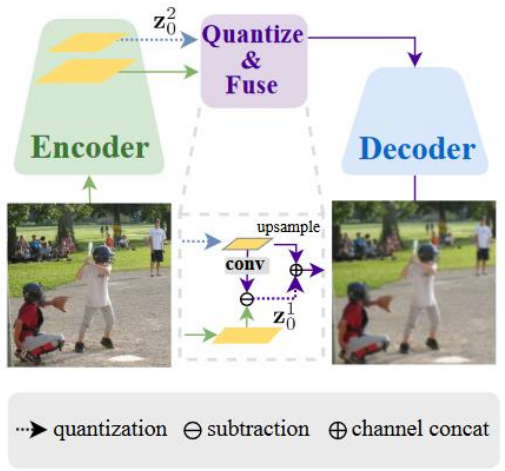


Super-Resolution

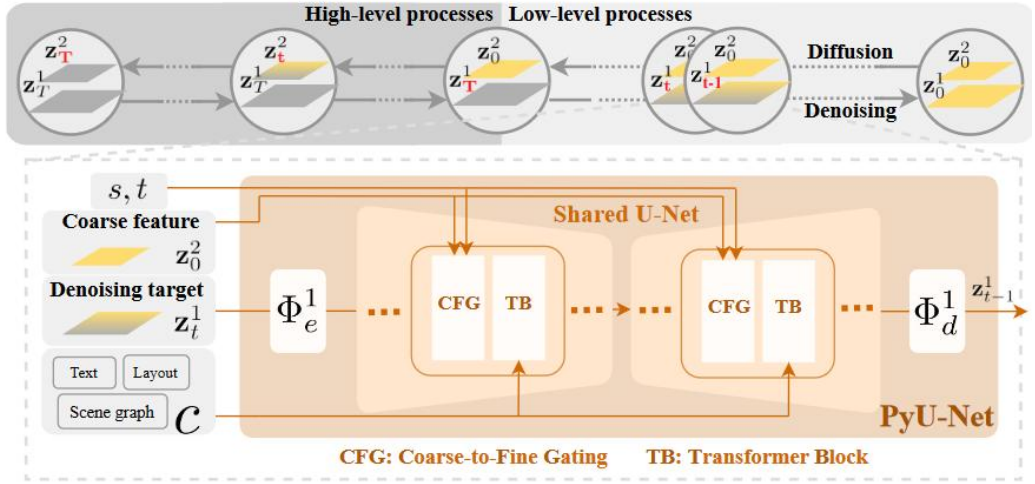
Inpainting

Method	Generator Compute	Classifier Compute	Overall Compute	Inference Throughput*	N_{params}	FID↓	IS↑	Precision↑	Recall↑
LSUN Churches 256^2									
StyleGAN2 [42]†	64	-	64	-	59M	3.86	-	-	-
LDM-8 (ours, 100 steps, 410K)	18	-	18	6.80	256M	4.02	-	0.64	0.52
LSUN Bedrooms 256^2									
ADM [15]† (1000 steps)	232	-	232	0.03	552M	1.9	-	0.66	0.51
LDM-4 (ours, 200 steps, 1.9M)	60	-	55	1.07	274M	2.95	-	0.66	0.48
CelebA-HQ 256^2									
LDM-4 (ours, 500 steps, 410K)	14.4	-	14.4	0.43	274M	5.11	-	0.72	0.49
FFHQ 256^2									
StyleGAN2 [42]	32.13‡	-	32.13†	-	59M	3.8	-	-	-
LDM-4 (ours, 200 steps, 635K)	26	-	26	1.07	274M	4.98	-	0.73	0.50
ImageNet 256^2									
VQGAN-f-4 (ours, first stage)	29	-	29	-	55M	0.58††	-	-	-
VQGAN-f-8 (ours, first stage)	66	-	66	-	68M	1.14††	-	-	-
BigGAN-deep [3]†	128-256		128-256	-	340M	6.95	$203.6_{\pm 2.6}$	0.87	0.28
ADM [15] (250 steps) †	916	-	916	0.12	554M	10.94	100.98	0.69	0.63
ADM-G [15] (25 steps) †	916	46	962	0.7	608M	5.58	-	0.81	0.49
ADM-G [15] (250 steps)†	916	46	962	0.07	608M	4.59	186.7	0.82	0.52
ADM-G,ADM-U [15] (250 steps)†	329	30	349	n/a	n/a	3.85	221.72	0.84	0.53
LDM-8-G (ours, 100, 2.9M)	79	12	91	1.93	506M	8.11	$190.4_{\pm 2.6}$	0.83	0.36
LDM-8 (ours, 200 ddim steps 2.9M, batch size 64)	79	-	79	1.9	395M	17.41	72.92	0.65	0.62
LDM-4 (ours, 250 ddim steps 178K, batch size 1200)	271	-	271	0.7	400M	10.56	$103.49_{\pm 1.24}$	0.71	0.62
LDM-4-G (ours, 250 ddim steps 178K, batch size 1200, classifier-free guidance [32] scale 1.25)	271	-	271	0.4	400M	3.95	$178.22_{\pm 2.43}$	0.81	0.55
LDM-4-G (ours, 250 ddim steps 178K, batch size 1200, classifier-free guidance [32] scale 1.5)	271	-	271	0.4	400M	3.60	$247.67_{\pm 5.59}$	0.87	0.48

Frido: Feature Pyramid Diffusion for Complex Scene Image Synthesis



(a) Architecture of MS-VQGAN.



(b) Details of the diffusion and denoising processes.

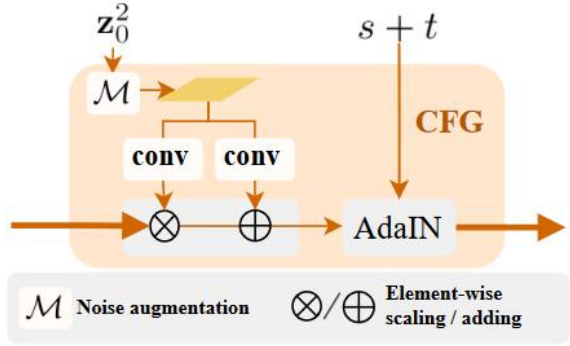
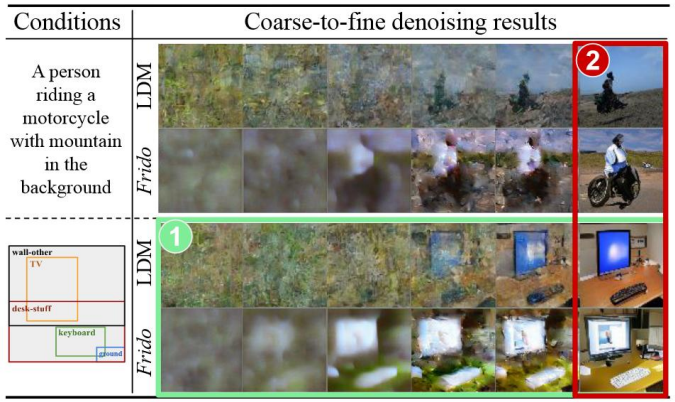


Figure 4: Framework of coarse-to-fine gating in PyU-Net.

