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Generative Model

ADB, CFG, GLIDE, DALL-E2

Sungjoon Choi, Korea University

kakaobrain

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ADM

"Diffusion Models Beat GANs on Image Synthesis," 2021

Ablated Diffusion Model

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- This paper presents **Ablated Diffusion Model** (ADM):
  - Several improvements techniques over DDPM
  - Conditioned generation via classifier-guidance

Ablated Diffusion Model

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- ADM improves existing DDPM via:
  - Non-constant variance:

$$\Sigma_\theta(x_t, t) = \exp(v \log \beta_t + (1 - v)\log \tilde{\beta}_t)$$

where $v_\theta(x_t, t)$ is the output of the neural network,

β_t (upper bound) is a scheduled constant ($\beta_1 = 10^{-4}$ to $\beta_T = 0.02$)

,and $\tilde{\beta}_t = \frac{1 - \bar{\alpha}_{t-1}}{1 - \bar{\alpha}_t}\beta_t$ (lower bound), $\alpha_t = 1 - \beta_t$, and $\bar{\alpha}_t = \prod_{s=0}^{t} \alpha_s$

  - Fewer steps sampling using DDIM

Architecture Improvements

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- Following architectural changes are considered:
  - Increasing depth versus width, holding model size relatively constant
  - Increasing the number of attention heads
  - Using attention at 32×32, 16×16, and 8×8 resolutions rather than only 16×16
  - Using the BigGAN residual block for upsampling and downsampling the activations
  - Rescaling residual connections with $\frac{1}{\sqrt{2}}$.

Classifier Guidance

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- For conditioned generation,
  - an additional classifier $p_\phi(y \mid x_t, t)$ is trained and use gradients $\nabla_{x_t} \log p_\phi(y \mid x_t, t)$ to guide the diffusion sampling process towards an arbitrary class label y.
  - Note that the classifier $p_\phi(y \mid x_t, t)$ should be trained on noisy images x_t (how?)

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

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

Samples from ImageNet

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Samples from LSUN (bedroom)

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Samples from LSUN (horse)

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Samples from LSUN (cat)

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CFG

"Classifier-Free Diffusion Guidance," 2021

Classifier-Free Guidance

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- Classifier guidance mixes a score estimate with a classifier gradient during sampling

$$x_{t-1} \leftarrow \mathcal{N}(\mu + s\Sigma \nabla_{x_t} \log p_\phi(y \mid x_t), \Sigma)$$ where s is gradient scale

- A downside classifier guidance is that it requires an additional classifier model and thus complicates the training pipeline.
- CFG only modifies the existing diffusion model by making the reverse process function approximator receives c an input (i.e., $e_\theta(z_\lambda, c)$).

$$\tilde{\epsilon}_\theta(z_\lambda, c) = (1 + w)\epsilon_\theta(z_\lambda, c) - w\epsilon_\theta(z_\lambda)$$

where c is the class label,$\epsilon_\theta(z_\lambda) = \epsilon_\theta(z_\lambda, c = 0)$, and w is the implied-classifier weights

Tradeoffs

- **FID**: sample variety
- **IS**: individual sample fidelity

Method	FID (↓)	IS (↑)
ADM [3]	2.07	-
CDM [6]	**1.48**	67.95
Ours, no guidance	1.80	53.71
Ours, with guidance		
$w = 0.1$	1.55	66.11
$w = 0.2$	2.04	78.91
$w = 0.3$	3.03	92.8
$w = 0.4$	4.30	106.2
$w = 0.5$	5.74	119.3
$w = 0.6$	7.19	131.1
$w = 0.7$	8.62	141.8
$w = 0.8$	10.08	151.6
$w = 0.9$	11.41	161
$w = 1.0$	12.6	170.1
$w = 2.0$	21.03	225.5
$w = 3.0$	24.83	250.4
$w = 4.0$	26.22	**260.2**

