
A living room with a fireplace at a wood cabin. Interior design.


a blue Porsche 356 parked in front of a yellow brick wall.


Eiffel Tower, landscape photography


A painting of a majestic royal tall ship in Age of Discovery.

Lecture 13: Text-to-Image Synthesis

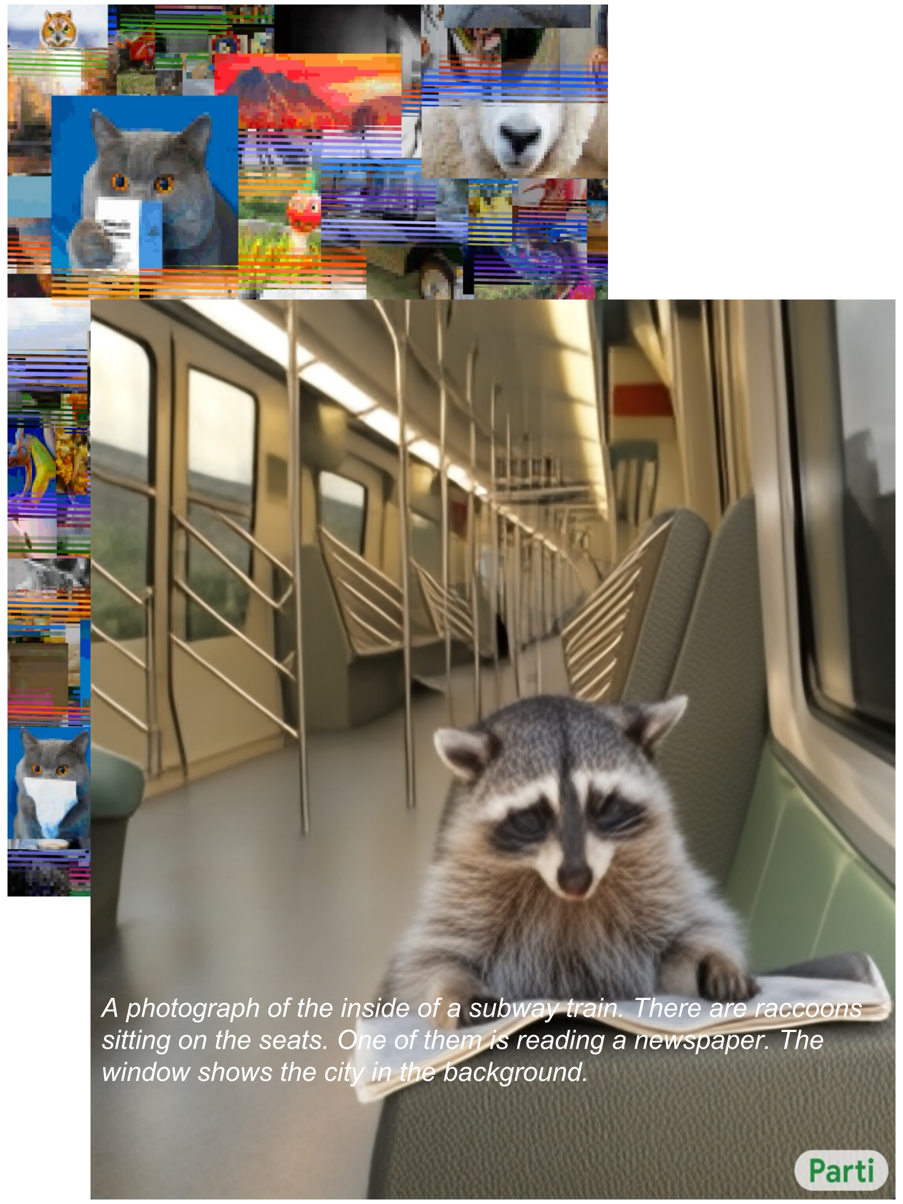
Jun-Yan Zhu

16-726 Spring 2023

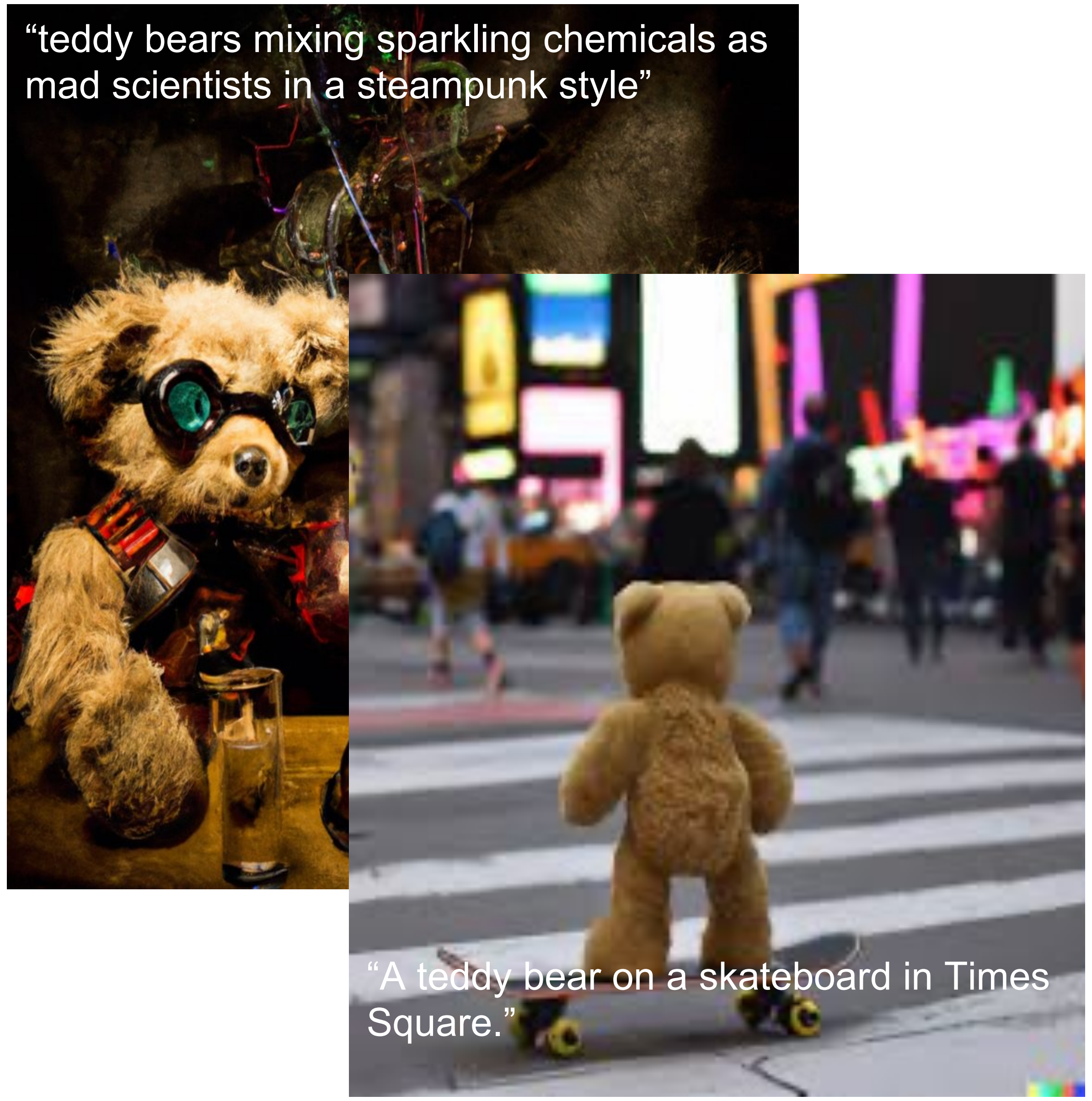
Slides credit: many slides are from Robin Rombach, Karsten Kreis, Ruiqi Gao, Arash Vahdat, etc.

Photo credit: Minguk Kang et al.

Text-to-Image Everywhere



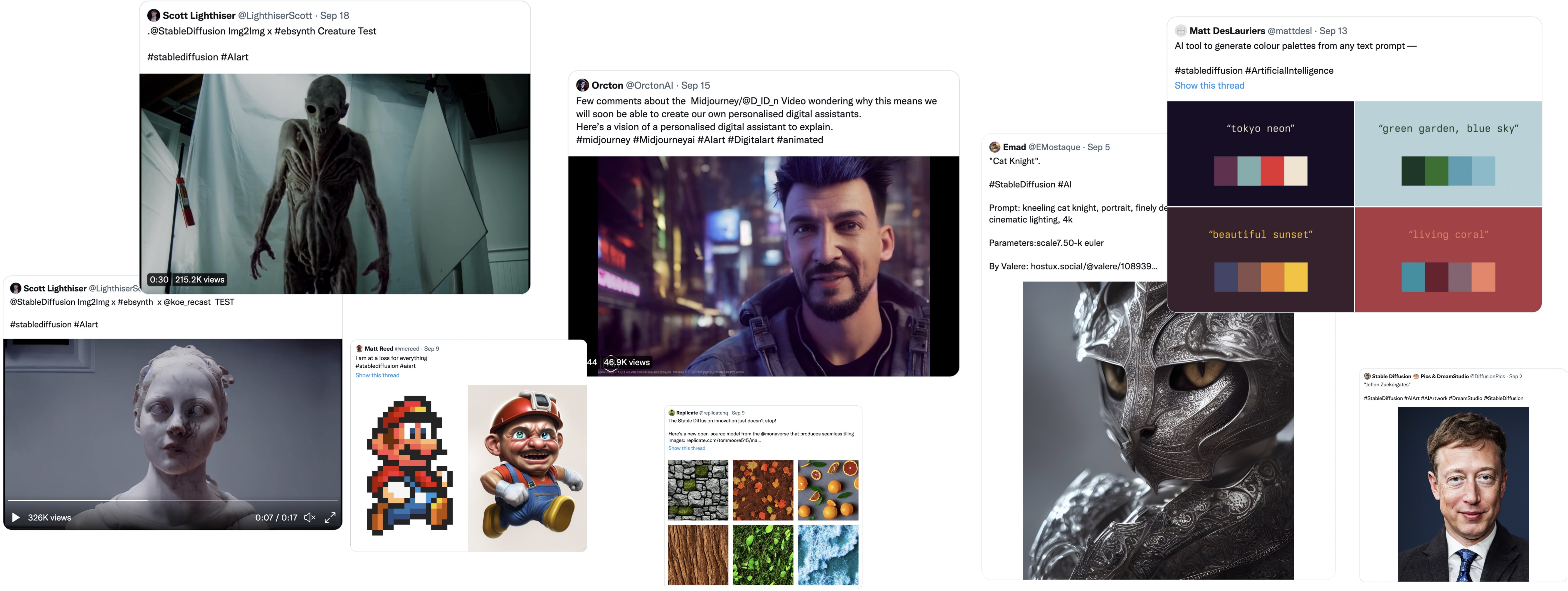
Autoregressive models
(Image GPT, Parti)



Diffusion models
(DALL-E 2, Imagen)

GANs, Masked GIT
(GigaGAN, MUSE)

Text-to-Image Everywhere



Slides credit: Robin Rombach

Where/when did it start?

First Text-to-Image System

Step 1: Image Selection.
Step 2: Layout Optimization (Minimum overlap, Centrality, Closeness)

A Text-to-Picture Synthesis System for Augmenting Communication
Xiaojin Zhu, Andrew Goldberg, Mohamed Eldawy, Charles Dyer, and Bradley Strock. AAAI 2007

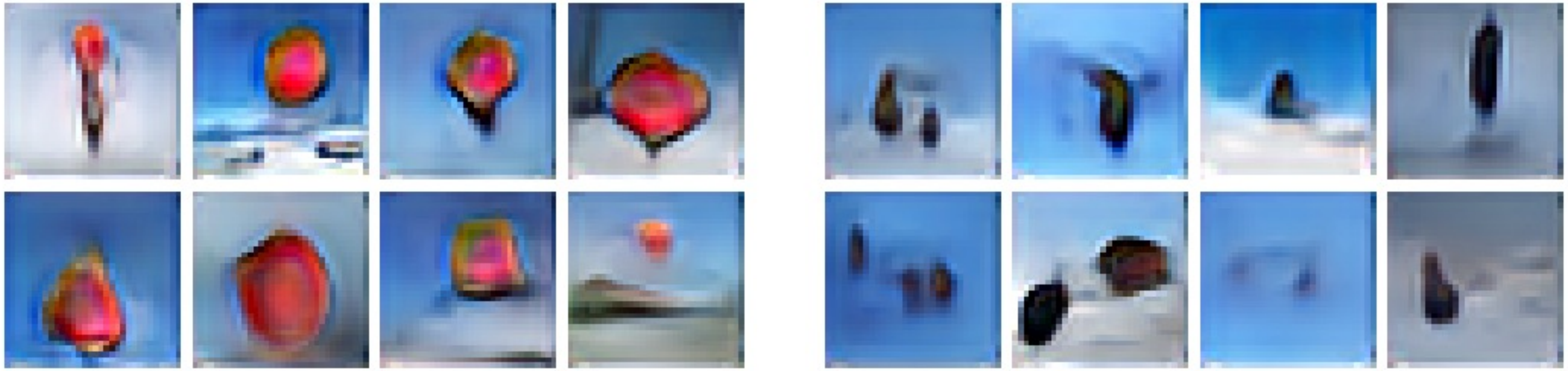
First Text-to-Image System

Therapy for people
with communicative disorders

Math learning and reading comprehension
for young children

A Text-to-Picture Synthesis System for Augmenting Communication
Xiaojin Zhu, Andrew Goldberg, Mohamed Eldawy, Charles Dyer, and Bradley Strock. AAAI 2007

First Deep Learning Work



A stop sign is flying in blue skies.

A herd of elephants flying in the blue skies.

Generating Images from Captions with Attention.
Elman Mansimov, Emilio Parisotto, Jimmy Lei Ba, Ruslan Salakhutdinov. ICLR 2016.