Frido: Feature Pyramid Diffusion for Complex Scene Image Synthesis



Problem:

Most of existing DMs might not be able to capture image semantics or compositions in real-world complex scenes

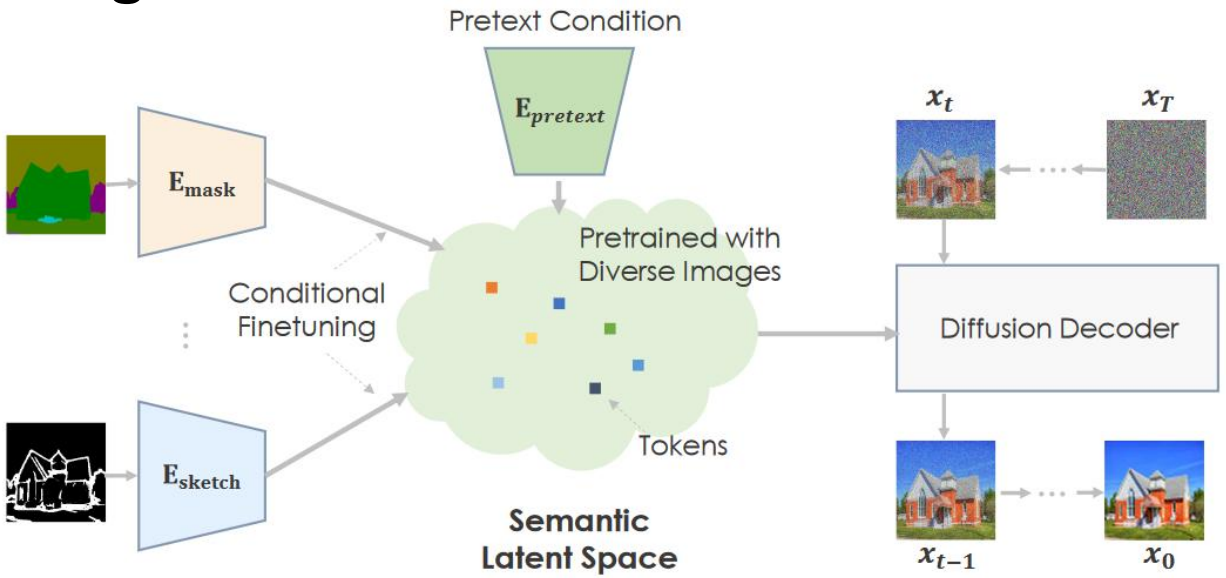
Methods	FID↓	IS↑	CLIP↑
Methods under standard T2I setting			
AttnGAN (Xu et al. 2018)	33.10	23.61	-
Obj-GAN (Li et al. 2019)	36.52	24.09	-
DM-GAN (Zhu et al. 2019)	27.34	**32.32**	-
DF-GAN (Tao et al. 2022)	21.42	-	-
LDM-8† (Rombach et al. 2022)	17.61	19.34	0.6500
VQ-diffusion‡ (Gu et al. 2022)	14.06	21.85	0.6770
LDM-8-G†	12.27	27.86	0.6927
Frido-f16f8	15.38	19.32	0.6607
Frido-f16f8-G	**11.24**	26.82	**0.7046**
Methods with external pre-trained CLIP			
LAFITE-CLIP‡ (Zhou et al. 2022)	**8.12**	**32.24**	0.7915
Frido-f16f8-G-CLIPr	8.97	27.43	**0.7991**

Pretraining is All You Need for Image-to-Image Translation

Old Method -> train the decoder with encoder fixed

First Step -> train the encoder with decoder fixed
Second Step -> finetune encoder and decoder jointly

GT | Condition | SPADE | OASIS | Ours

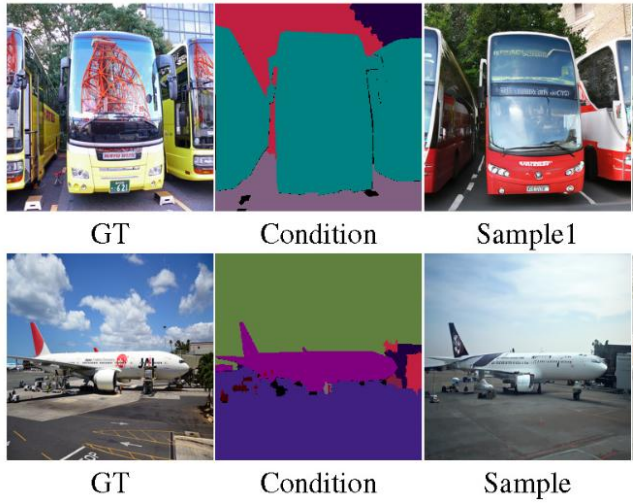


Pretraining is All You Need for Image-to-Image Translation

Input | Fixed decoder | Full model | Input | Fixed decoder | Full model

(a) Finetune strategy.

Finetune strategy	FID
Fixed decoder	12.6
One-stage finetune	13.3
Two-stage finetune	8.9



GT | Condition | Sample1

GT | Condition | Sample

Fixed encoder -> DMs don't know the semanteme which get from image encoder

Fixed decoder -> DMs don't konw the semanteme which represents spatial properties

One-stage finetune -> Change the DMs' semanteme and image encoder's semanteme

Two-stage finetune -> First, image encoder learn the semanteme of DMs
Second, change the DMs' semanteme and image encoder's semanteme of spatial properties

Other problems

Downstream task of Deep Generative Model

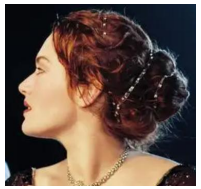
00 Subject-Driven Generation

01 Image Edition

Subject-Driven Generation

[identifier]

"...draw me like one of your French girls."



what Rose looks like

a subset of Jack's prior

1、describe

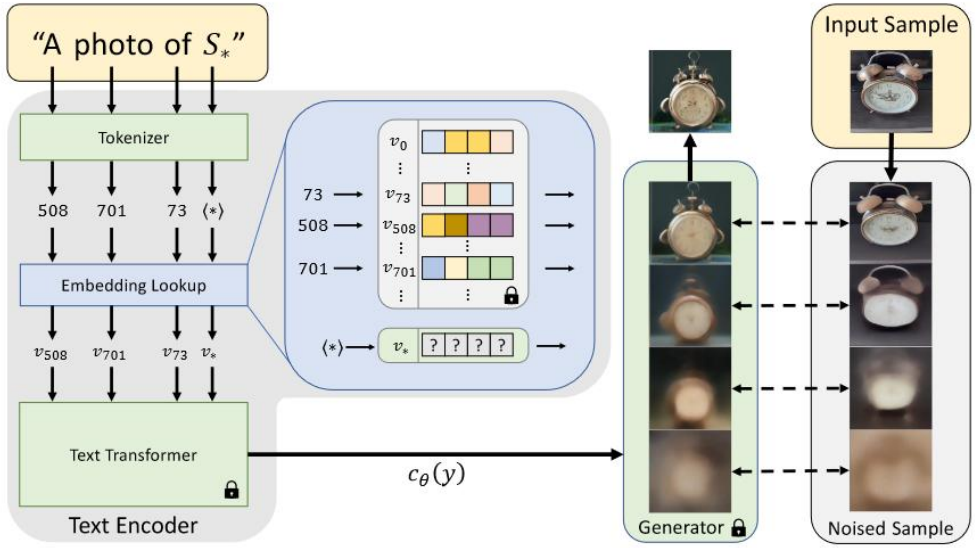
Blonde hair, Blue eyes.....