Figure 1: ImageNet 64x64 results

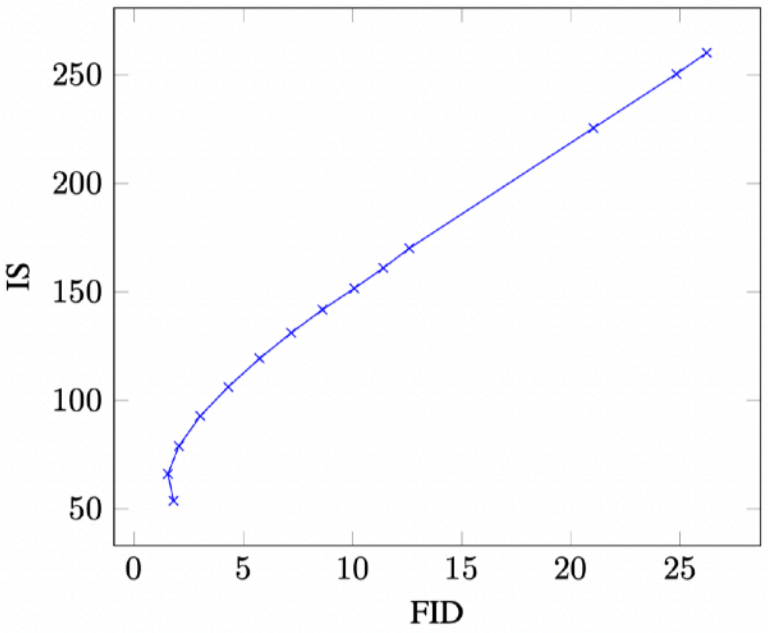
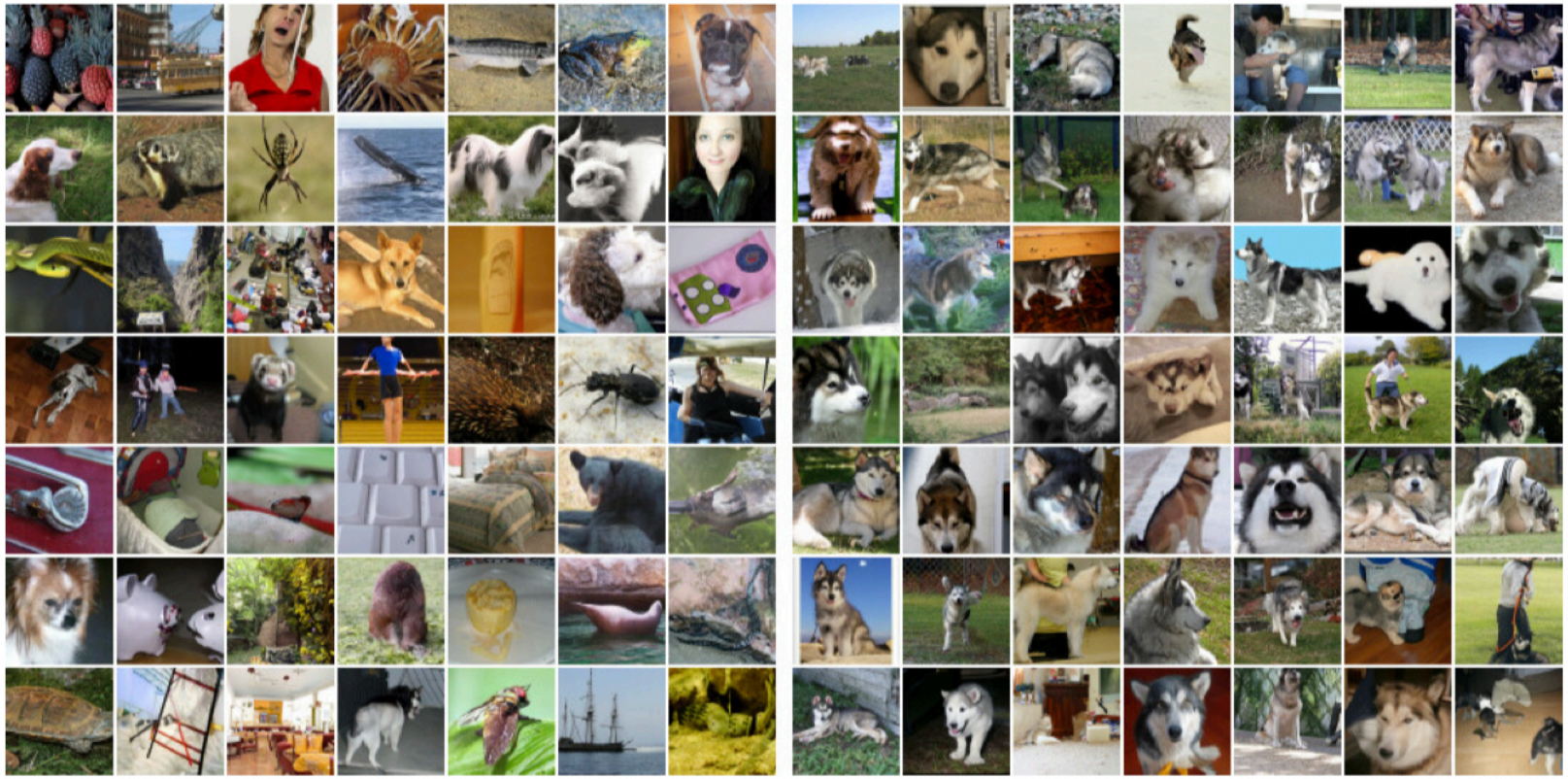