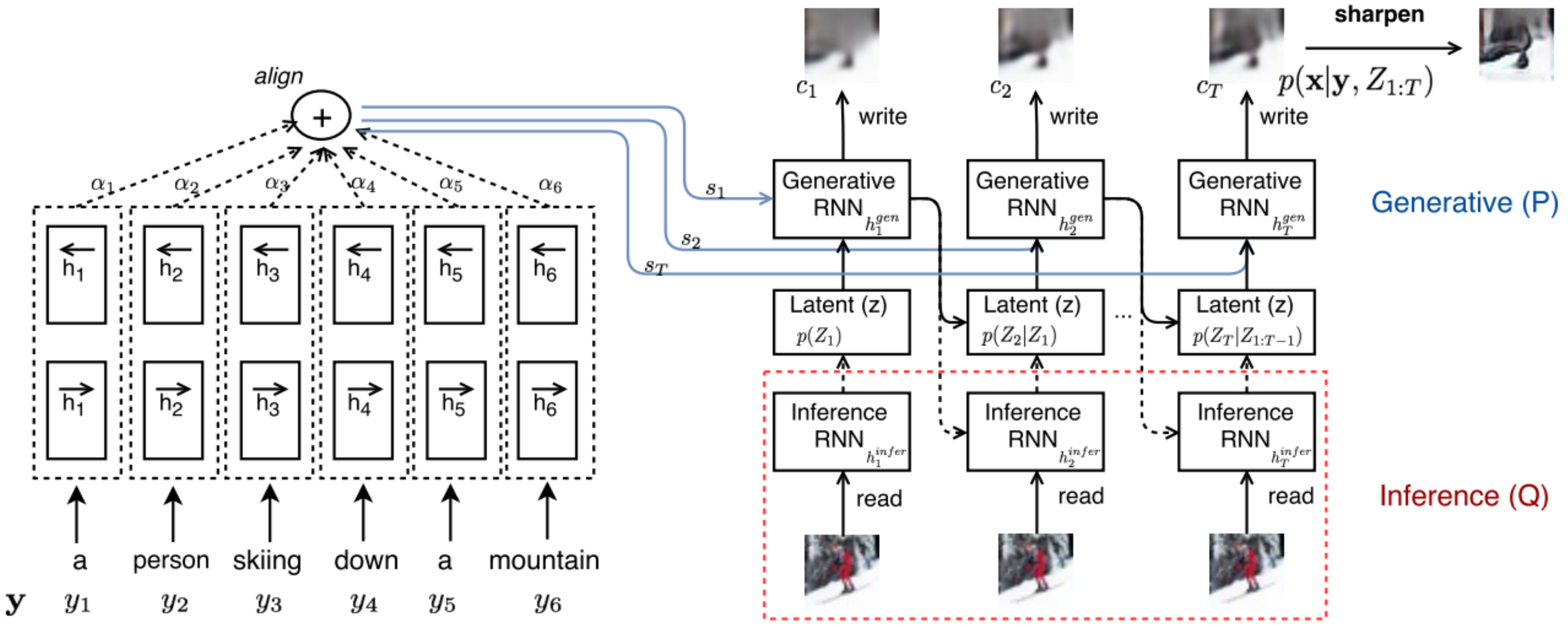
First Deep Learning Work

A toilet seat sits open in the grass field.

A person skiing on sand clad vast desert.

Generating Images from Captions with Attention.
Elman Mansimov, Emilio Parisotto, Jimmy Lei Ba, Ruslan Salakhutdinov. ICLR 2016.

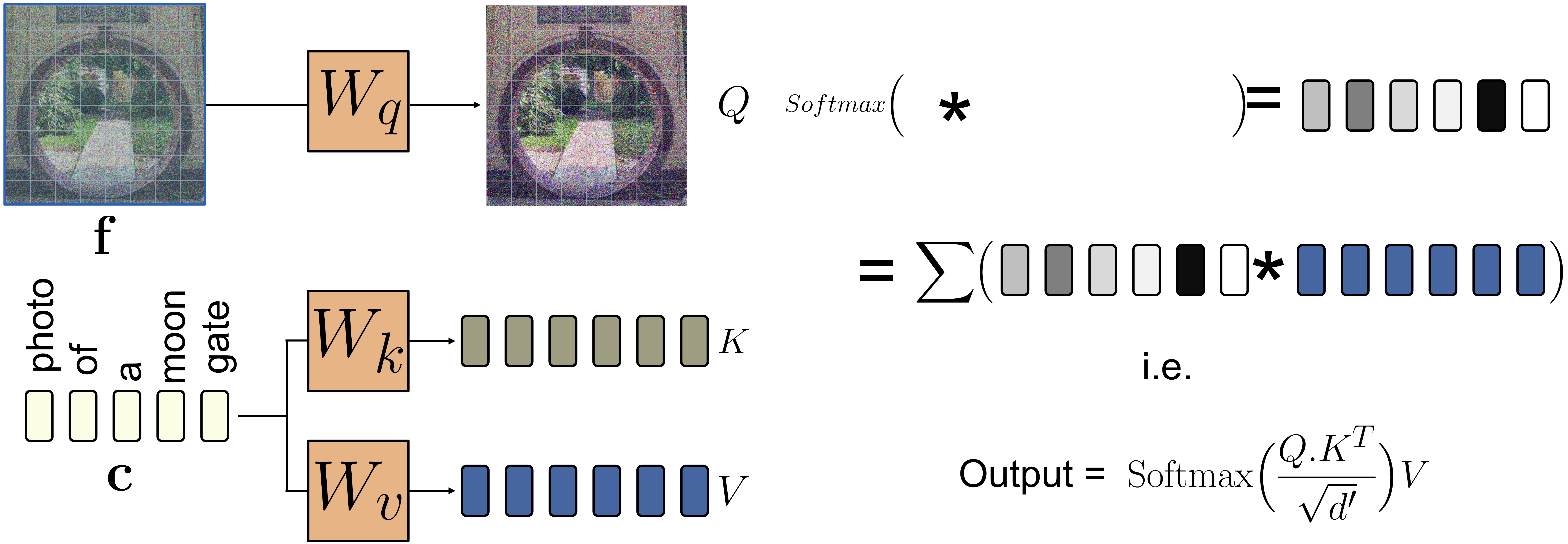
First Deep Learning Work



VAES + RNN+ cross-attention

Generating Images from Captions with Attention.
Elman Mansimov, Emilio Parisotto, Jimmy Lei Ba, Ruslan Salakhutdinov. ICLR 2016.

Text-Image Cross-Attention



i.e.

Output = $\mathrm{Softmax}\left(\frac{Q.K^T}{\sqrt{d'}}\right)V$

Slides from [Kumari et al., CVPR 2023]

How could we improve it?

How could we improve it?

- Better generative modeling techniques.
- Better text encoders.
- Better generator architectures.
- Better ways to connect text and image.
- Bigger data + more GPU/TPU computing.
- Bigger model sizes.

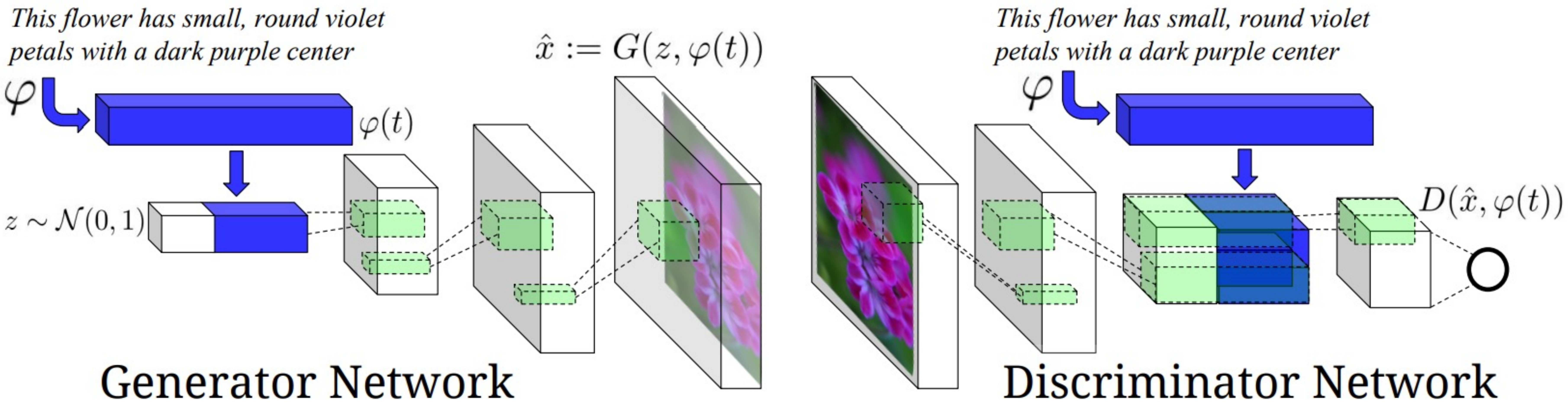
GANs-based Text-to-Image

Generative Adversarial Text to Image Synthesis
Scott Reed et al., ICML 2016

GANs-based Text-to-Image

Generative Adversarial Text to Image Synthesis
Scott Reed et al., ICML 2016

GANs-based Text-to-Image

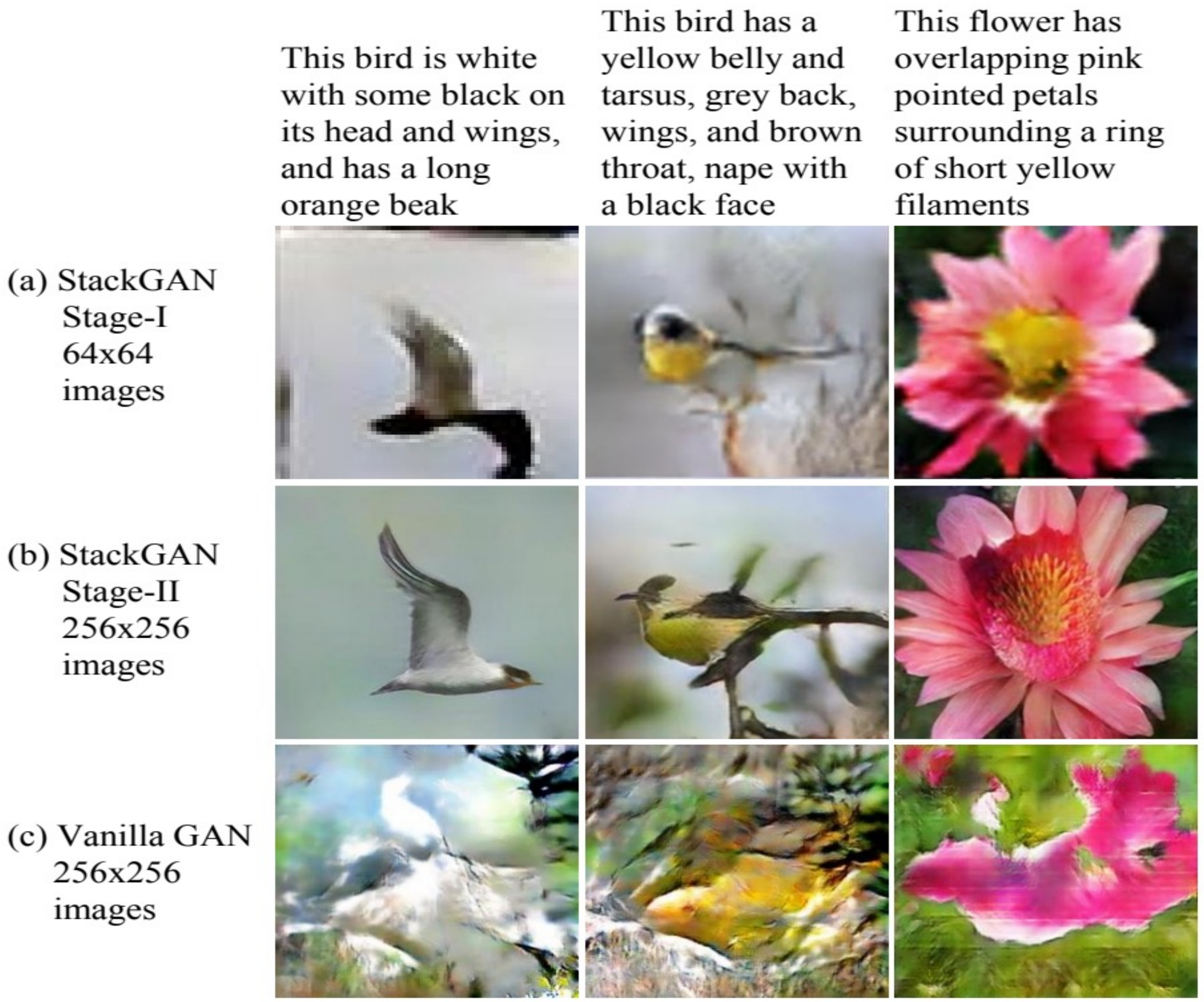


Conditional GAN + CNN + concatenation

Generative Adversarial Text to Image Synthesis
Scott Reed et al., ICML 2016

How to increase resolution?