2、fine-tuning

Deep Generation Model

Embedding

for computer



An Image is Worth One Word: Personalizing Text-to-Image Generation using Textual Inversion

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

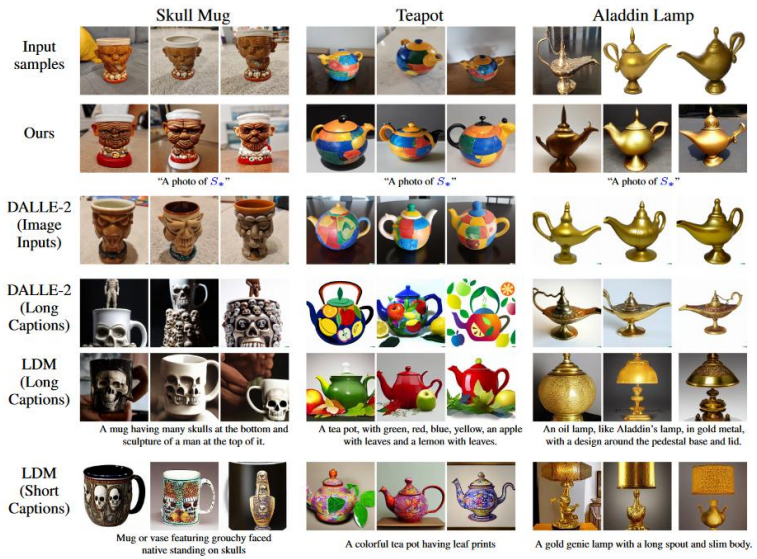
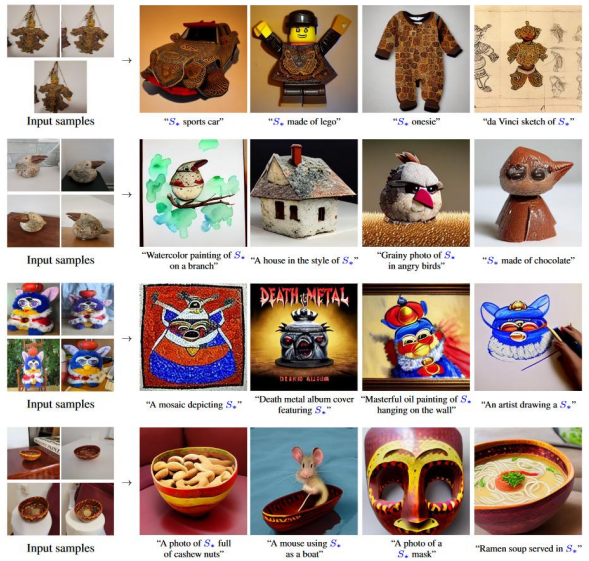


Image Variations



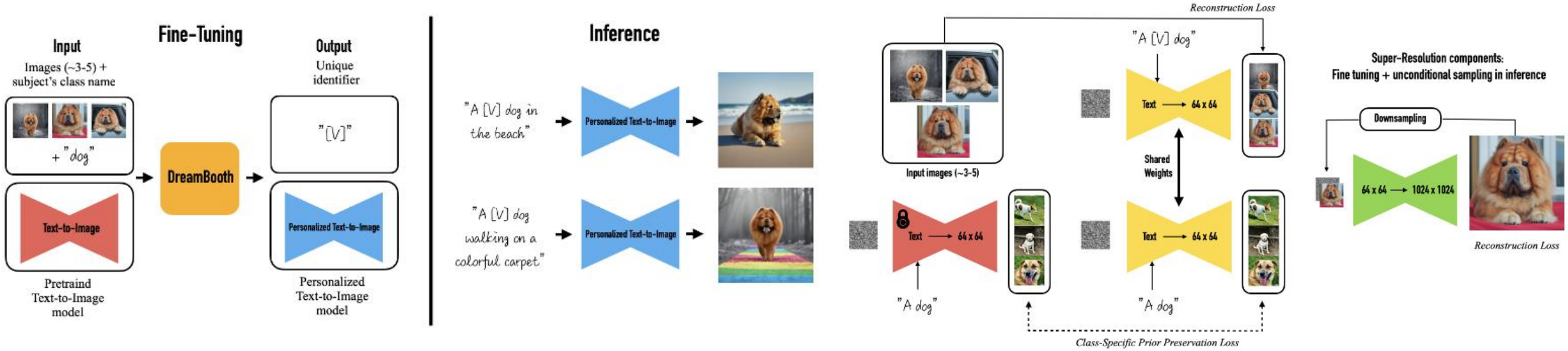
Text-guided synthesis

Style transfer

Concept compositons

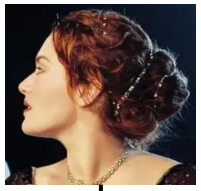
Subject-Driven Generation

[identifier][class noun]



DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation

1、describe



Blonde hair

Blue eyes

necklace

T2I domain

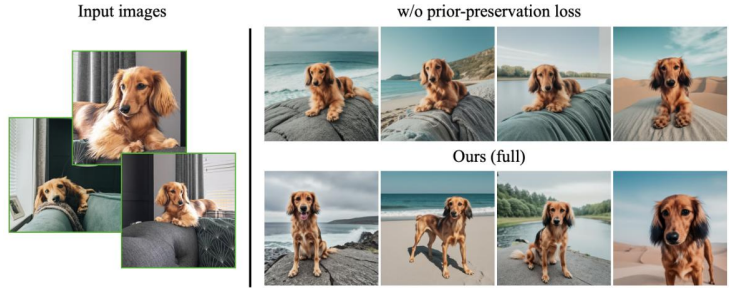
2、fine-tuning

girl celled Rose

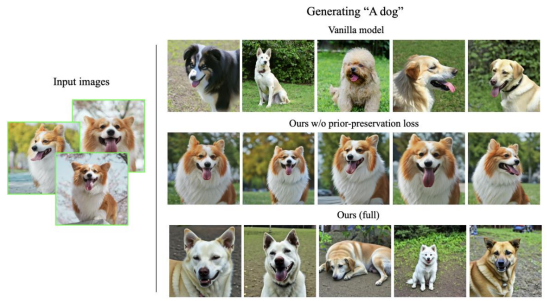
girl with Blonde hair

girl with Blue eyes

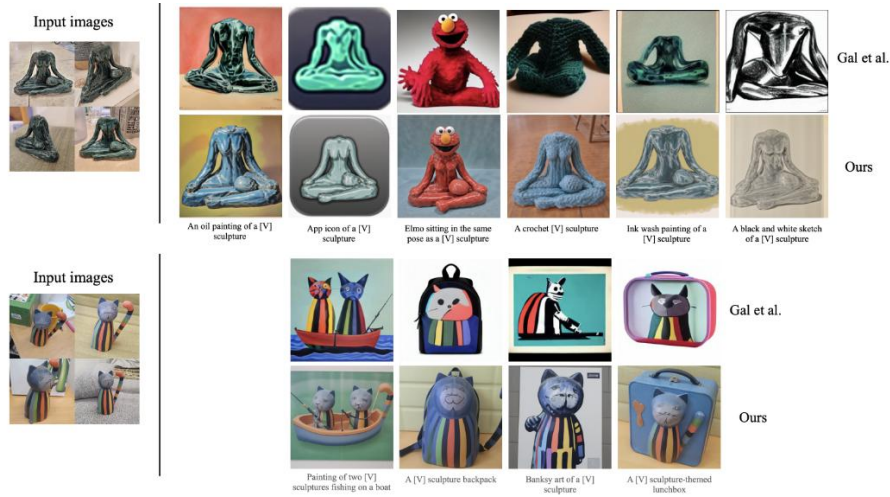
T2I domain



Overfitting



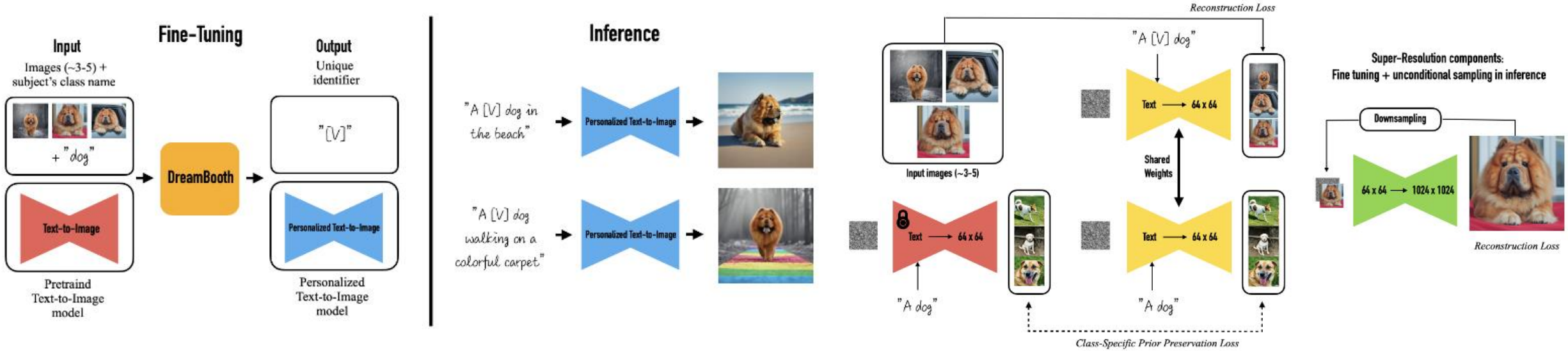
Language-drift



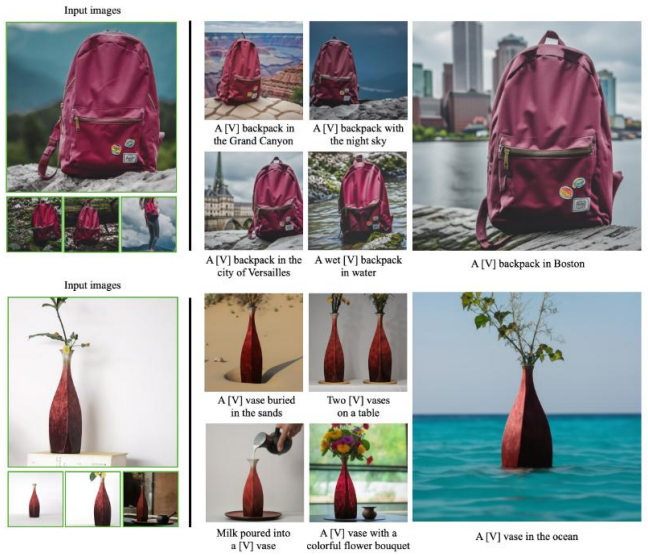
Comparison with Text Inversion

Subject-Driven Generation

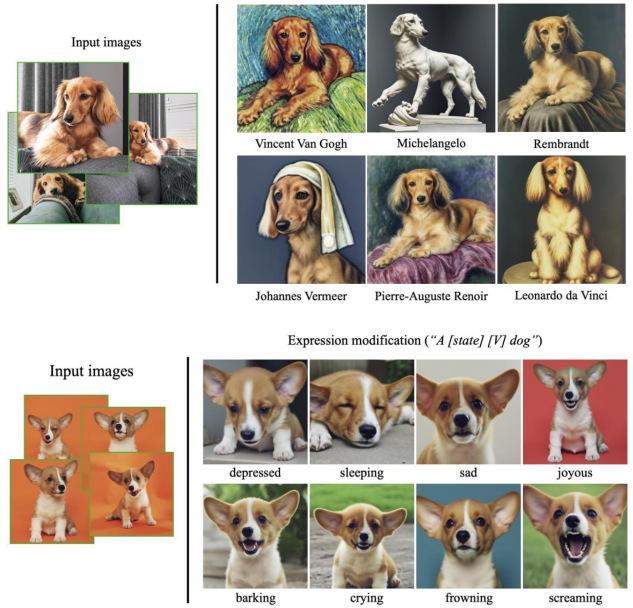
[identifier][class noun]