Figure 2: ImageNet 64x64 FID vs. IS

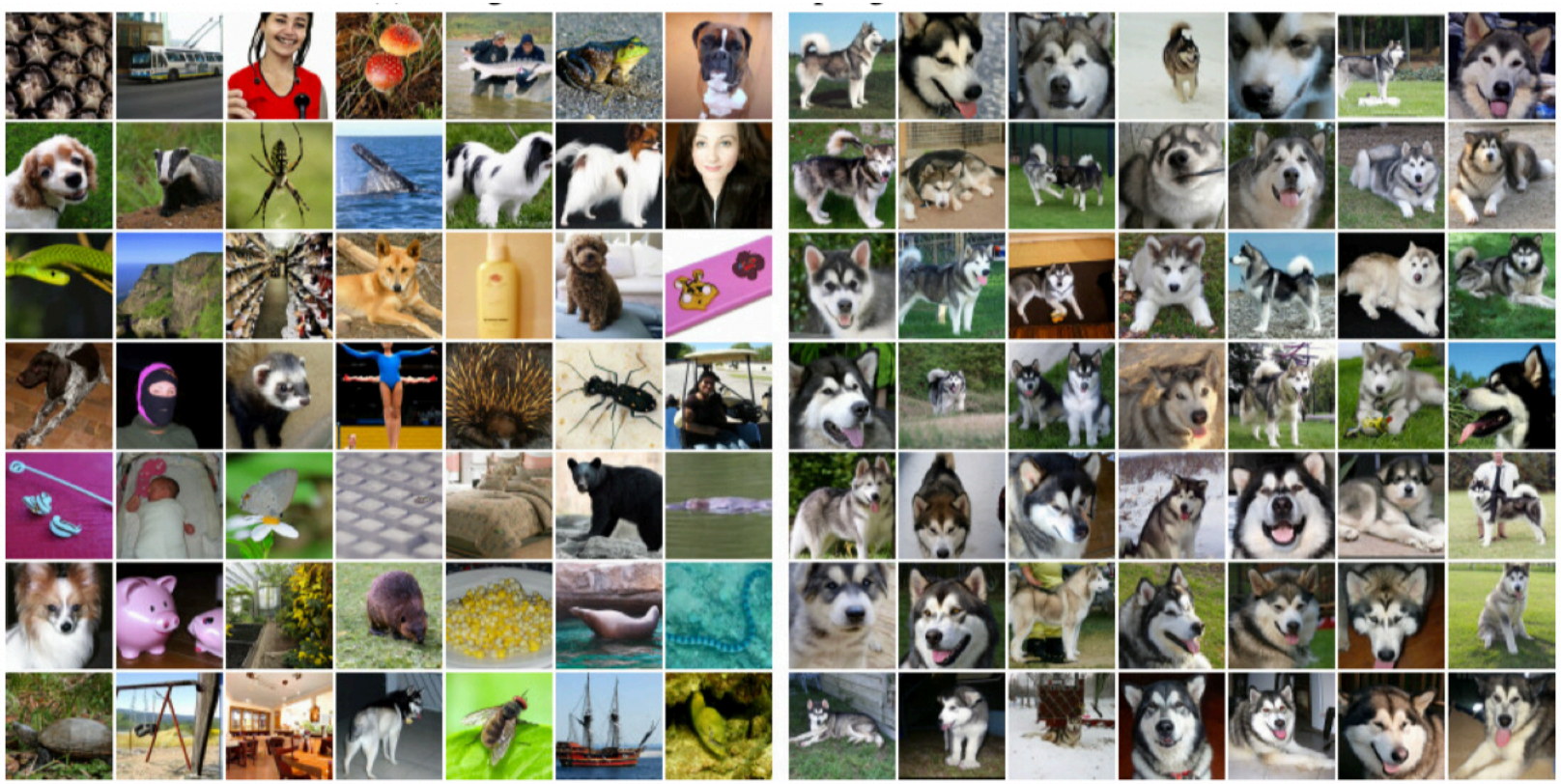
Non-guided



(a) Non-guided conditional sampling: FID=1.80, IS=53.71

- Low FID (the lower the better) -> High Variability
- Low IS (the higher the better) -> Low Image Quality