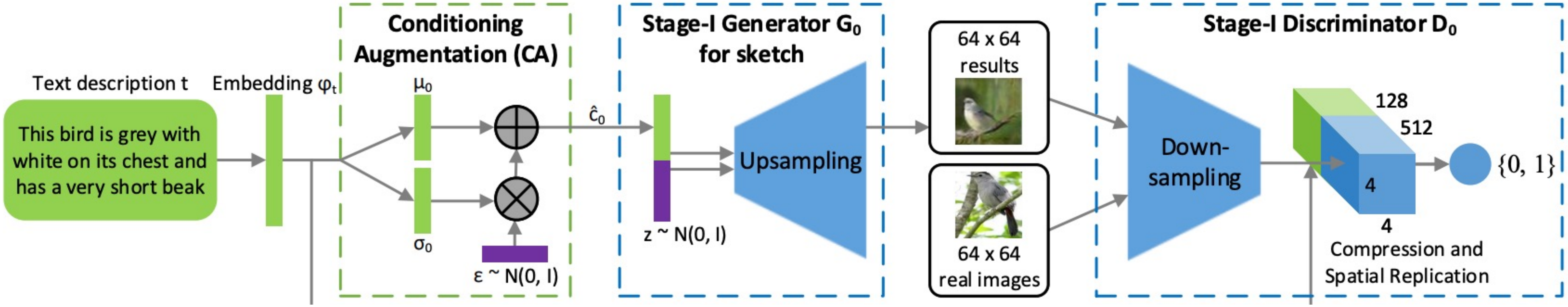
+Two-stage Models



Two-stage Conditional GAN + CNN + concatenation

StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
Han Zhang et al., ICCV 2017

+Two-stage Models



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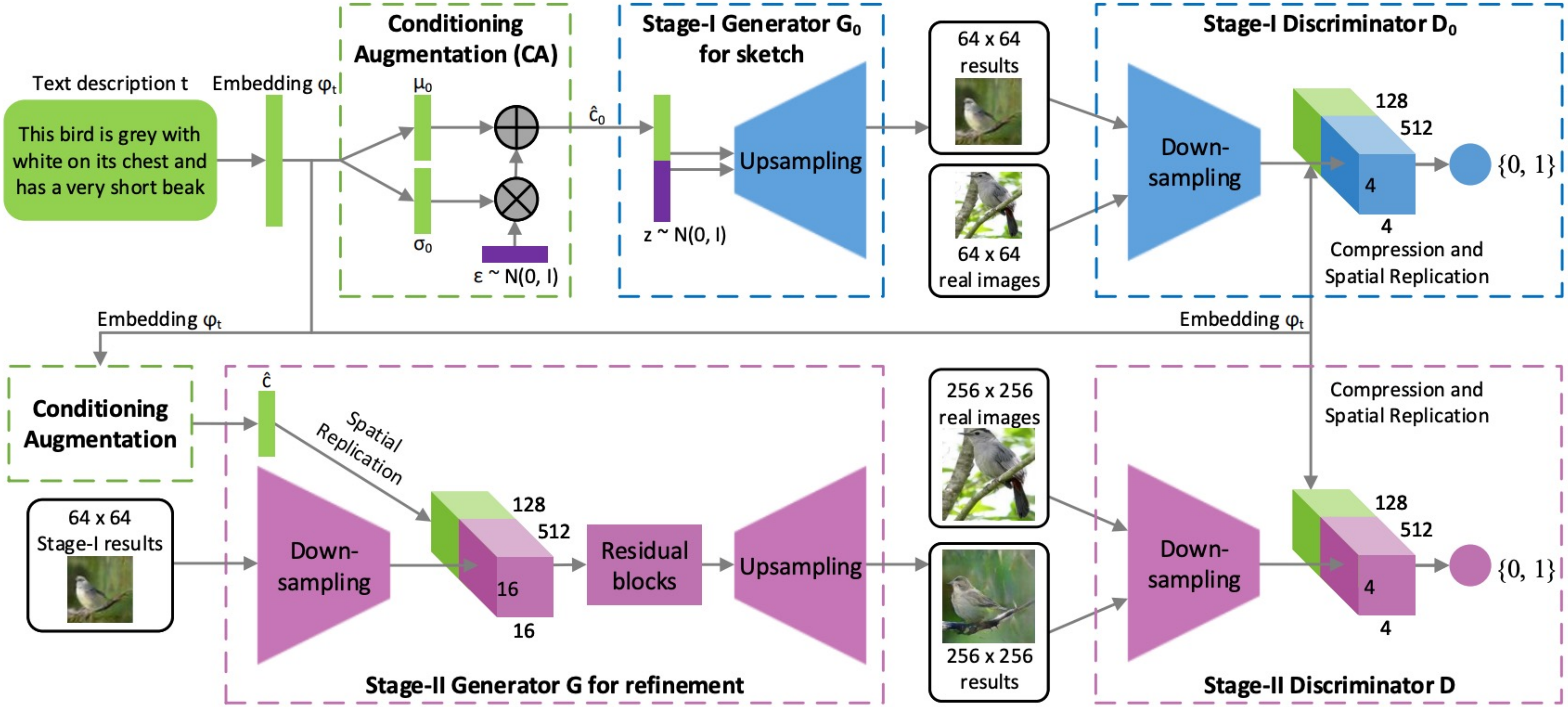
Han Zhang et al., ICCV 2017

+Two-stage Models



Two-stage Conditional GAN + CNN + concatenation

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Han Zhang et al., ICCV 2017

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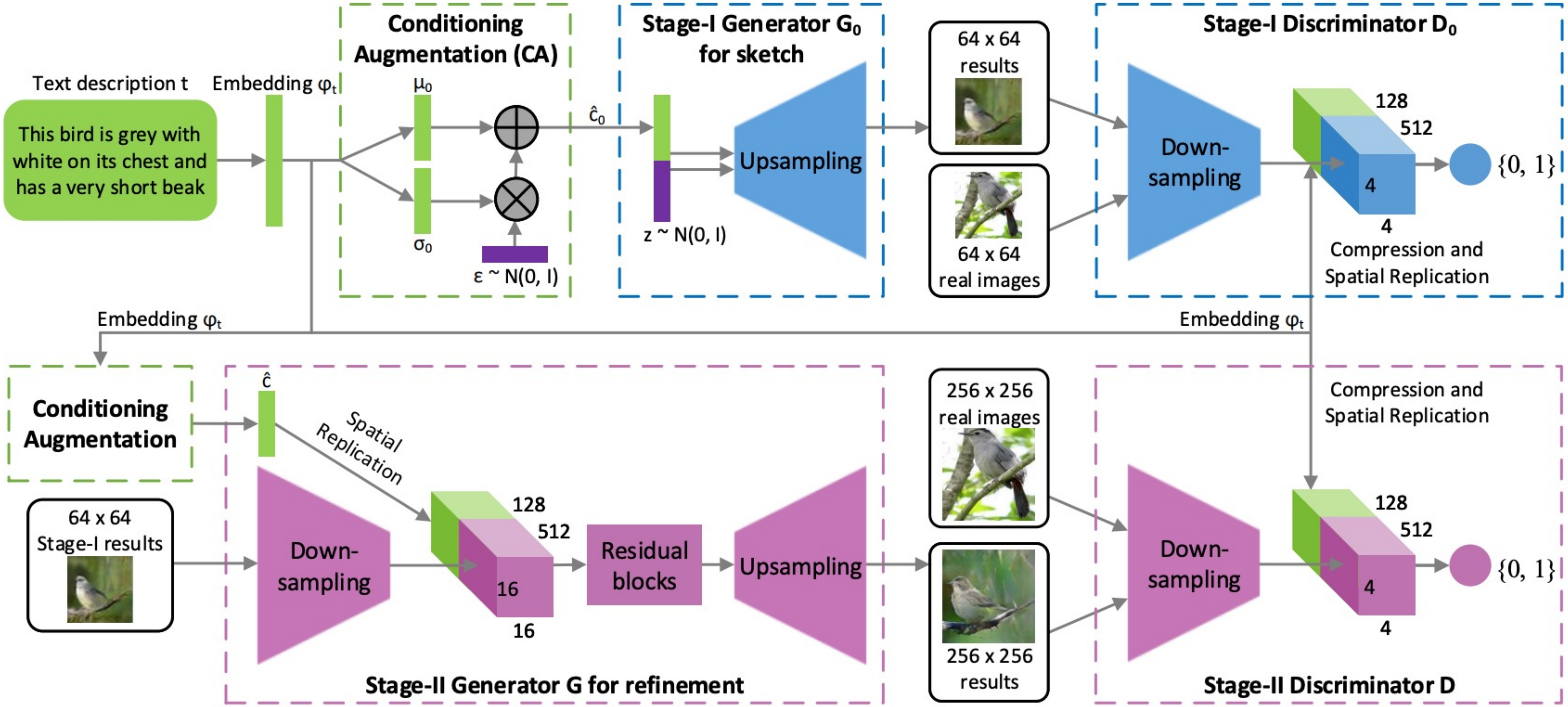

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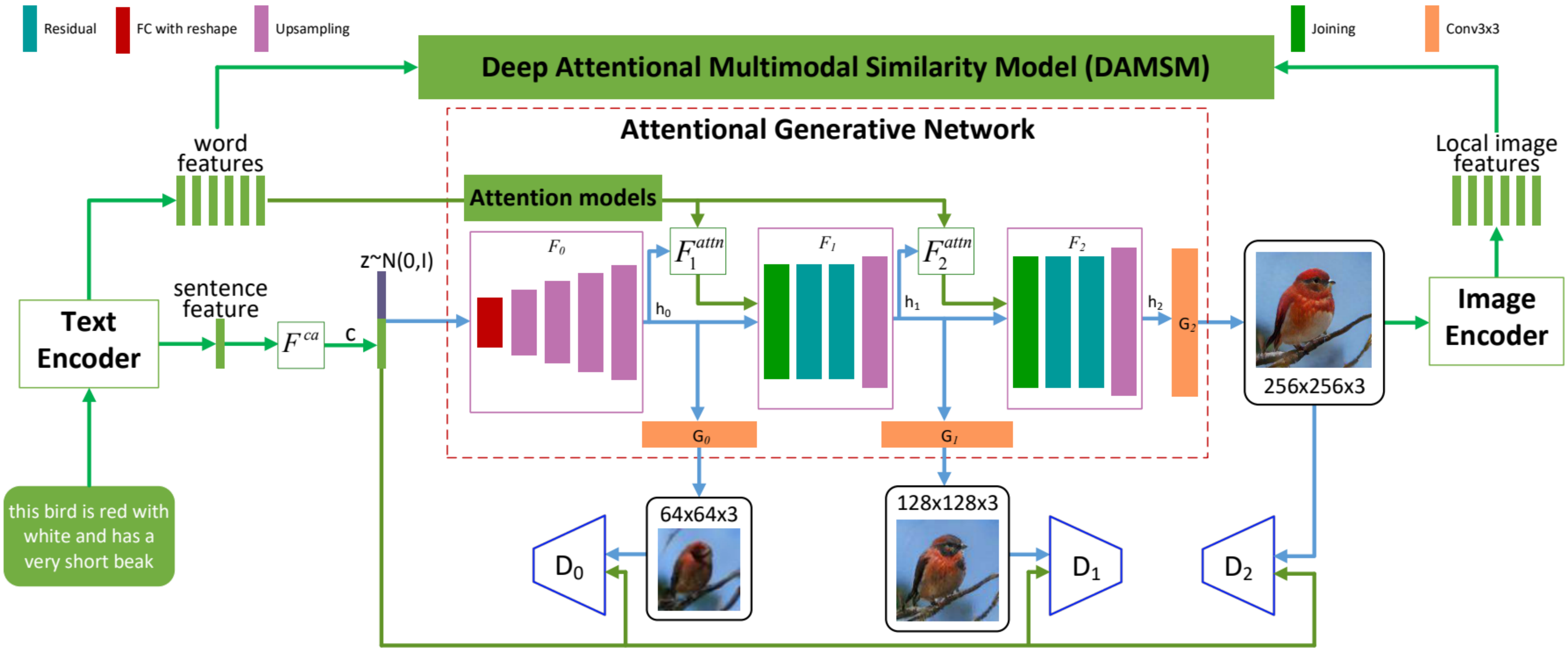
StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
Han Zhang et al., ICCV 2017

+ Cross-attention to connect Text and Image

AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks
Tao Xu et al., CVPR 2018

+ Cross-attention to connect Text and Image



AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks
Tao Xu et al., CVPR 2018

Got Stuck in 2018-2020 (Birds, MS COCO)

Who shall we blame?

- Better generative modeling techniques: VAEs, GANs?
- Better text encoders: LSTM/RNN?
- Better generator architectures: CNNs?
- Better ways to connect text and image.
- Bigger data + more GPU/TPU computing.
- Bigger model sizes.

How could we synthesize images beyond single or a few categories

Taming Transformers for High-Resolution Image Synthesis

Patrick Esser* Robin Rombach* Björn Ommer
Heidelberg Collaboratory for Image Processing, IWR, Heidelberg University, Germany
*Both authors contributed equally to this work

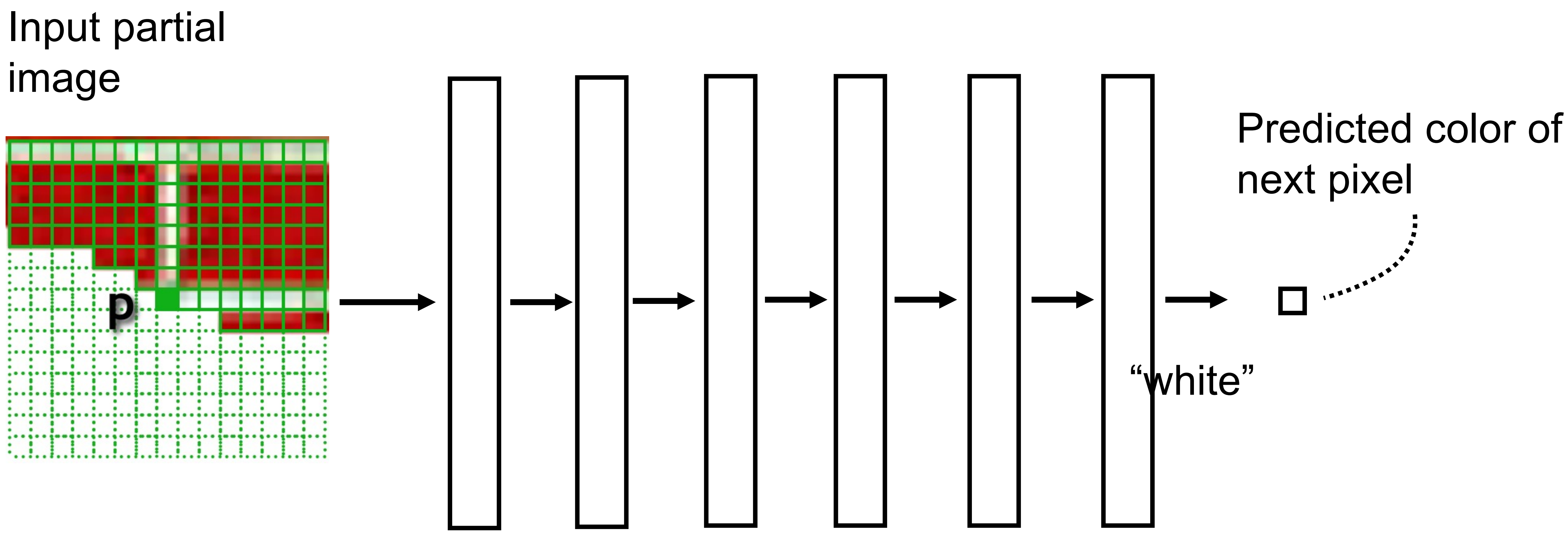
Figure 1. Our approach enables transformers to synthesize high-resolution images like this one, which contains 1280x460 pixels.