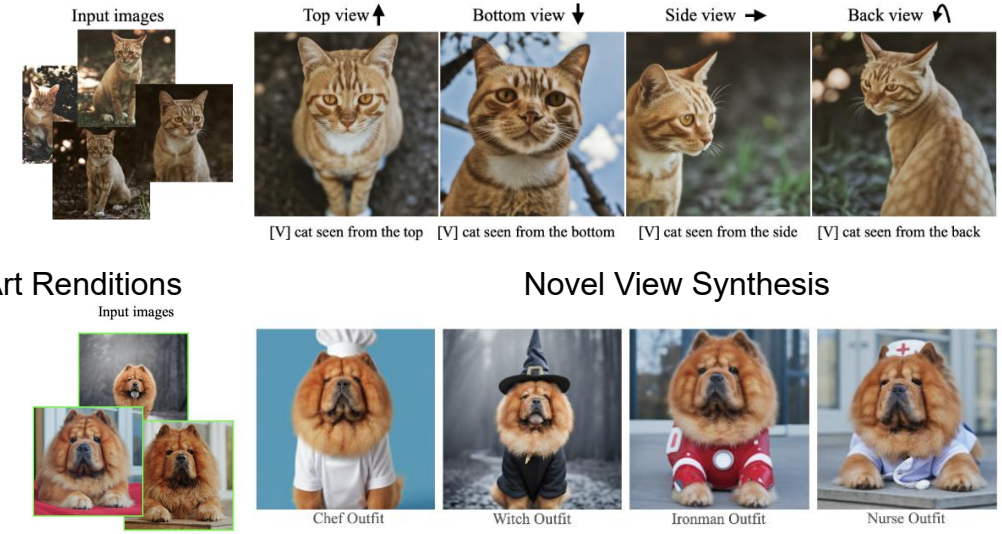


DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation

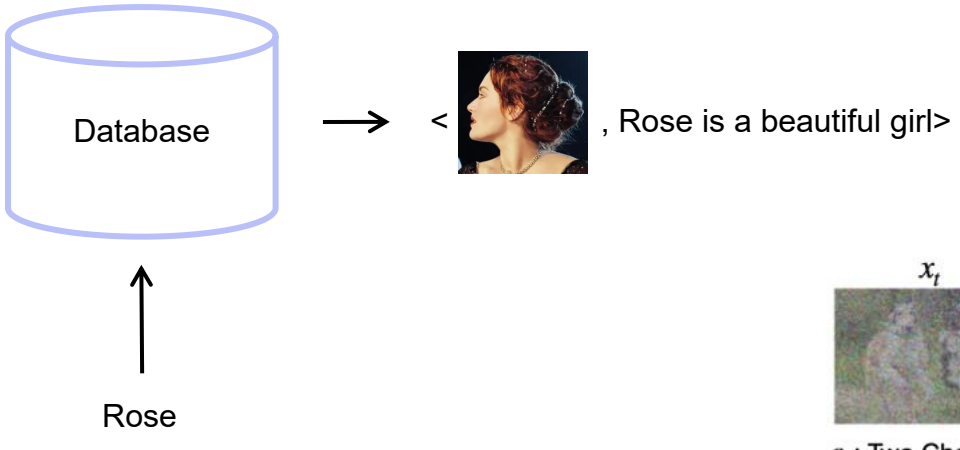


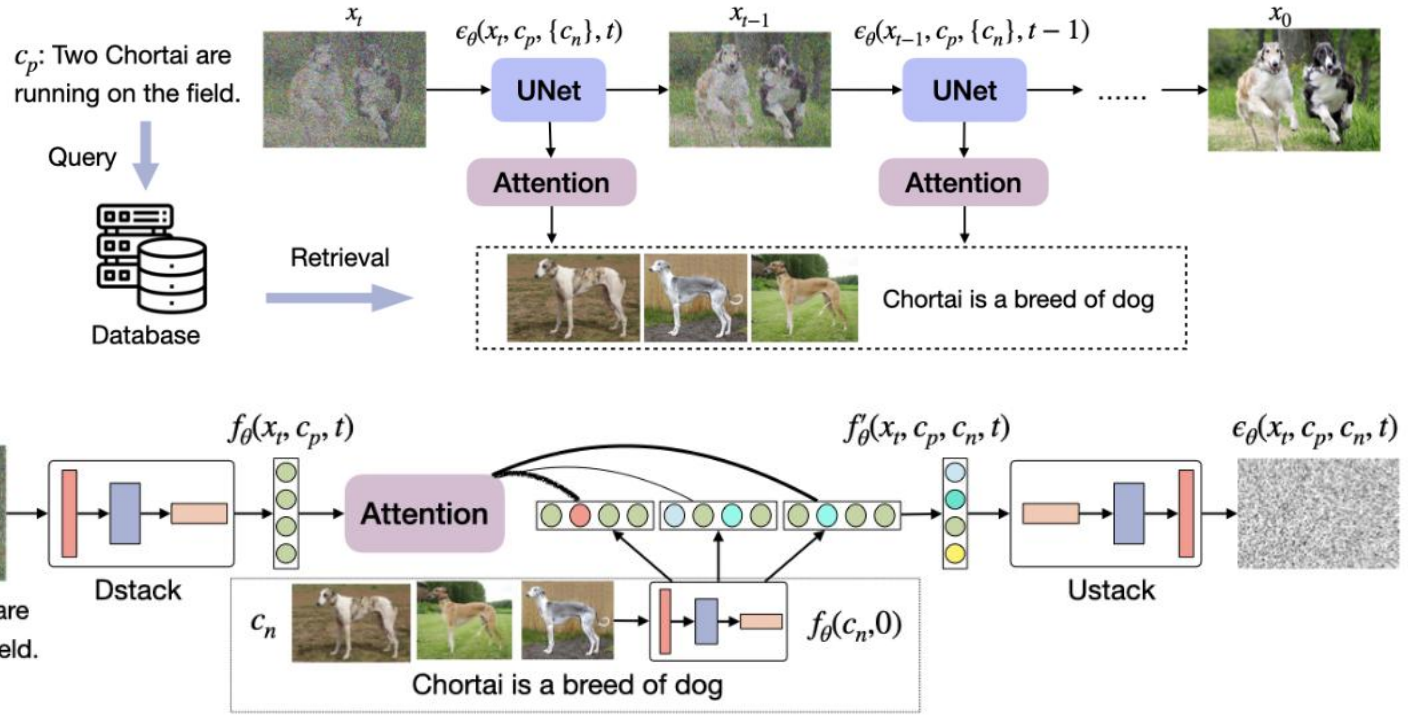
Recontextualization





Retrieval-Augmented Generation





Re-imagen: retrieval-augmented test-to-image generator

$$\hat{\epsilon}_p = w_p \cdot \epsilon_\theta(\boldsymbol{x}_t, \boldsymbol{c}_p, \boldsymbol{c}_n, t) - (w_p - 1) \cdot \epsilon_\theta(\boldsymbol{x}_t, \boldsymbol{c}_n, t)$$
$$\hat{\epsilon}_n = w_n \cdot \epsilon_\theta(\boldsymbol{x}_t, \boldsymbol{c}_p, \boldsymbol{c}_n, t) - (w_n - 1) \cdot \epsilon_\theta(\boldsymbol{x}_t, \boldsymbol{c}_p, t)$$

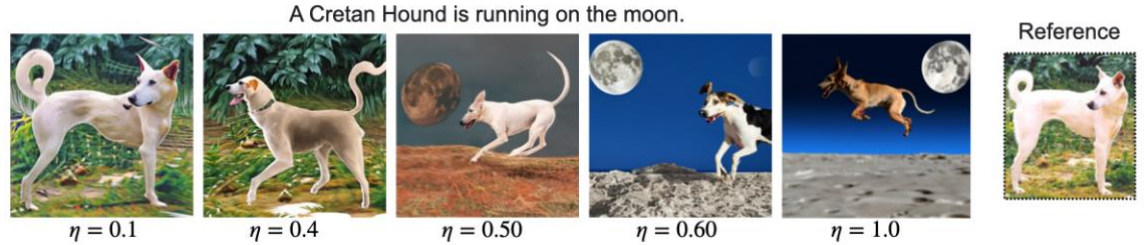


Image Edition

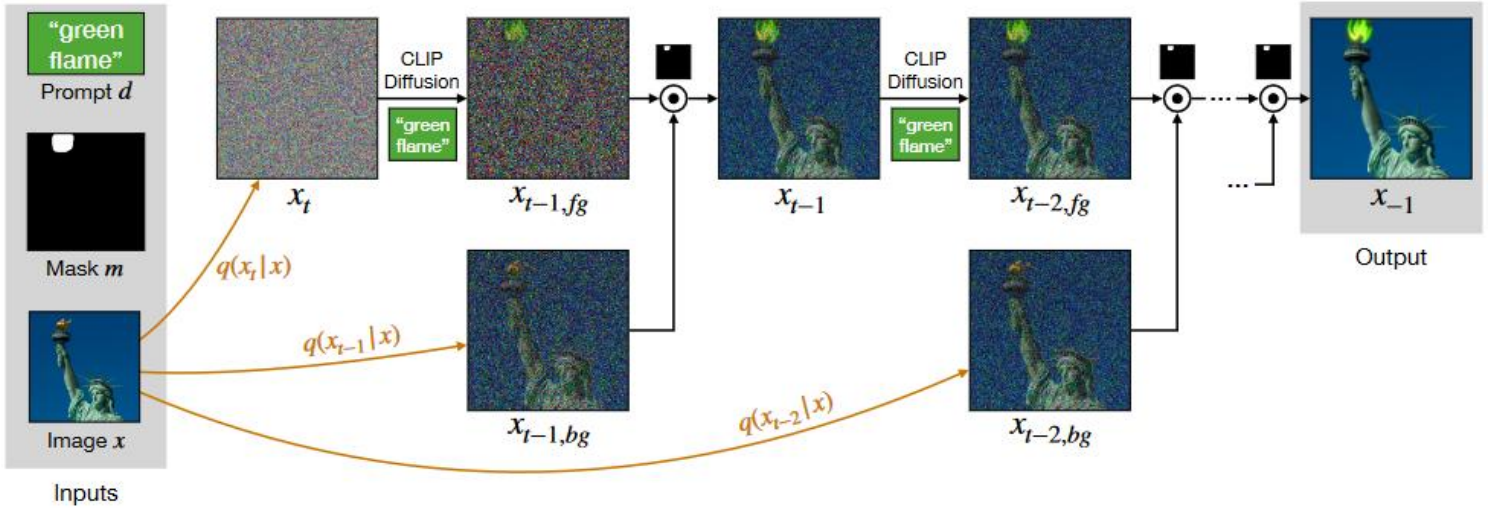
foreground preservation loss:

$$\mathcal{D}_{CLIP}(x, d, m) = D_c(CLIP_{img}(x \odot m), CLIP_{txt}(d))$$

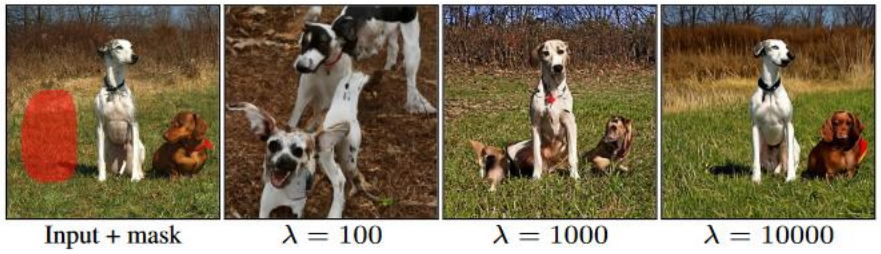
background preservation loss:

$$\mathcal{D}_{bg}(x_1, x_2, m) = d(x_1 \odot (1 - m), x_2 \odot (1 - m))$$

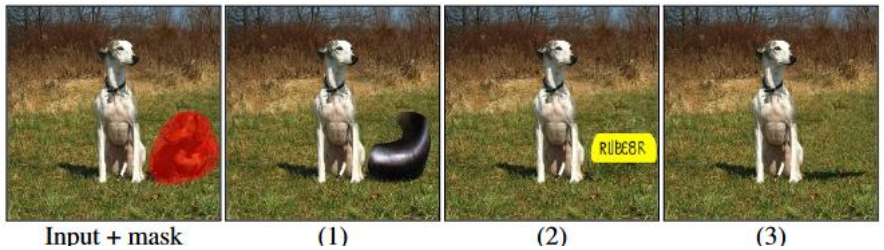
$$d(x_1, x_2) = \frac{1}{2}(MSE(x_1, x_2) + LPIPS(x_1, x_2))$$



Blended Diffusion for Text-driven Editing of Natural Images



problem: Local CLIP-guided diffusion



problem: Text-driven blended diffusion

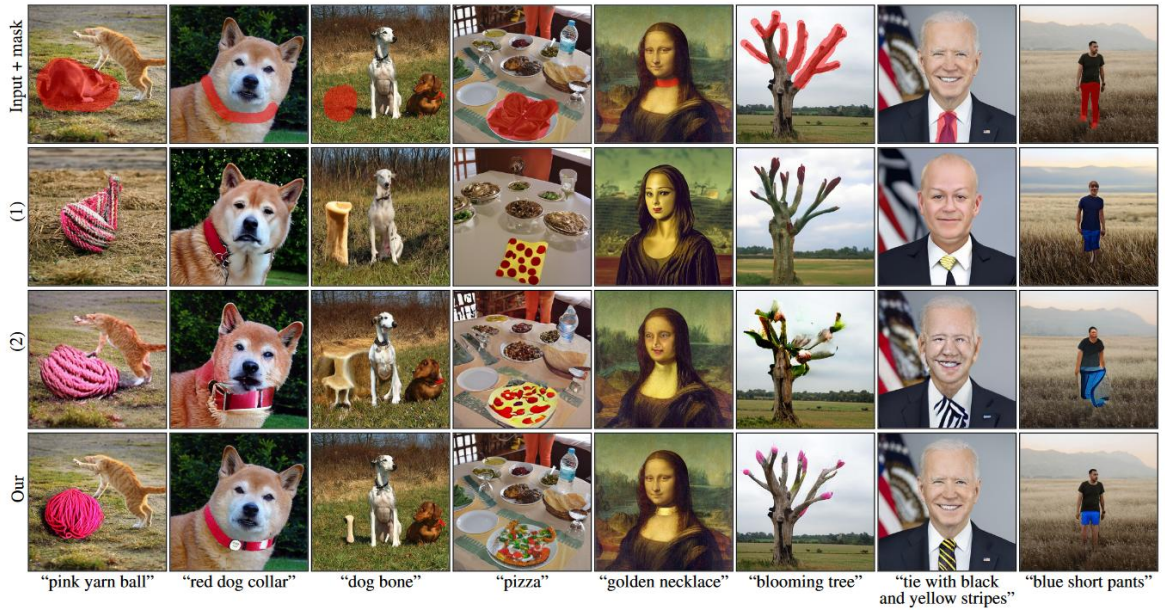
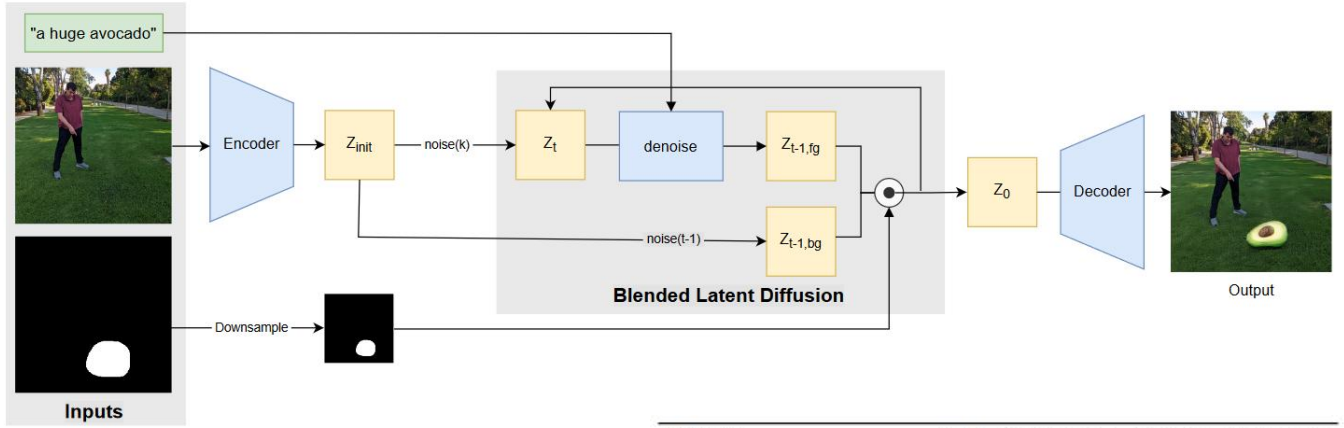


Image Edition

Blended Diffusion VS Blended Latent Diffusion

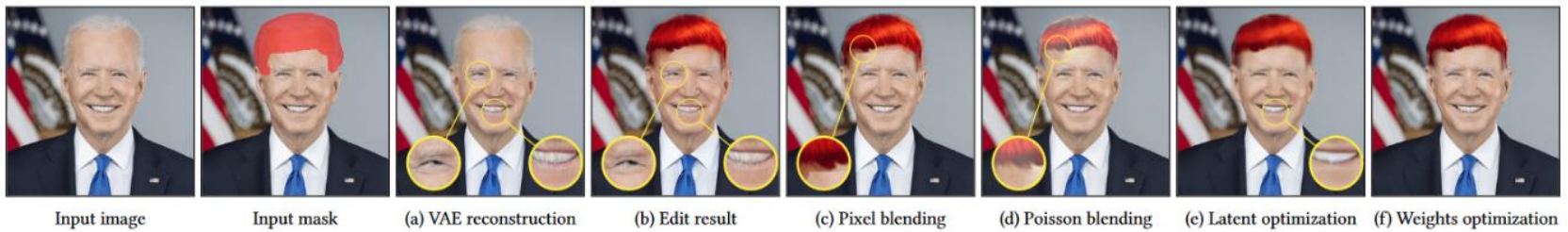
Other problems

Blended Latent Diffusion



Method	Batch Precision ↑	Batch Diversity ↑	Best Result Precision ↑
Blended Diffusion	10.4%	0.106	36%
Local CLIP-guided diffusion	10.49%	**0.419**	38%
PaintByWord++	-	-	0%
GLIDE-filtered	1.87%	0.114	4%
Ours	**28.66%**	0.115	**54%**