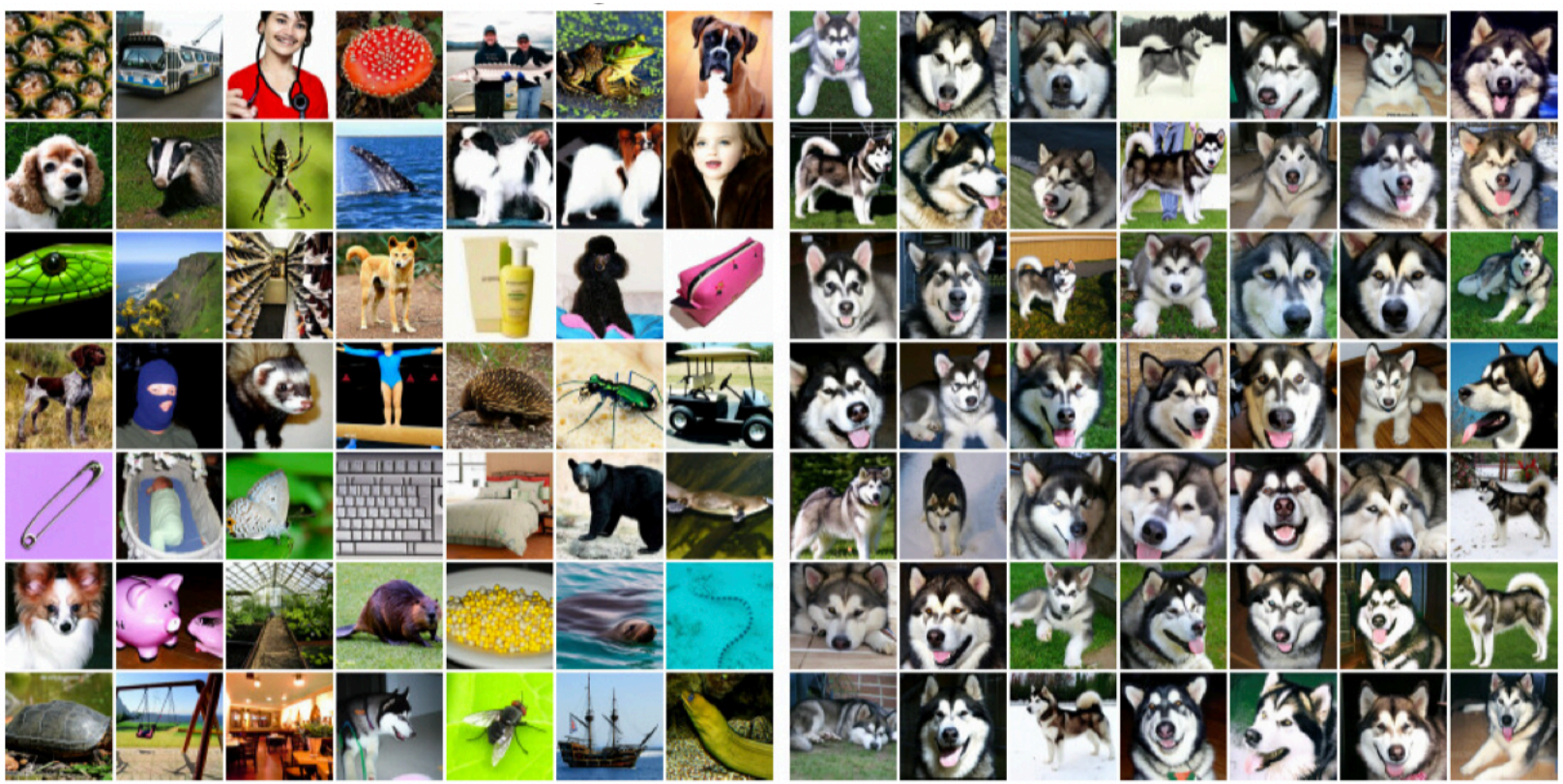
CFG with Small Guidance



(b) Classifier-free guidance with $w = 1.0$: FID=12.6, IS=170.1

- Middle FID (the lower the better) -> Middle Variability
- Middle IS (the higher the better) -> Middle Image Quality

CFG with High Guidance



(c) Classifier-free guidance with $w = 3.0$: FID=24.83, IS=250.4

- High FID (the lower the better) -> Low Variability
- High IS (the higher the better) -> High Image Quality

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GLIDE

"GLIDE: Towards Photorealistic Image Generation and Editing with Text-Guided Diffusion Models," 2022

GLIDE

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Guided Language to Image Diffusion for Generation and Editing (GLIDE)

Diffusion version of **DALL-E** (or precursor of **DALL-E2**)

GLIDE

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Two different approaches are presented: CLIP guidance and classifier-free guidance
+
Editing capabilities (e.g., image inpainting)

Background

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- Diffusion Models
  - Forward diffusion: $q(x_t \mid x_{t-1}) = \mathcal{N}(x_t; \sqrt{\alpha_t} x_{t-1}, (1-\alpha_t)I)$
  - Backward model: $p_\theta(x_{t-1} \mid x_t) = \mathcal{N}(\mu_\theta(x_t), \Sigma_\theta(x_t))$
  - Objective: generate samples $x_t \sim q(x_t \mid x_0)$ by applying Gaussian noise ϵ to x_0, then train a model ϵ_θ to predict the added noise using a standard mean-squared error loss

Background

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- Guided Diffusion
  - Perturbed mean: $\hat{\mu}_\theta(x_t \mid y) = \mu_\theta(x_t \mid y) + s \cdot \Sigma_\theta(x_t \mid y) \nabla_{x_t} \log p_\phi(y \mid x_t)$
  - Note that $p_\phi(y \mid x_t)$ is a classifier trained with noisy images and s is the guidance scale
- Classifier-free Guidance
  - Class-conditional diffusion model: $\epsilon_\theta(x_t \mid y)$
  - Extrapolated error prediction: $\hat{\epsilon}_\theta(x_t \mid y) = \epsilon_\theta(x_t \mid \varnothing) + s(\epsilon_\theta(x_t \mid y) - \epsilon_\theta(x_t \mid \varnothing))$ where $s \geq 1$ is the guidance scale
- CLIP Guidance
  - CLIP: $f(x) \cdot g(c)$ is high for matching image x and caption c
  - Perturbed mean: $\hat{\mu}_\theta(x_t \mid c) = \mu_\theta(x_t \mid c) + s \cdot \Sigma_\theta(x_t \mid y) \nabla_{x_t}(f(x_t) \cdot g(c))$
  - Note that the CLIP $f(x_t) \cdot g(c)$ should be trained on noisy images

Text-Conditional Diffusion Models

- ADM model with text conditioning information (CLIP guidance and classifier-free guidance)
  - Visual part: ImageNet 64×64 model of ADM with 512 channels -> 2.3B parameters
  - Text part: Transformer encoder with 24 residual blocks of width 2048 -> 1.2B parameters
  - Upsampler: 64×64 resolution to 256×256 resolution -> 1.5B parameters
- Trained on the same dataset as DALL-E.. ~~(not public)~~

Image Inpainting

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- Inpainting with a diffusion model can be done by replacing the known region of the image with a sample from $q(x_t|x_0)$ after each sampling step.
  - It is **NOT** replacing the known region of the image directly.
  - But what about the unknown region of x_0?
  - It has the disadvantage that the model cannot see that entire context but only a noised version sampled from $q(x_t|x_0)$.
- Glide explicitly **fine-tune** the model to preform inpainting.
  - During fine-tuning, random regions of training images are erased, and the remaining portions are fed into to model with a mask channel as additional conditioning information.
  - The input of the model has four additional channels: a second set of RGB channels and a mask channel.