Abstract

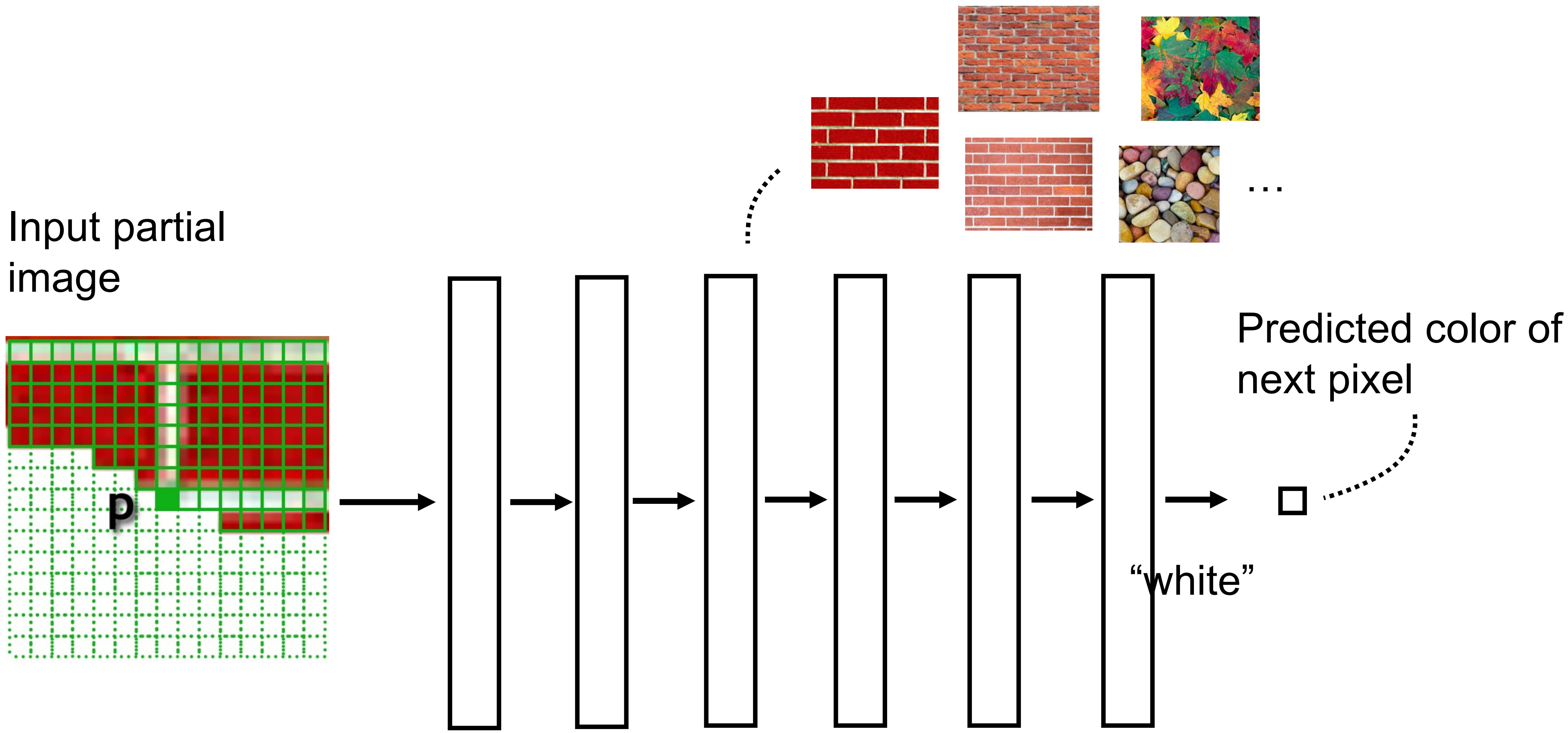
Designed to learn long-range interactions on sequential ... of-the-art results

and are increasingly adapted in other areas such as audio [12] and vision [8, 16]. In contrast to the predominant vision architecture, convolutional neural networks (CNNs), the transformer architecture contains no built-in inductive ... the locality of interactions and is therefore free ... However,

Autoregressive (AR) image synthesis

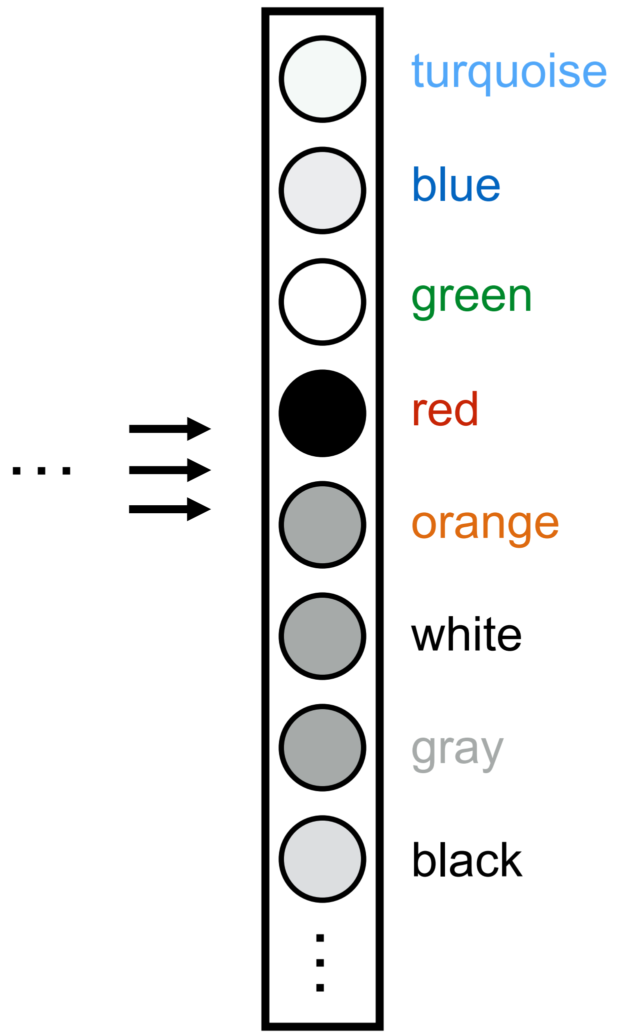


[PixelRNN, PixelCNN, van der Oord et al. 2016]



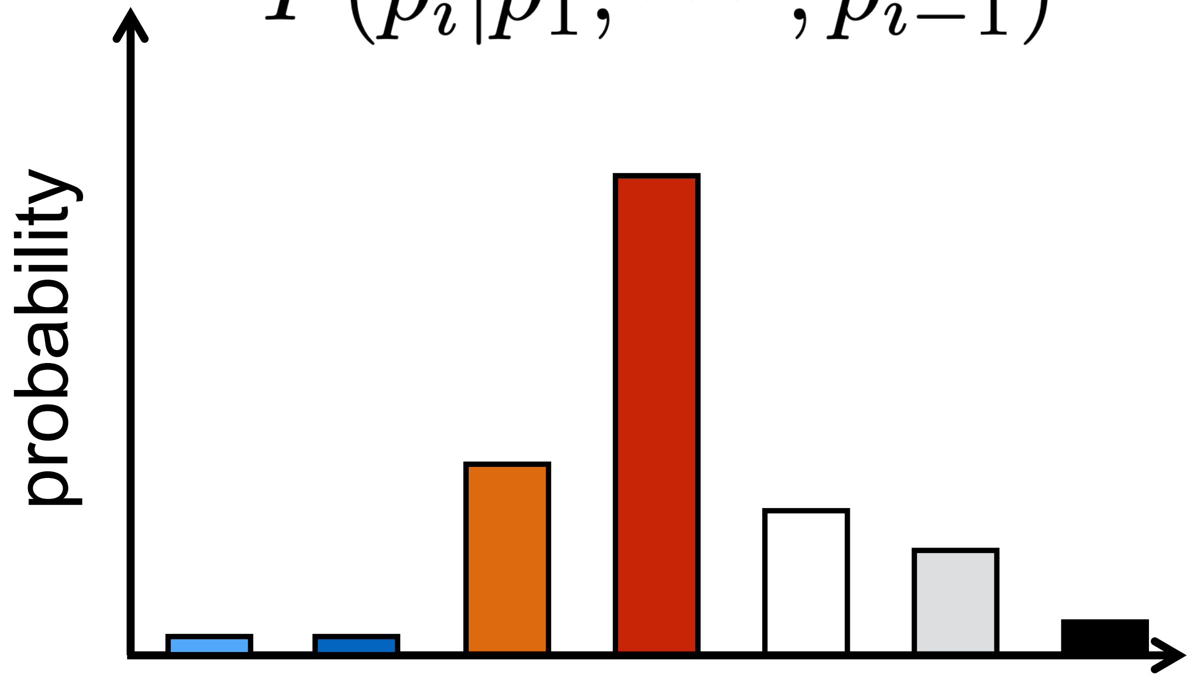
[PixelRNN, PixelCNN, van der Oord et al. 2016]

Network output

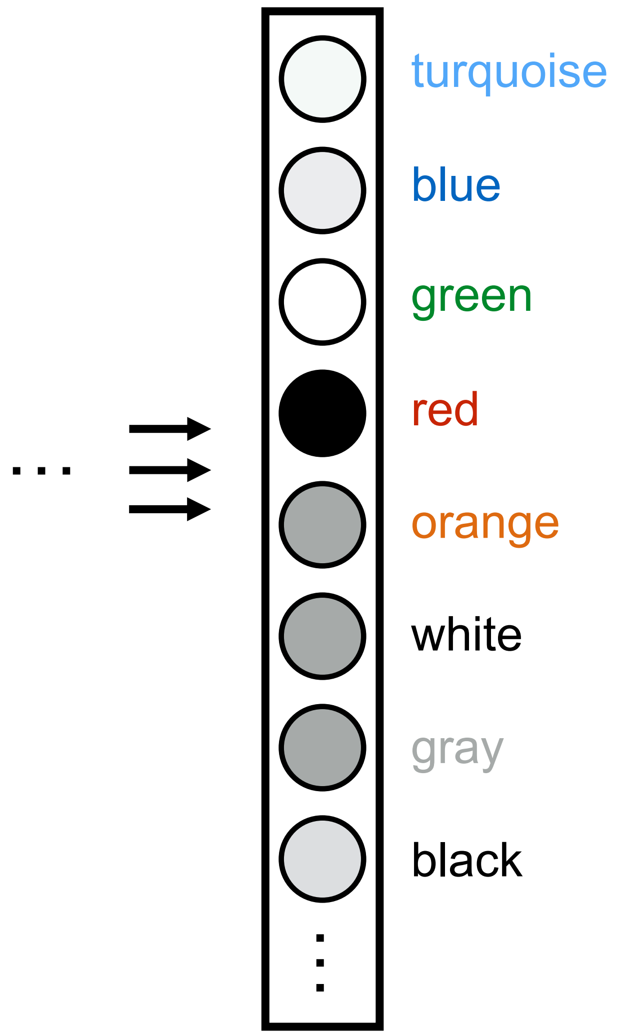


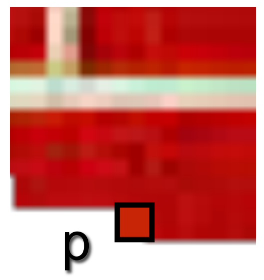
P(next pixel | previous pixels)