Method	Batch Size	Single Image (sec) ↓	Full Batch (sec) ↓	Per Image in Batch (sec) ↓
Blended Diffusion	64	27	1472	23
Blended Diffusion	24*	27	552	23
Local CLIP-guided diffusion	64	27	1472	23
Local CLIP-guided diffusion	24*	27	552	23
PaintByWord++	-	78	-	-
GLIDE-filtered	24	7	89	3.7
Ours (without background opt.)	24	6	53	2.2
Ours (with background opt.)	24	25	72	3



(a) VAE重建效果； (b) LDM编辑效果； (c) LDM编辑后与图像重叠； (d) 泊松混合后； (e) 隐变量优化后； (f) 微调decoder后

Problem one: Imperfect reconstruction

Method A: latent optimization $z^* = \underset{z}{\operatorname{argmin}} \|D(z)\odot m, \hat{x}\odot m\| + \lambda \|D(z)\odot(1-m), x\odot(1-m)\|$

Method B: fine-tuning the decoder's weights $\theta^* = \underset{\theta}{\operatorname{argmin}} \|D_\theta(z_0)\odot m, \hat{x}\odot m\| + \lambda \|D_\theta(z_0)\odot(1-m), x\odot(1-m)\|,$

Problem two: Thin mask

Image Edition

CLIP loss:

Global target loss:

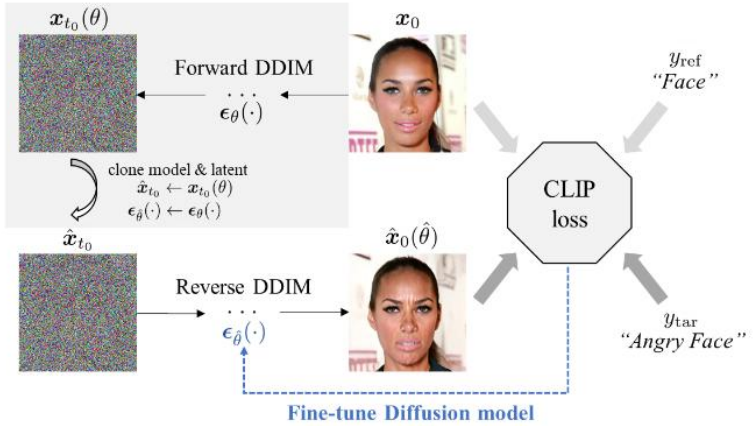
$$\mathcal{L}_{\text{global}}(\boldsymbol{x}_{\text{gen}}, y_{\text{tar}}) = D_{\text{CLIP}}(\boldsymbol{x}_{\text{gen}}, y_{\text{tar}}),$$

Local directional loss:

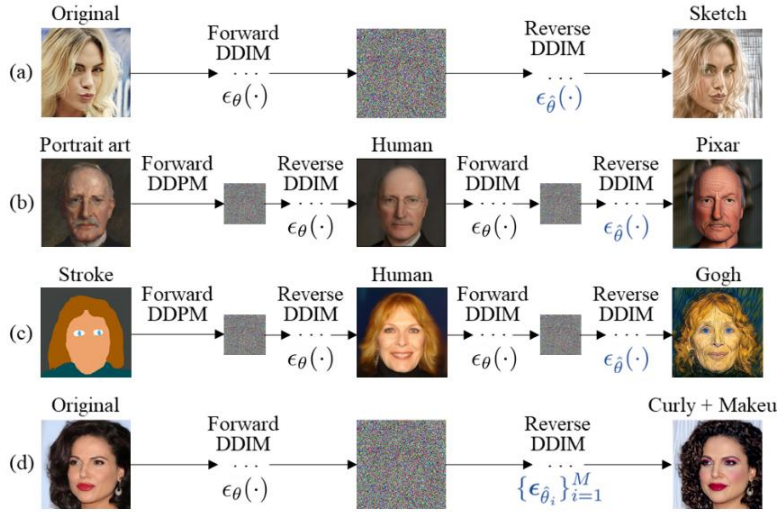
$$\mathcal{L}_{\text{direction}}(\boldsymbol{x}_{\text{gen}}, y_{\text{tar}}; \boldsymbol{x}_{\text{ref}}, y_{\text{ref}}) := 1 - \frac{\langle \Delta I, \Delta T \rangle}{\|\Delta I\| \|\Delta T\|}, \qquad (9)$$

where

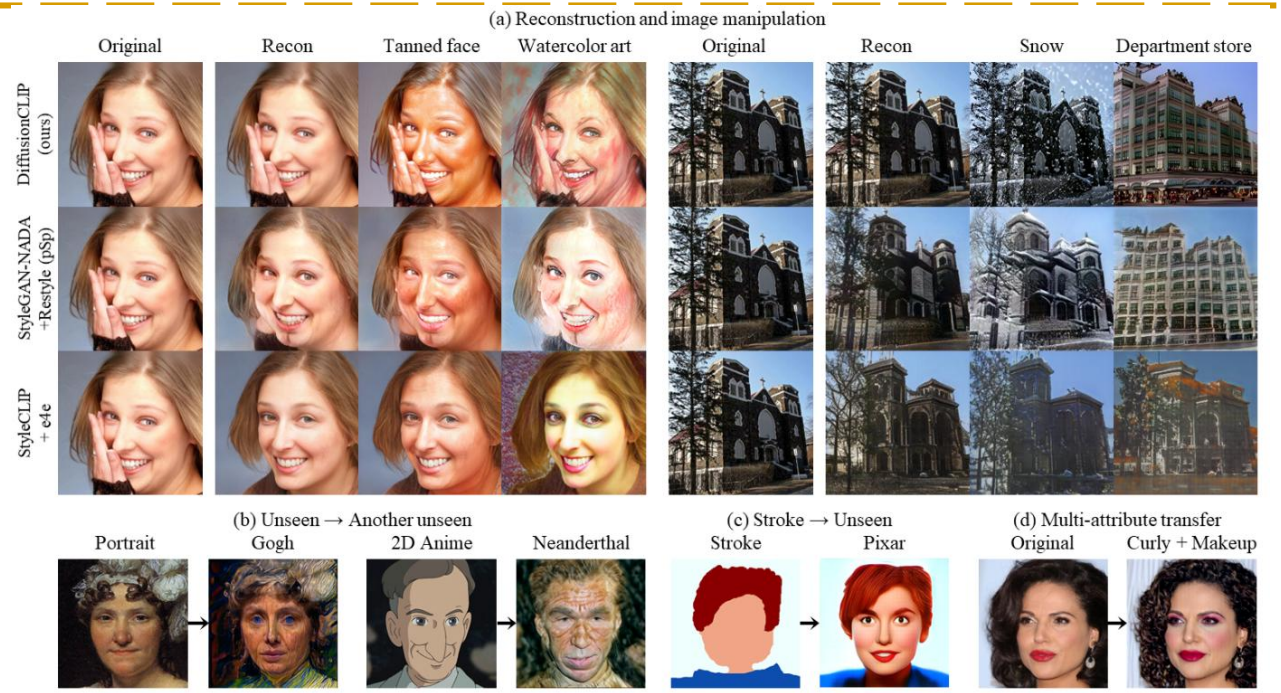
$$\Delta T = E_T(y_{\text{tar}}) - E_T(y_{\text{ref}}),\ \Delta I = E_I(\boldsymbol{x}_{\text{gen}}) - E_I(\boldsymbol{x}_{\text{ref}}).$$