Results

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"a hedgehog using a calculator"

"a corgi wearing a red bowtie and a purple party hat"

"robots meditating in a vipassana retreat"

"a fall landscape with a small cottage next to a lake"

"a surrealist dream-like oil painting by salvador dalí

"a professional photo of a sunset behind the grand

"a high-quality oil painting of a psychedelic hamster

"an illustration of albert einstein wearing a superhero

Results

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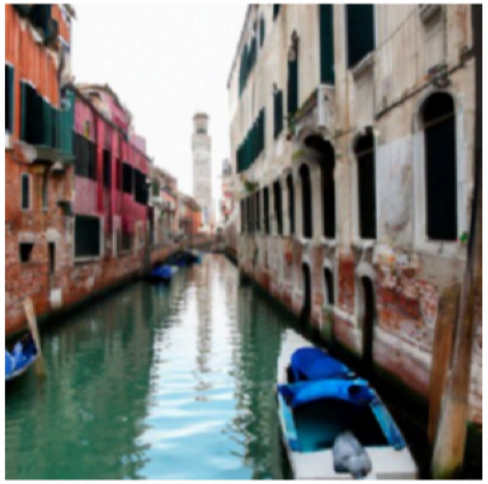
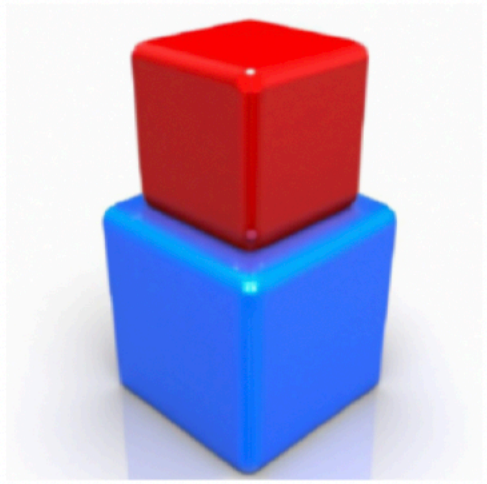
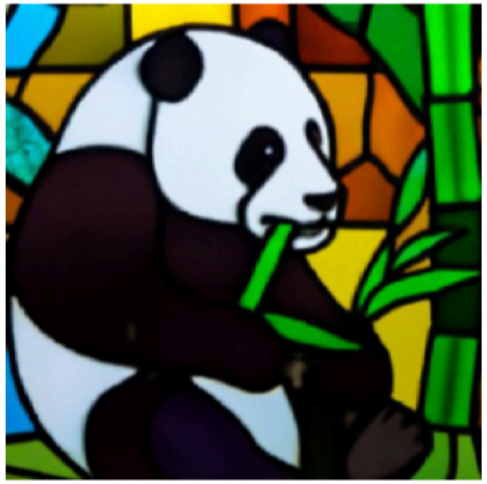


"a boat in the canals of venice"

"a painting of a fox in the style of starry night"



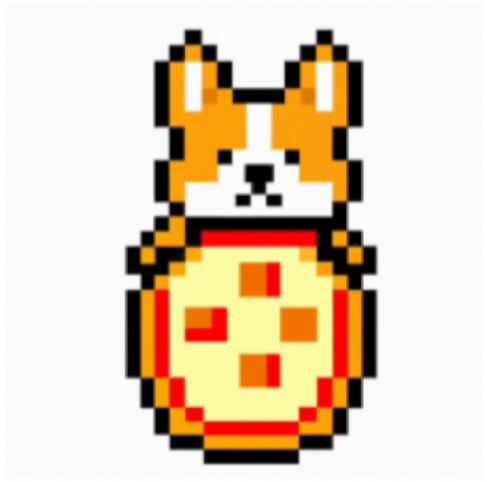
"a red cube on top of a blue cube"



"a stained glass window of a panda eating bamboo"

"a crayon drawing of a space elevator"

"a futuristic city in synthwave style"



"a pixel art corgi pizza"

"a fog rolling into new york"

Results

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"a cozy living room"

"a painting of a corgi on the wall above a couch"

"a round coffee table in front of a couch"

"a vase of flowers on a coffee table"

"a couch in the corner of a room"

Results

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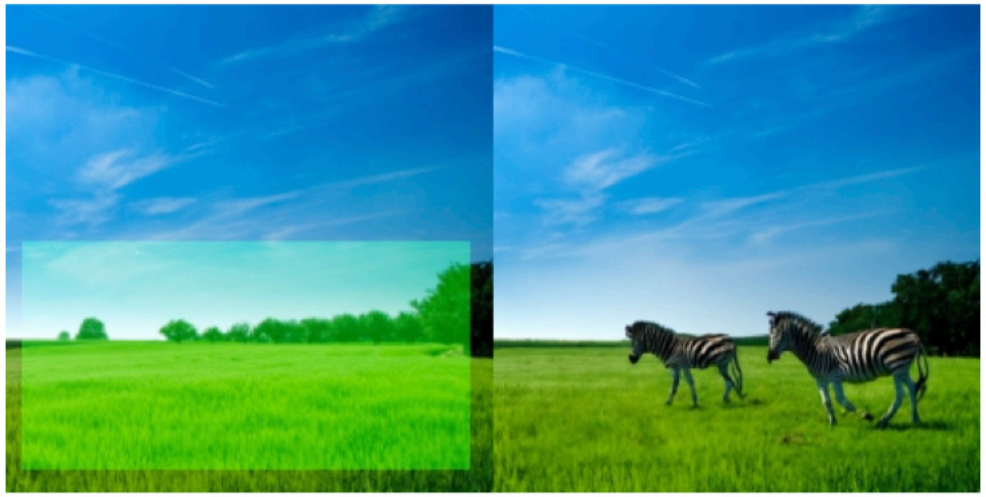

"zebras roaming in the field"

"a girl hugging a corgi on a pedestal"

"a man with red hair"

"a vase of flowers"