$$P(p_i | p_1, \cdots, p_{i-1})$$

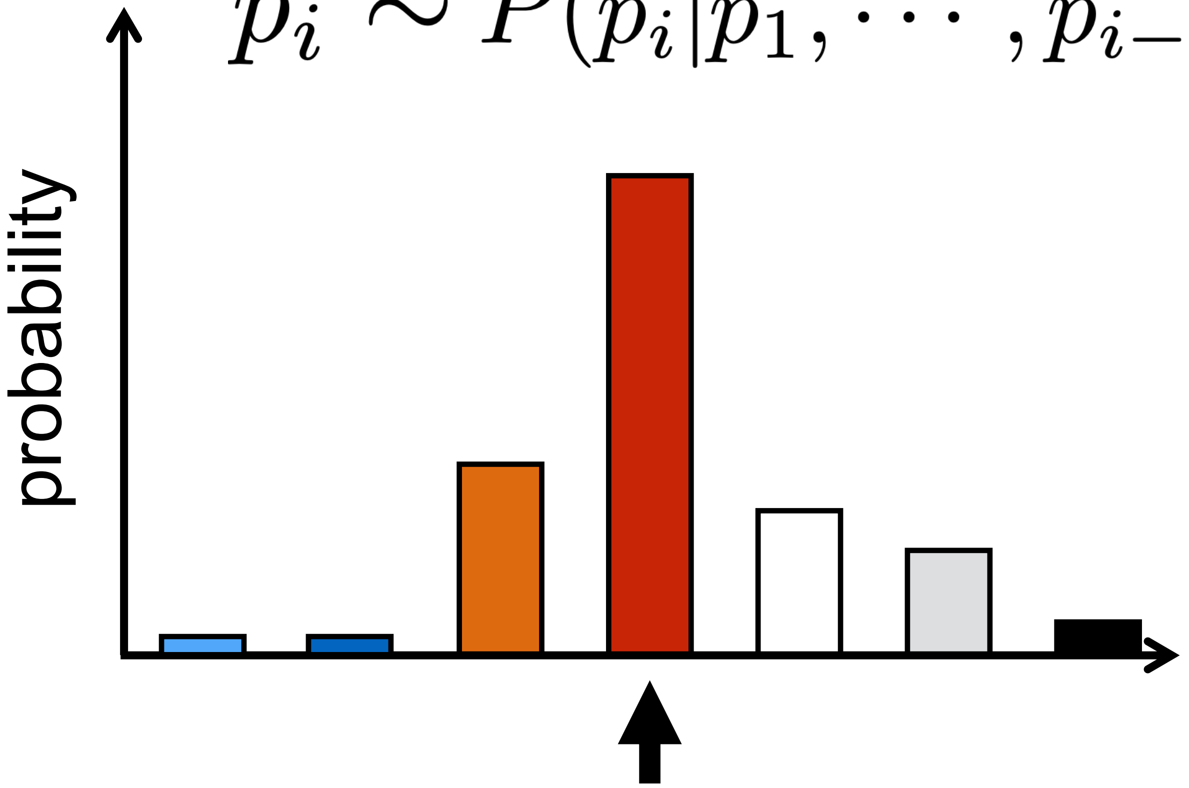


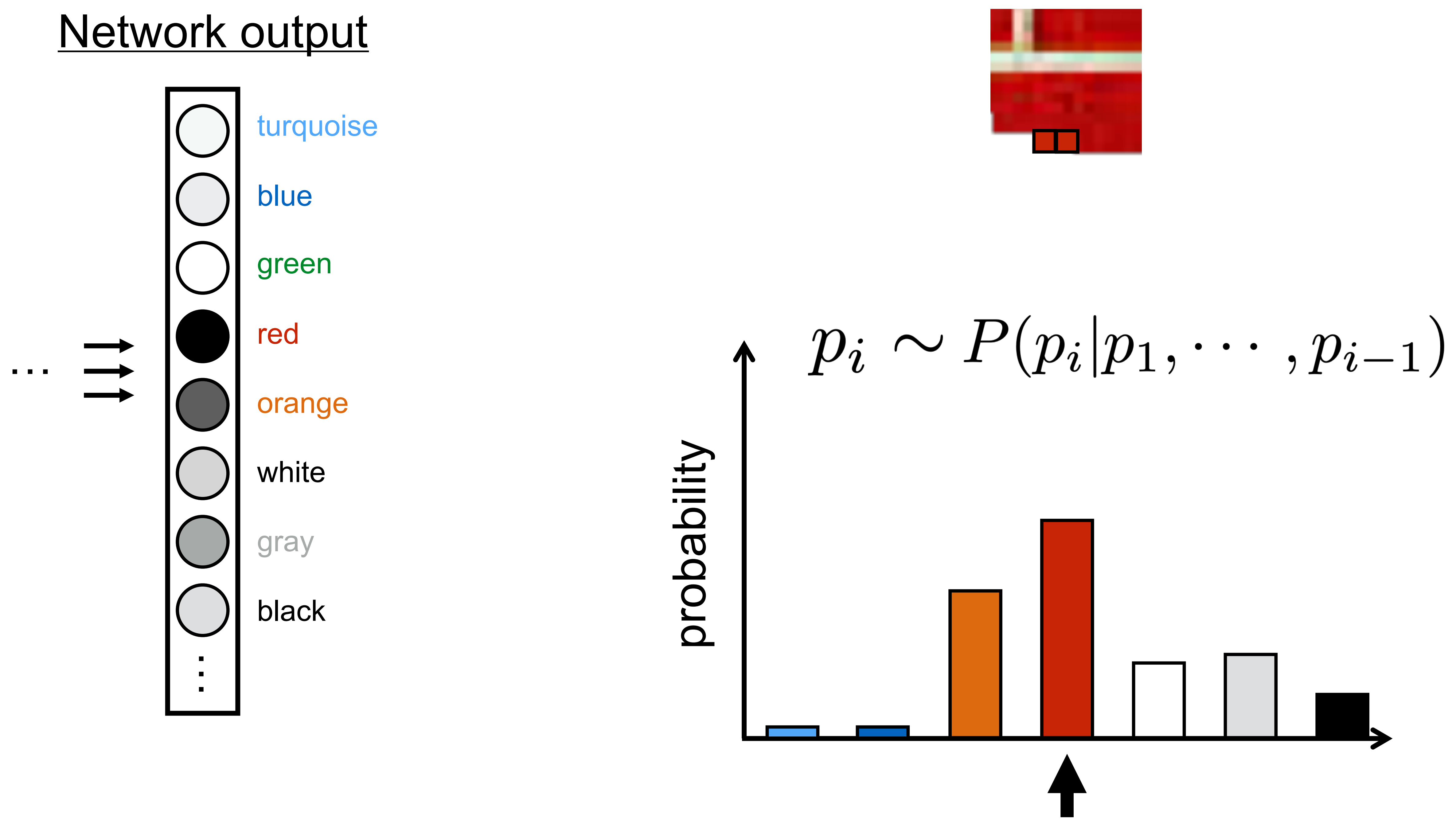
Network output



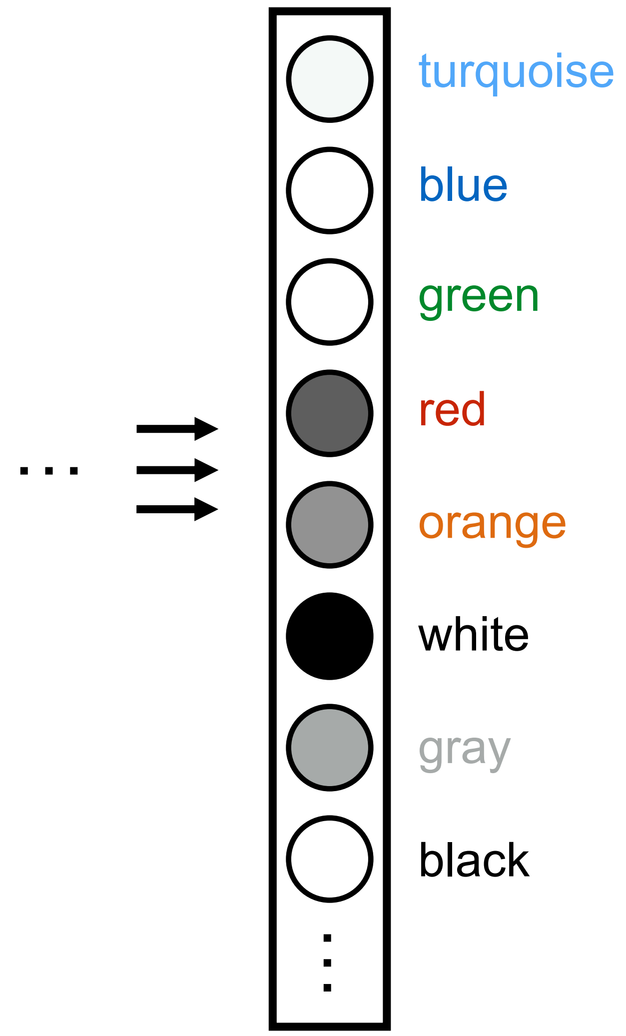


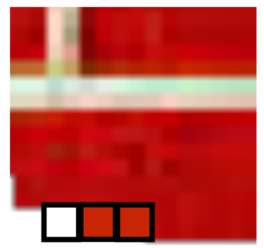
$$p_i \sim P(p_i | p_1, \cdots, p_{i-1})$$



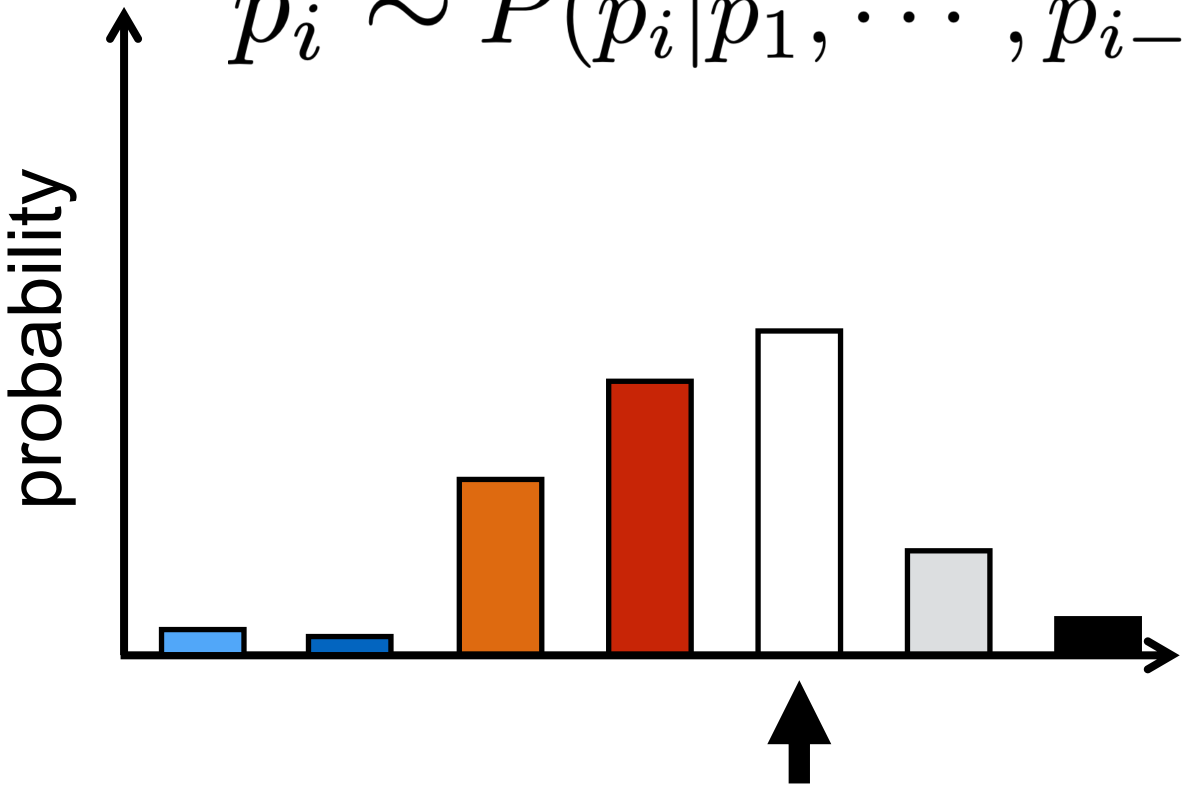

Network output
turquoise
blue
green
red
orange
white
gray
black
$p_i \sim P(p_i|p_1, \cdots, p_{i-1})$
probability

Network output

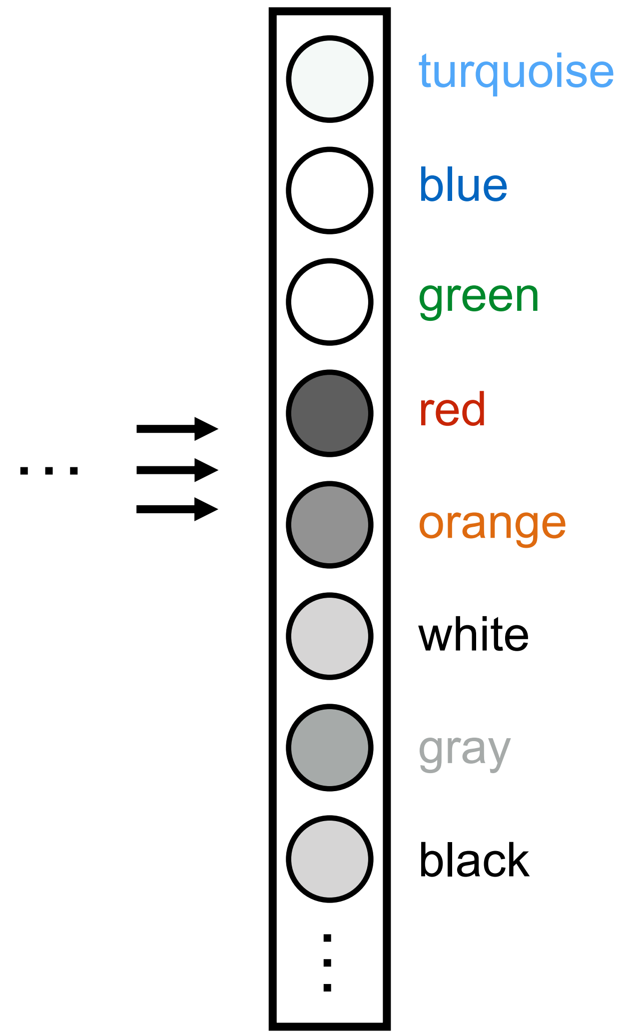




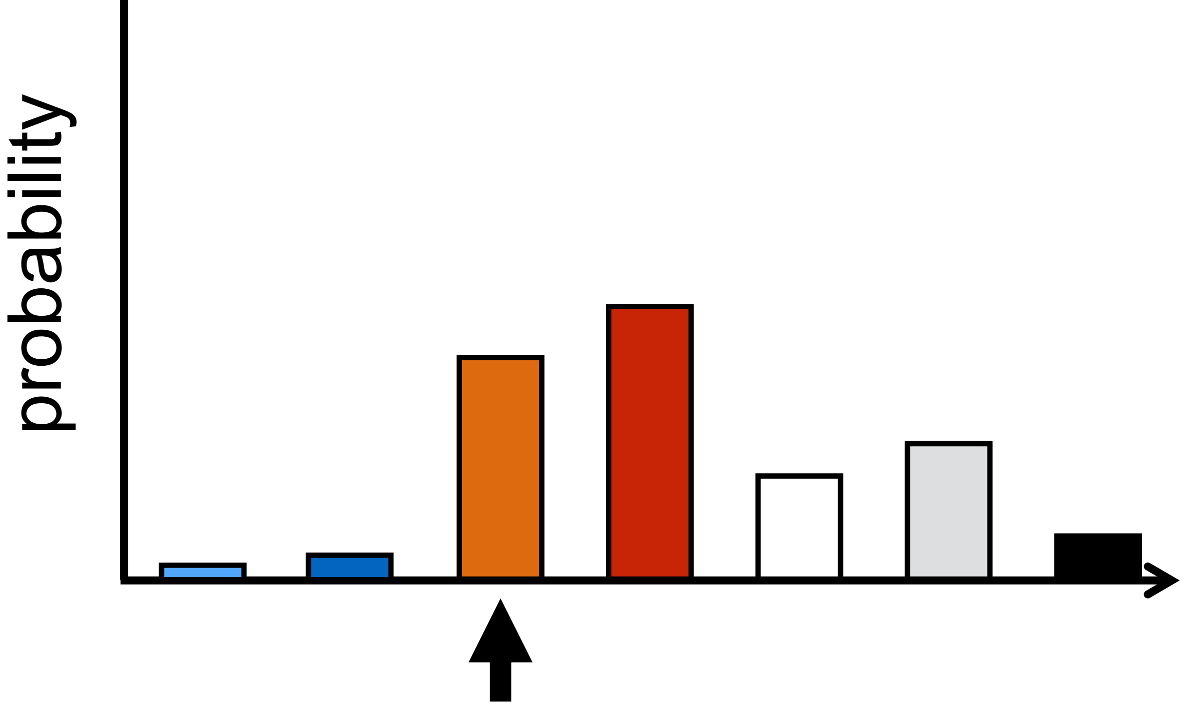
$$p_i \sim P(p_i | p_1, \cdots, p_{i-1})$$