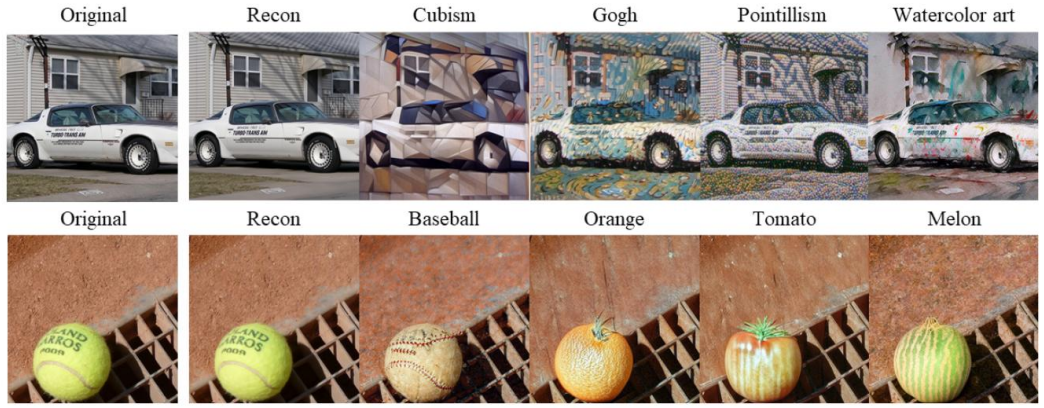


$$\mathcal{L}_{\text{direction}}\left(\hat{\boldsymbol{x}}_0(\hat{\theta}), y_{\text{tar}}; \boldsymbol{x}_0, y_{\text{ref}}\right) + \mathcal{L}_{\text{id}}(\hat{\boldsymbol{x}}_0(\hat{\theta}), \boldsymbol{x}_0),$$



DiffusionCLIP: Text-Guided Diffusion Models for Robust Image Manipulation





	CelebA-HQ			LSUN-Church	
	$\mathcal{S}_{\text{dir}}\uparrow$	SC↑	ID↑	$\mathcal{S}_{\text{dir}}\uparrow$	SC↑
StyleCLIP	0.13	86.8%	0.35	0.13	67.9%
StyleGAN-NADA	0.16	89.4%	0.42	0.15	73.2%
DiffusionCLIP (Ours)	**0.17**	**93.7%**	**0.70**	**0.20**	**78.1%**

Image Edition

qkv

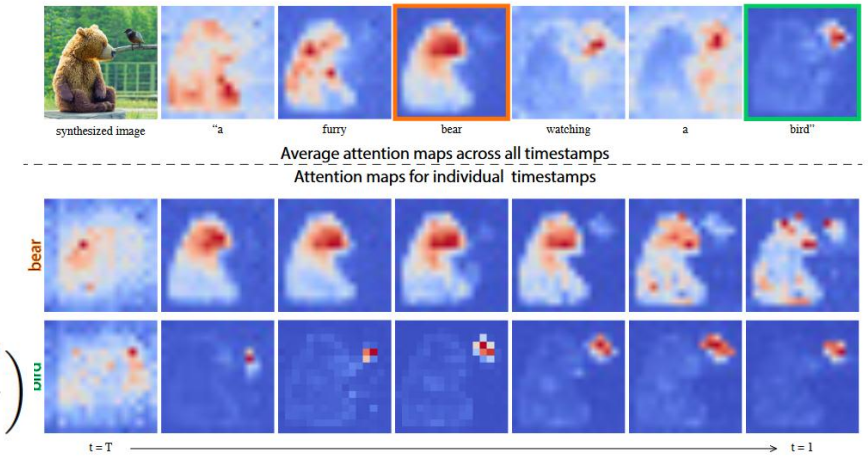
$$Q = W_Q^{(i)} \cdot \varphi_i(z_t),$$

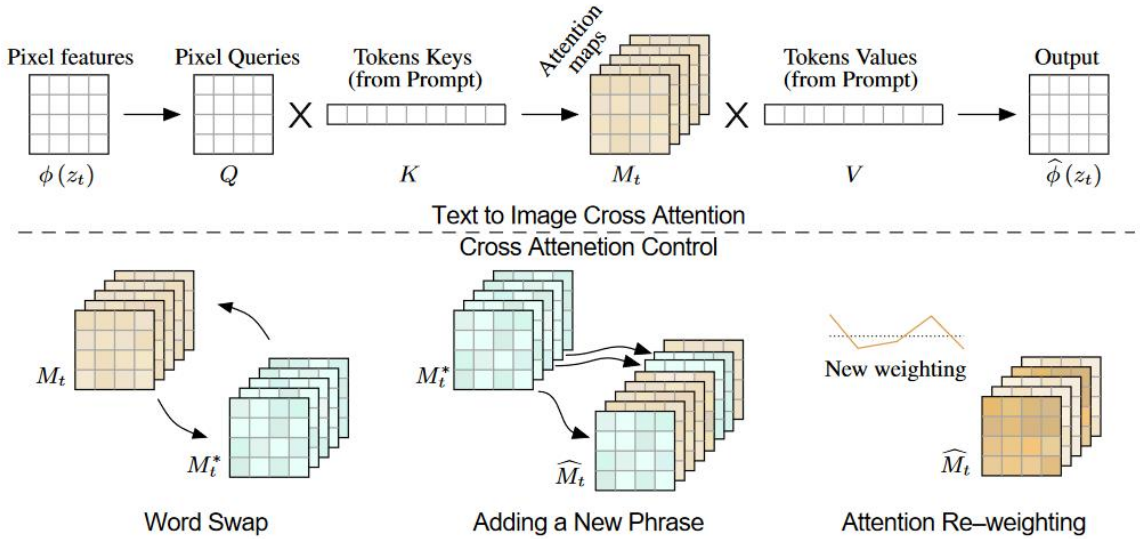
$$K = W_K^{(i)} \cdot \tau_\theta(y),$$

$$V = W_V^{(i)} \cdot \tau_\theta(y).$$

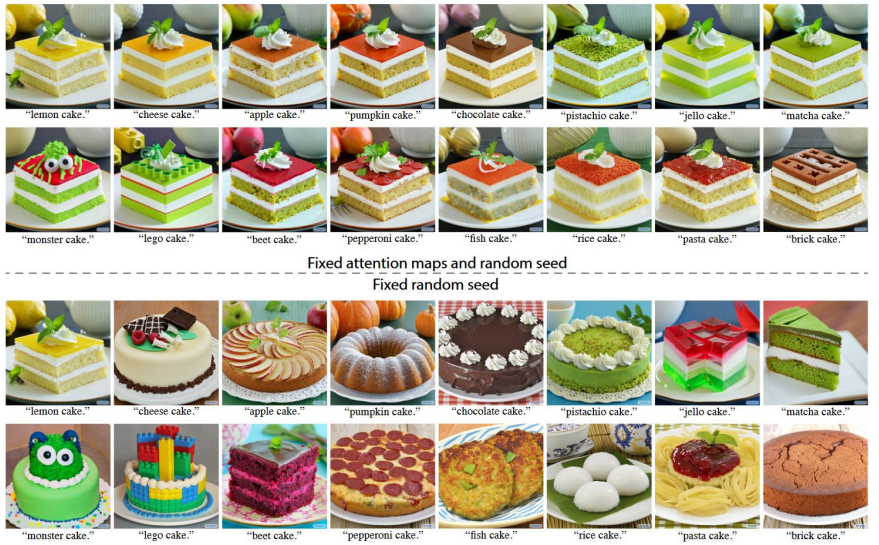
$$M = \text{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right)$$

cross-attention





Prompt-to-Prompt Image Editing with Cross Attention Control



- Edit objects in an image
- Globally edit an image
- Amplify or attenuate the semantic effect of a word

Thanks