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DALL-E2

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

unCLIP

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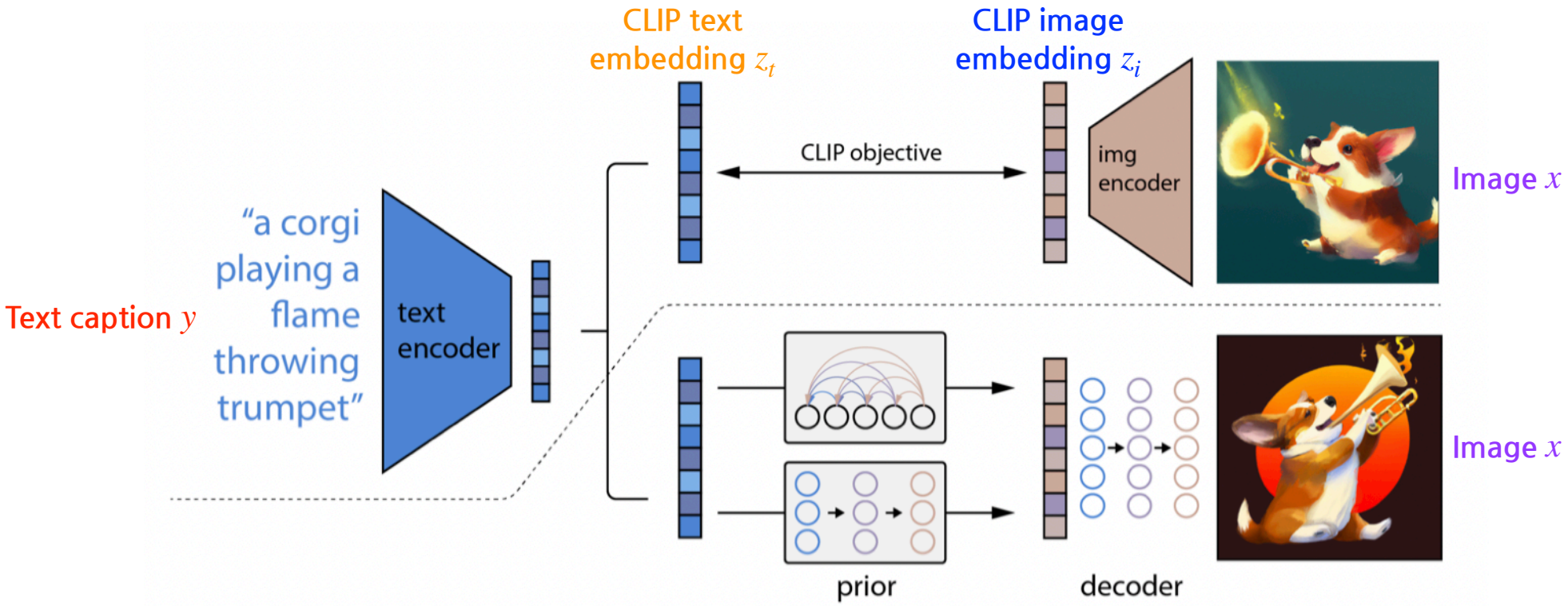
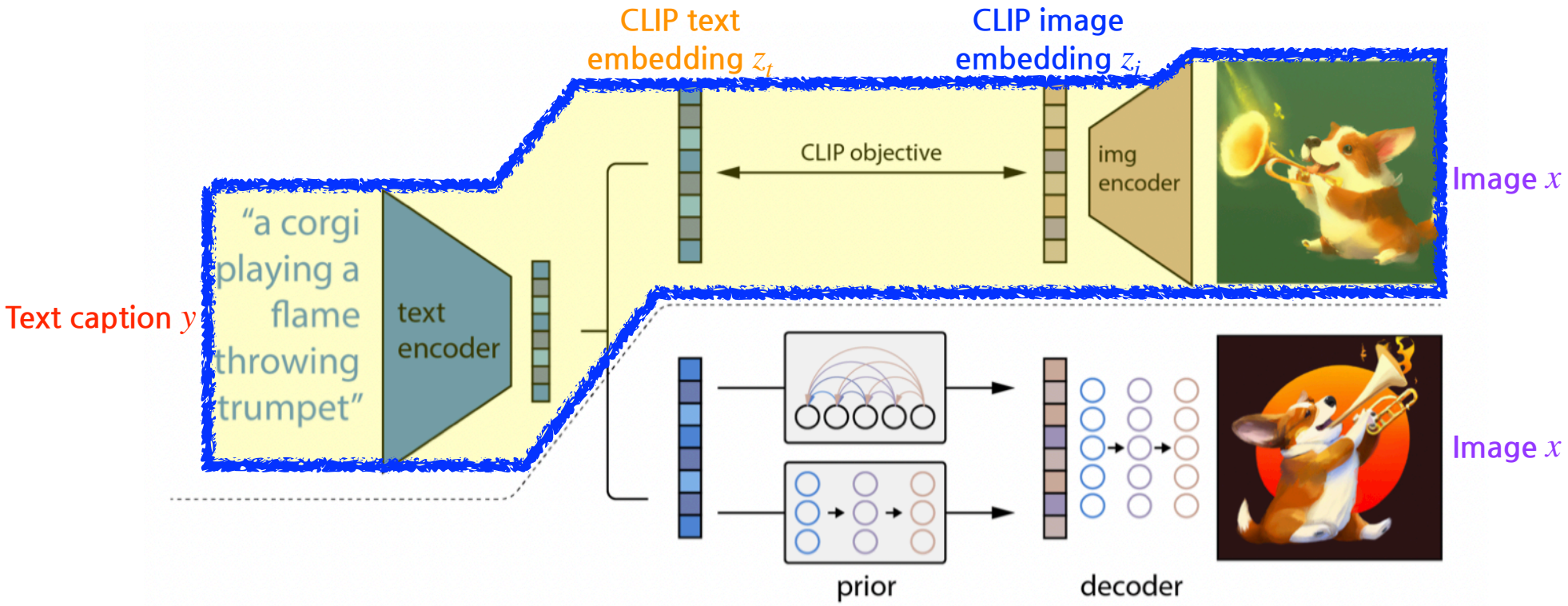
This is the famous **DALL-E 2** paper
(the name of the proposed text-to-image stack is **unCLIP**)