Network output



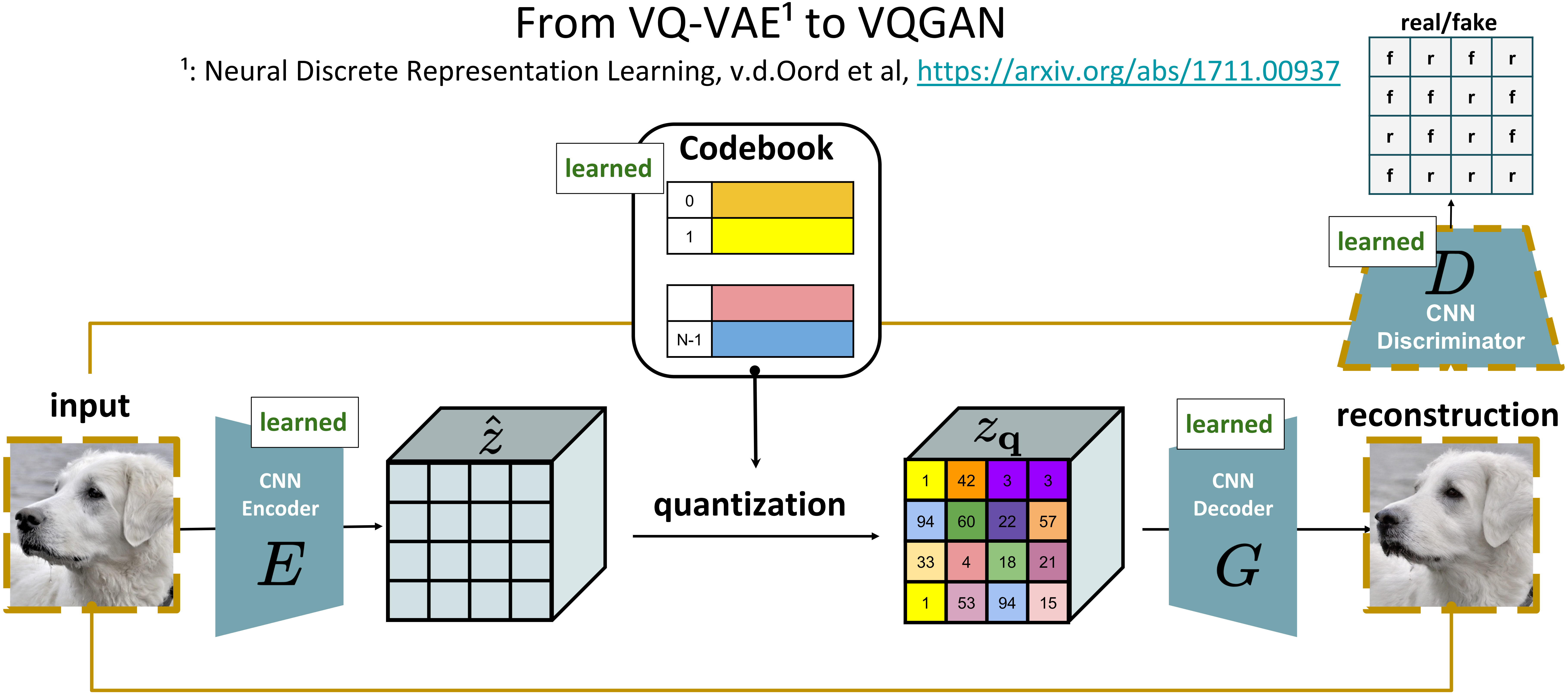
$$p_i \sim P(p_i | p_1, \cdots, p_{i-1})$$



Generation is super slow?
What should we do?

From VQ-VAE[1] to VQGAN

[1]: Neural Discrete Representation Learning, v.d.Oord et al, https://arxiv.org/abs/1711.00937



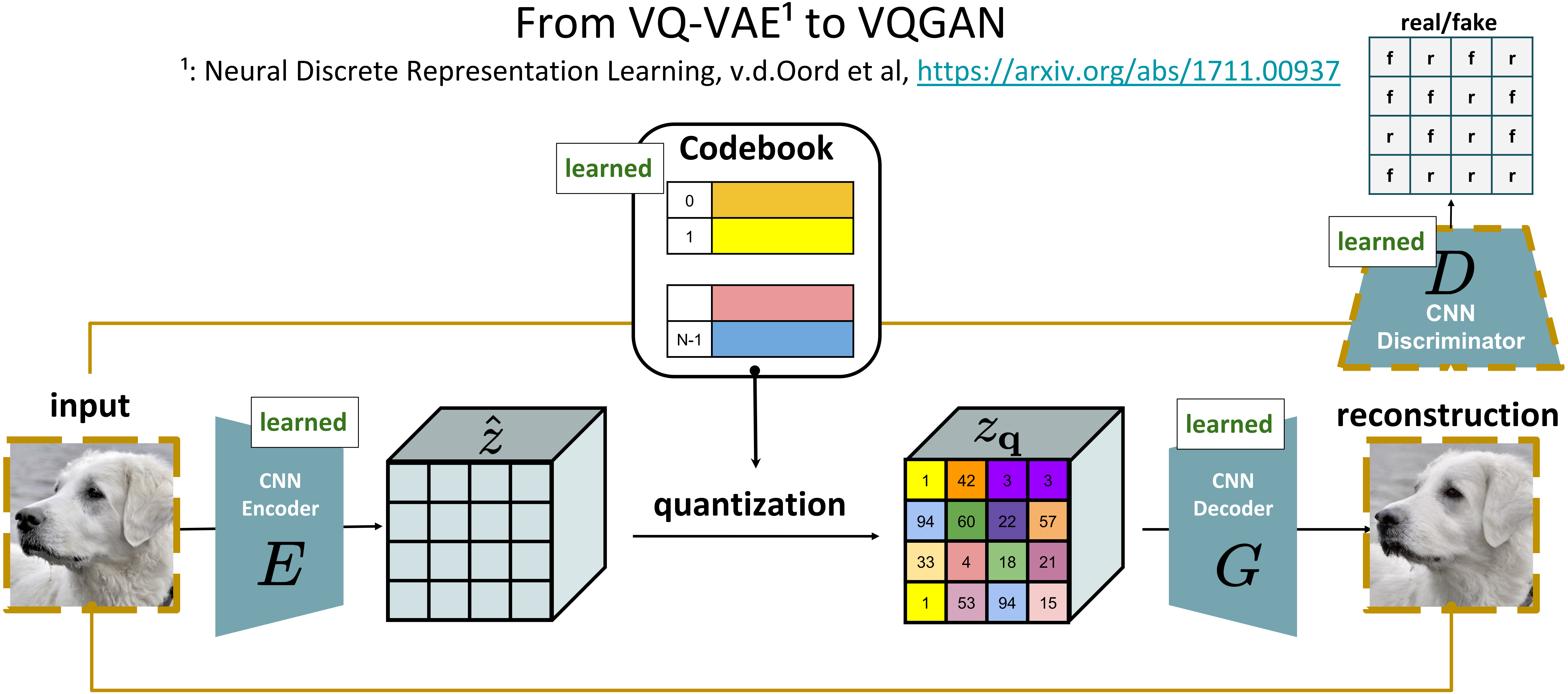
i) replace L2/L1 rec. loss with Perceptual loss (includes pixel-level)

ii) add (patch-wise) Discriminator to favor realism over perfect reconstruction

Slide credit: Robin Rombach

From VQ-VAE[1] to VQGAN

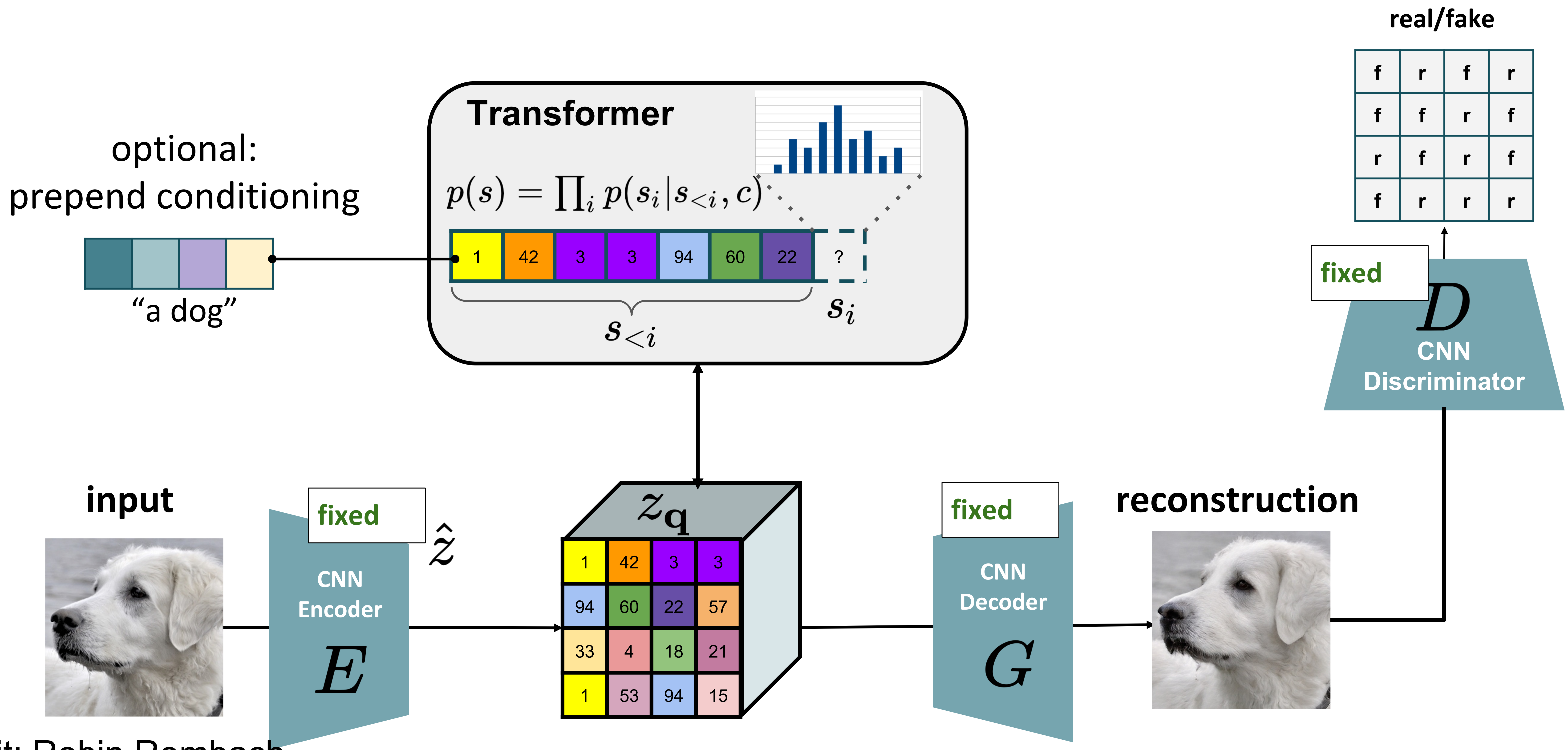
[1]: Neural Discrete Representation Learning, v.d.Oord et al, https://arxiv.org/abs/1711.00937



$$\mathcal{L}_{\text{total}} = \mathcal{L}_{rec} + \mathcal{L}_{VQ} + \lambda\mathcal{L}_{GAN} \quad \text{where} \quad \lambda = \frac{\nabla_{G_L}[\mathcal{L}_{rec}]}{\nabla_{G_L}[\mathcal{L}_{GAN}]+\delta}$$

Slide credit: Robin Rombach

Transformer Training



Slide credit: Robin Rombach

Slide credit: Robin Rombach

Scaling VQGAN for Text-to-Image!

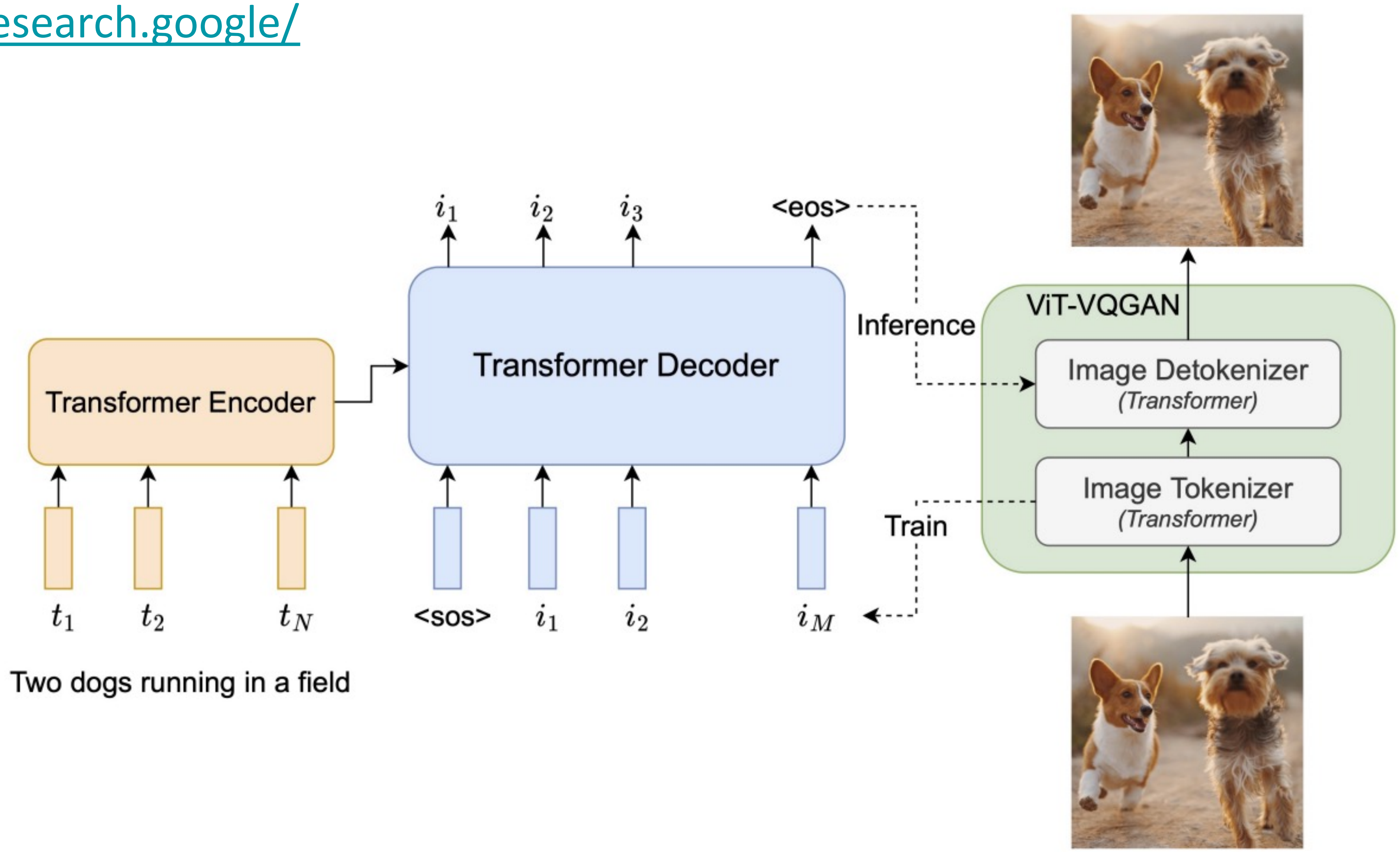
- see recently released “Parti” paper by Google (text-to-image model)
  - https://parti.research.google/

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!