unCLIP

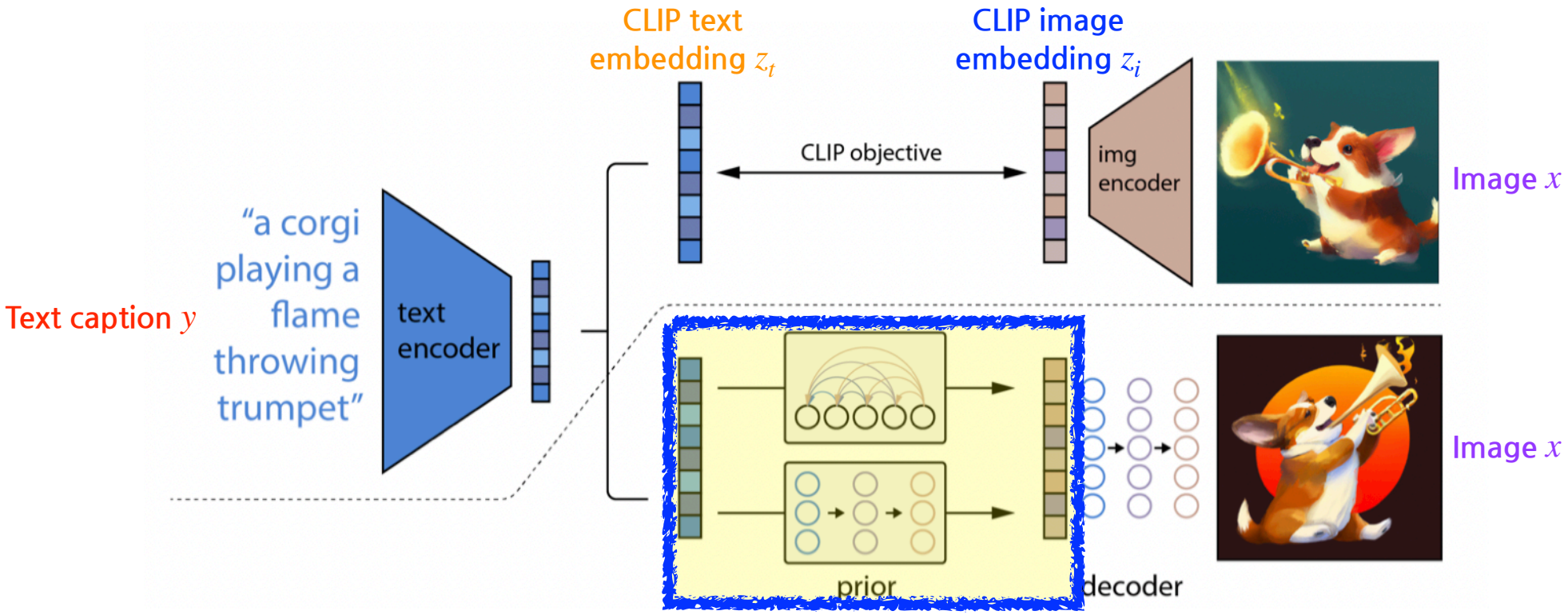

CLIP text embedding z_t
CLIP image embedding z_i
CLIP objective
img encoder
Image x
Text caption y
"a corgi playing a flame throwing trumpet"
text encoder
prior
decoder
Image x

unCLIP



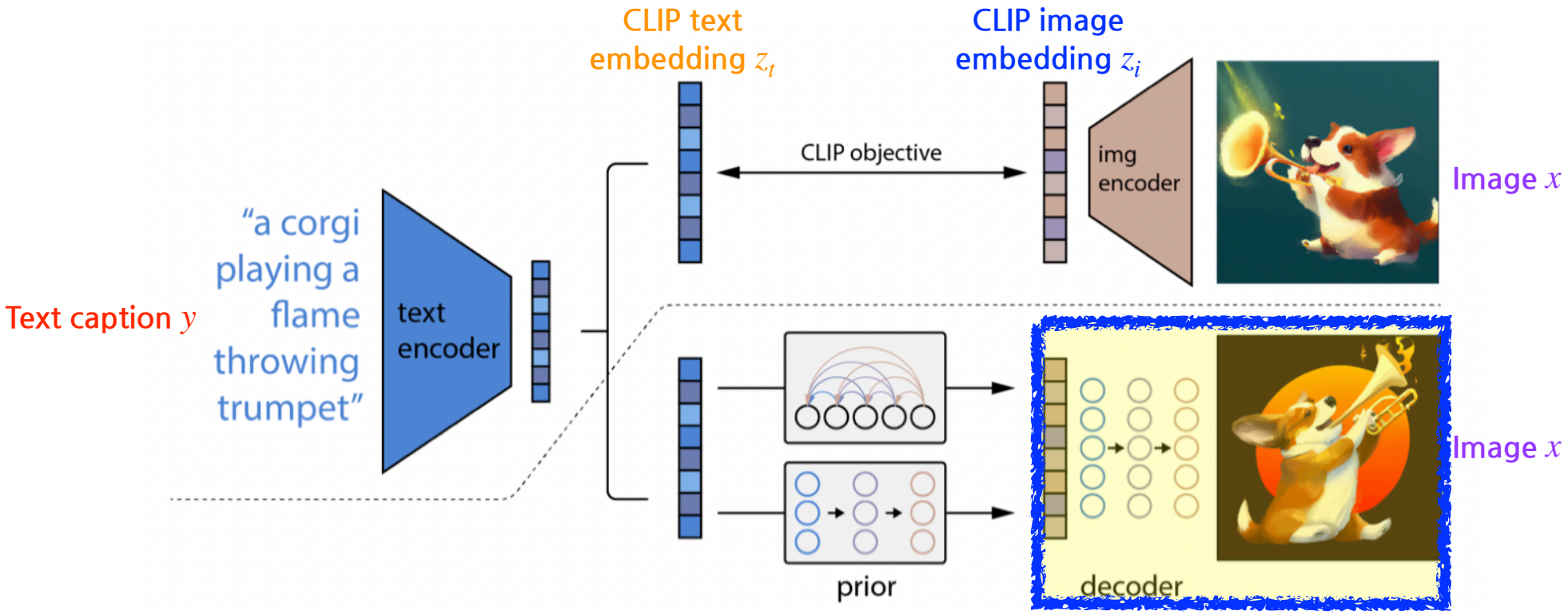
This part is the same as the original CLIP

unCLIP



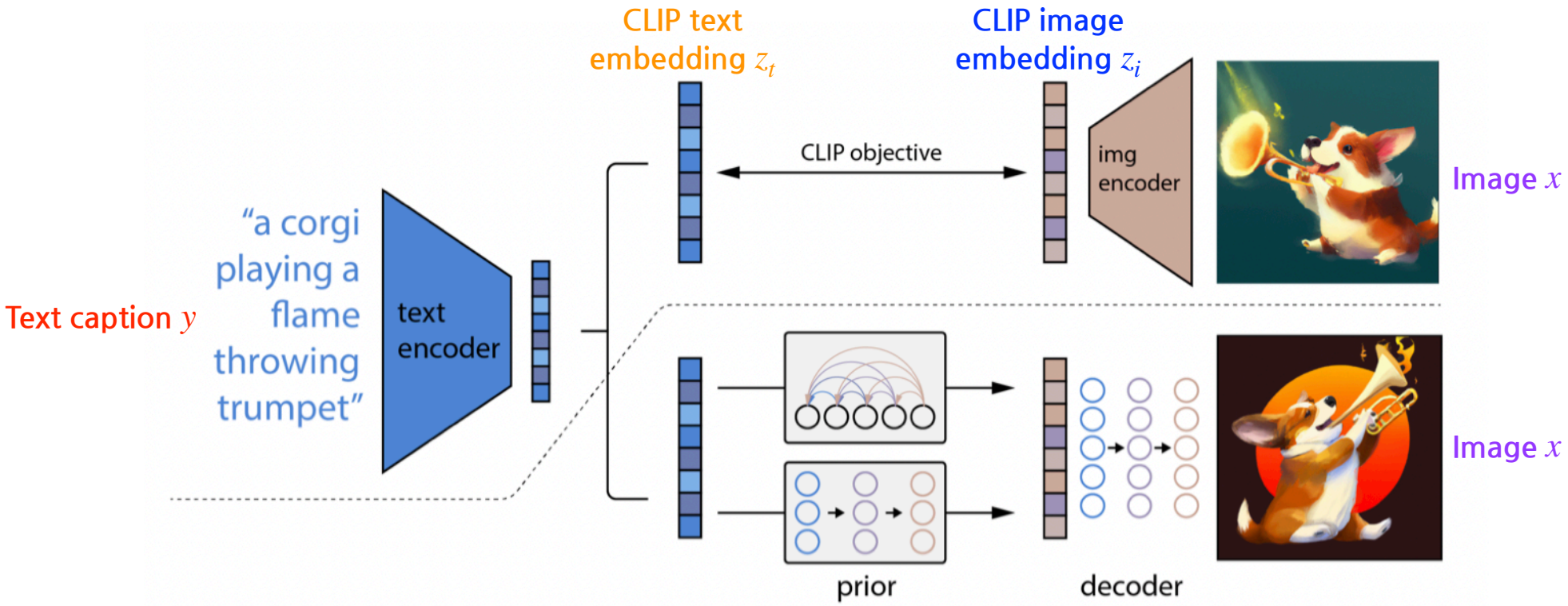
Prior: CLIP text embedding z_t -> CLIP image embedding z_i

unCLIP



Decoder: CLIP image embedding z_i-> Image x

unCLIP



- **unCLIP**: Text encoder: text caption => text embedding; Prior: => image embedding; Decoder: => image

Results

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vibrant portrait painting of Salvador Dalí with a robotic half face

a shiba inu wearing a beret and black turtleneck

a close up of a handpalm with leaves growing from it

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

Interpolation

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a photo of a cat → an anime drawing of a super saiyan cat, artstation

a photo of a victorian house → a photo of a modern house

a photo of an adult lion → a photo of lion cub

a photo of a landscape in winter → a photo of a landscape in fall

Failures

Figure 16: Samples from unCLIP for the prompt, “A sign that says deep learning.”

Failures

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(a) A high quality photo of a dog playing in a green field next to a lake.

(b) A high quality photo of Times Square.

Figure 17: unCLIP samples show low levels of detail for some complex scenes.

Thank You