Slide credit: Robin Rombach

Scaling VQGAN for Text-to-Image!

- see recently released “Parti” paper by Google (text-to-image model)
  - https://parti.research.google/



Transformer-based Encoder/Decoder + Transformer-based Autoregressive models

Another Approach: Diffusion Models!

great results for image synthesis

Denoising Diffusion Probabilistic Models

Jonathan Ho, Ajay Jain, et al

https://arxiv.org/abs/2006.11239

Diffusion Models beat GANs on Image Synthesis

Prafulla Dhariwal, Alex Nichol

https://arxiv.org/abs/2105.05233

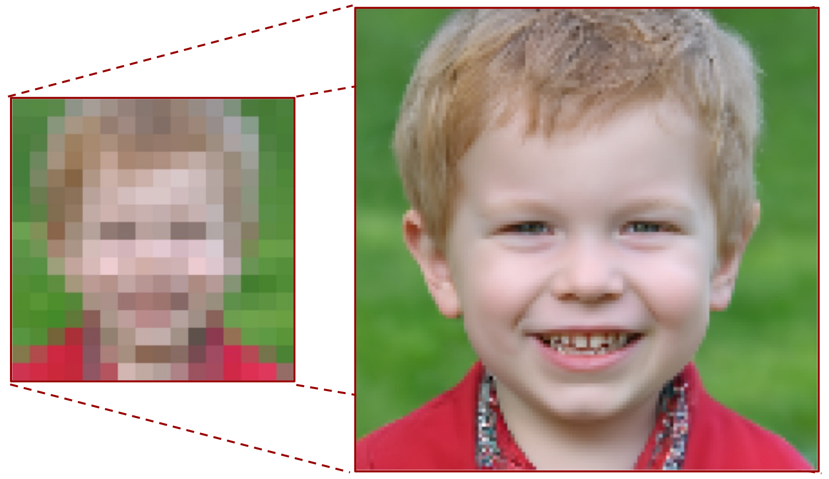


Image Super-Resolution via Iterative Refinement

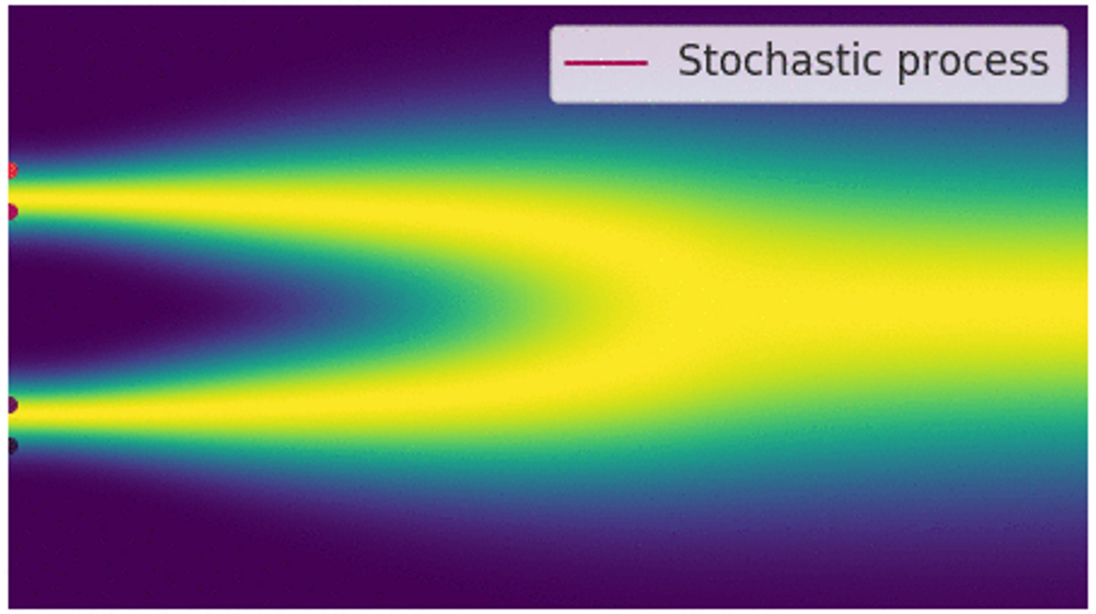
Chitwan Saharia, et al

https://arxiv.org/abs/2104.07636

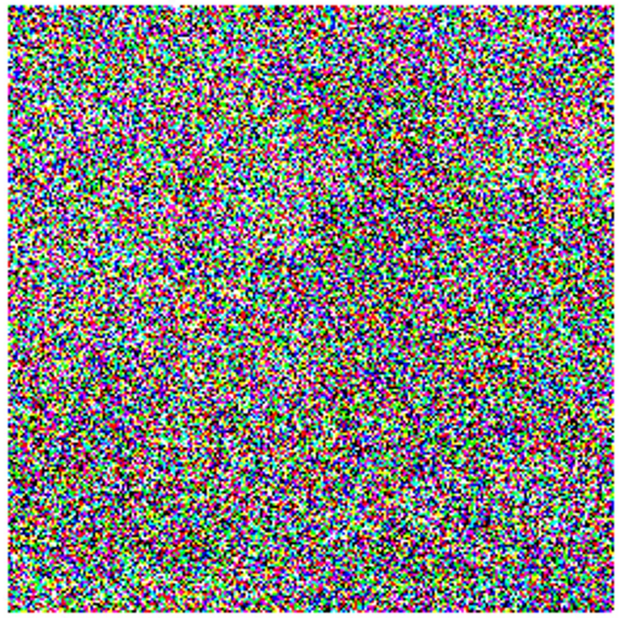
… but very expensive :(

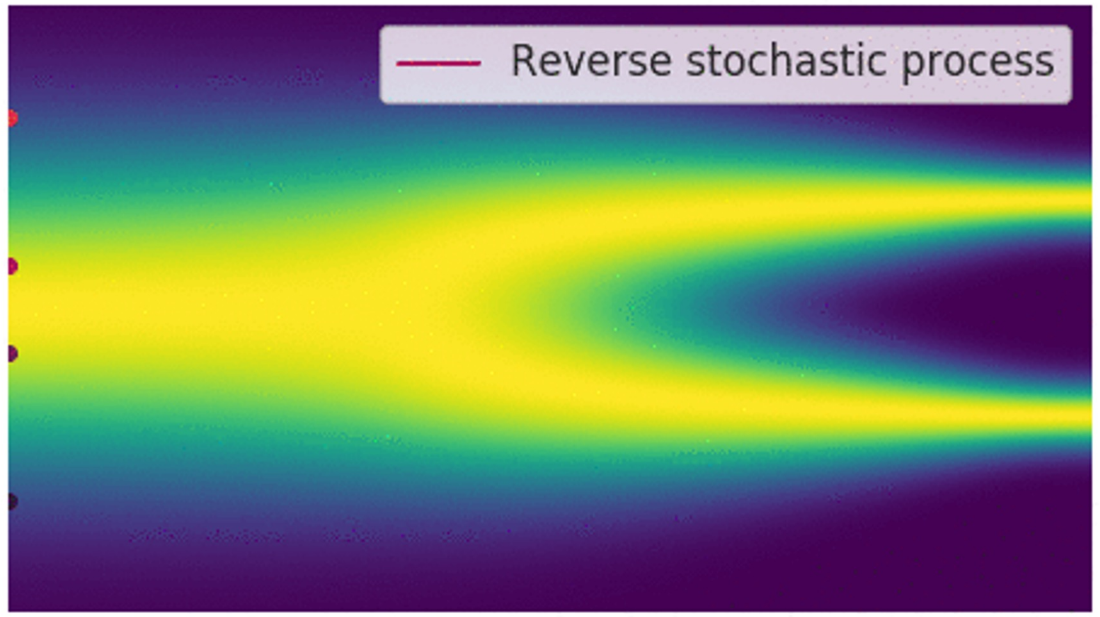
Slide credit: Robin Rombach

Brief Overview of Diffusion Models



- “destroy” the data by gradually adding small amounts of gaussian noise





- “create” data by gradually denoising a noisy code from a stationary distribution

Animations from https://yang-song.github.io/blog/2021/score/

Denoising Diffusion Models

Learning to generate by denoising

Denoising diffusion models consist of two processes:

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

Forward diffusion process (fixed)

Data

Noise

Reverse denoising process (generative)

[Sohl-Dickstein et al., Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML 2015]
[Ho et al., Denoising Diffusion Probabilistic Models, NeurIPS 2020]
[Song et al., Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021]

Slide credit: Karsten Kreis et al.

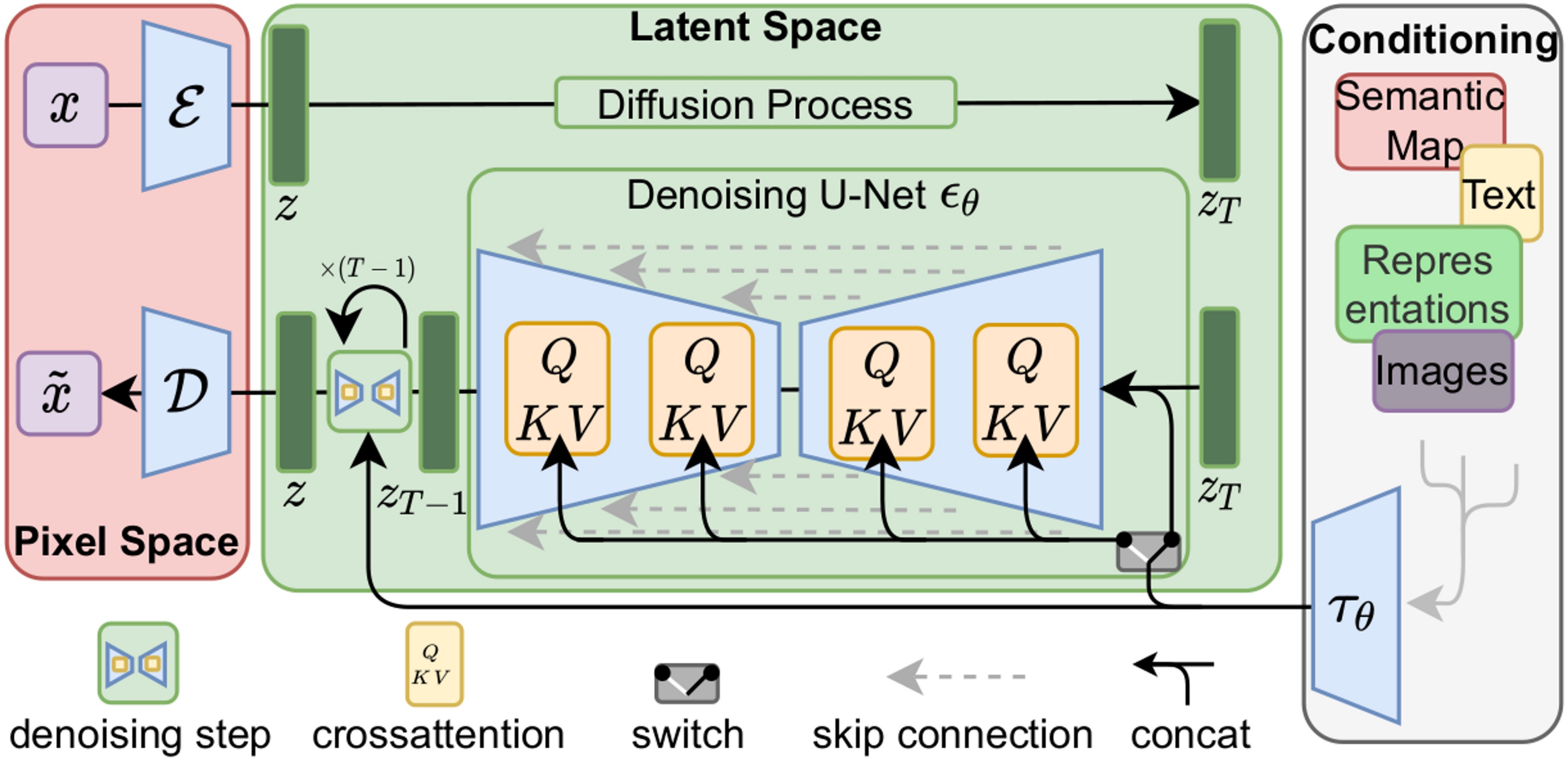
Latent Diffusion Modeling: Architecture

Autoencoder with KL or VQ regularization.

VQ-reg.: $\mathcal{L}_{\text{total}} = \mathcal{L}_{rec} + \mathcal{L}_{VQ} + \lambda \mathcal{L}_{GAN}$

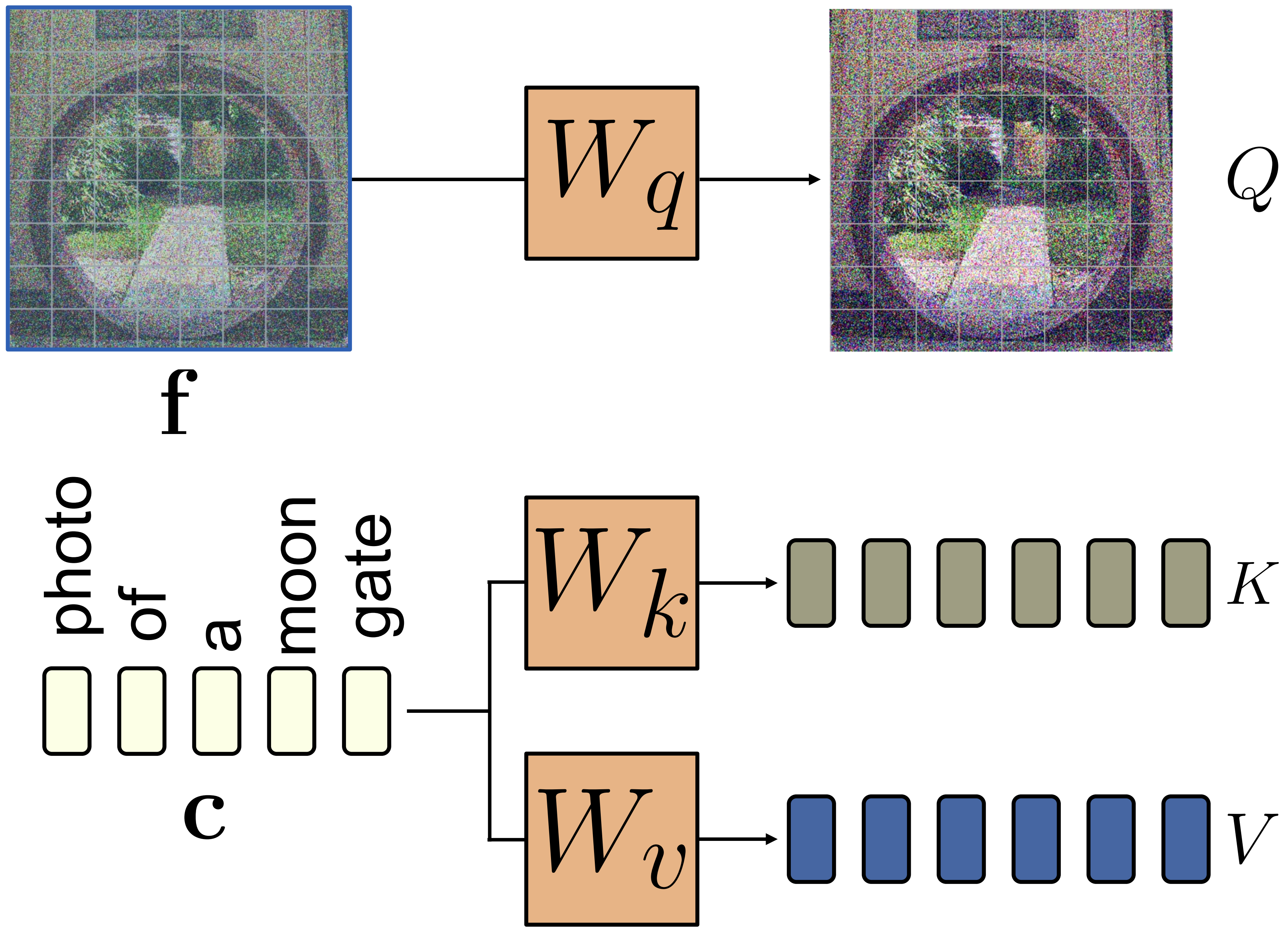
KL-reg.: $\mathcal{L}_{\text{total}} = \mathcal{L}_{rec} + \beta \mathcal{L}_{KL} + \lambda \mathcal{L}_{GAN}$

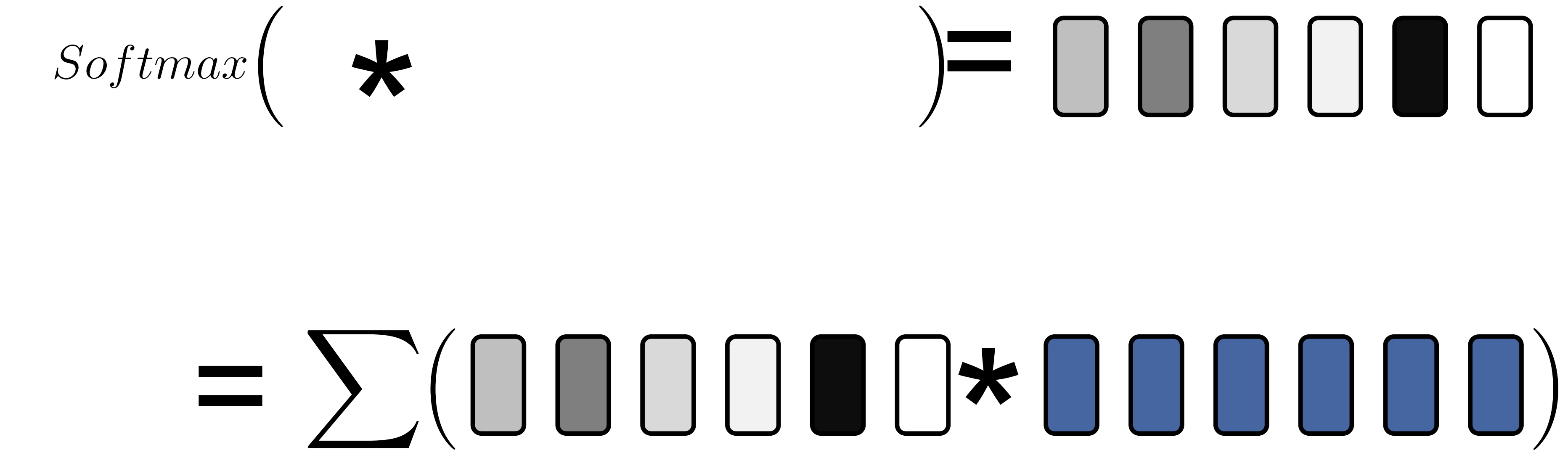
where $\lambda = \frac{\nabla_{G_L}[\mathcal{L}_{rec}]}{\nabla_{G_L}[\mathcal{L}_{GAN}]+\delta}$



Slide credit: Robin Rombach

Text-Image Cross-Attention



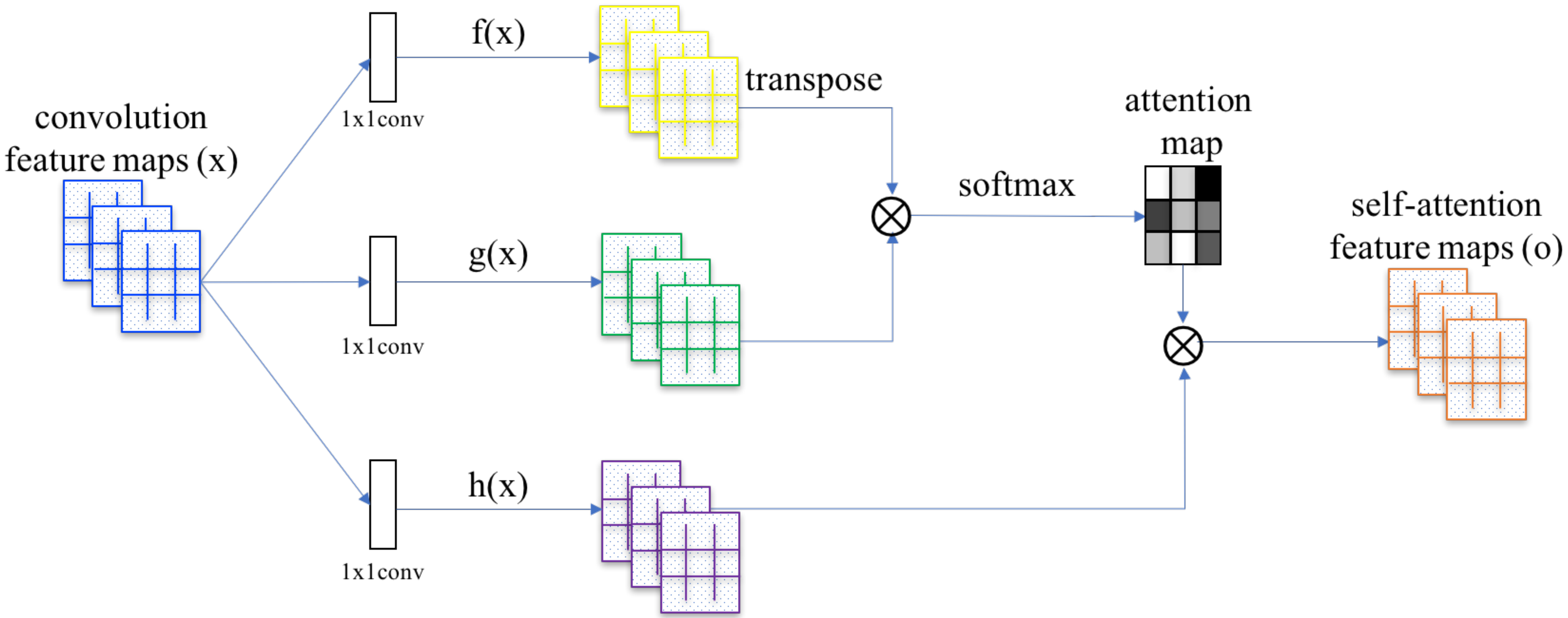


i.e.

Output = $\mathrm{Softmax}\left(\frac{Q.K^T}{\sqrt{d'}}\right)V$

Slides from [Kumari et al., CVPR 2023]

(Spatial) Self-attention Layer



Han Zhang et al, “Self-Attention Generative Adversarial Networks”, ICML 2018

LDMs for Text-to-Image Synthesis

- 32x32 cont. space
- 600M Transformer
- 800M UNet
- 400M Image/Text Pairs

Text-to-Image Synthesis on LAION. 1.4B Model.

'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!".'*

Slide credit: Robin Rombach

LDMs for Text-to-Image Synthesis

convolutional sampling (train on 256^2, generate on $>256^2$)

"A sunset over a mountain range, vector image"

"A sunset over a mountain range, oil on canvas"

Slide credit: Robin Rombach

“Cheat Code”: Classifier-Free Diffusion Guidance

Jonathan Ho, Tim Salimans

- see https://arxiv.org/abs/2207.12598
- works very well for conditional image generation:

e.g. empty string

$$\hat{\epsilon_\theta}(x_t; y, t) \leftarrow \epsilon_\theta(x_t; \emptyset, t) + s \cdot (\epsilon_\theta(x_t; y, t) - \epsilon_\theta(x_t; \emptyset, t)), \quad s \geq 1.0$$

$s = 1.0$

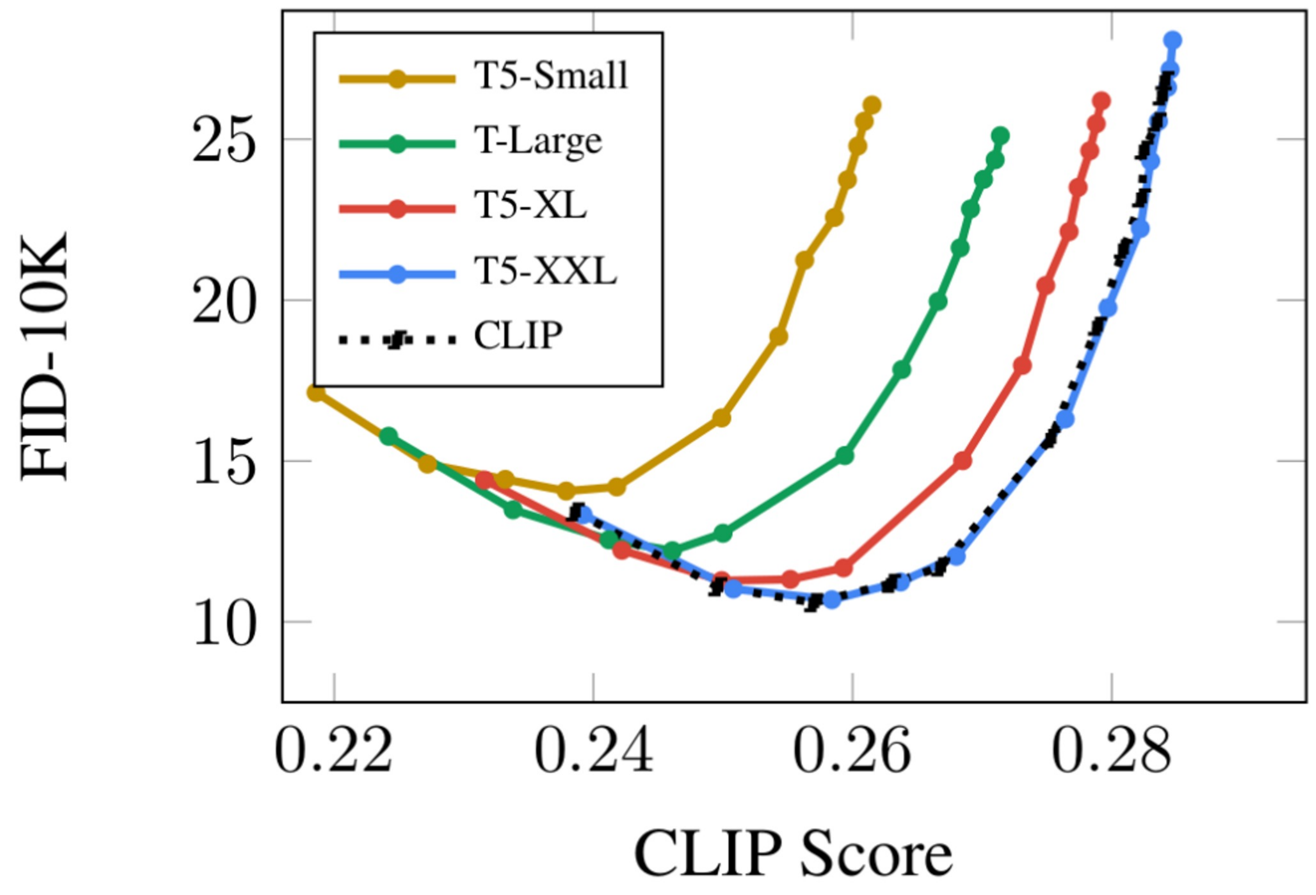
$s = 7.5$

Stable Diffusion

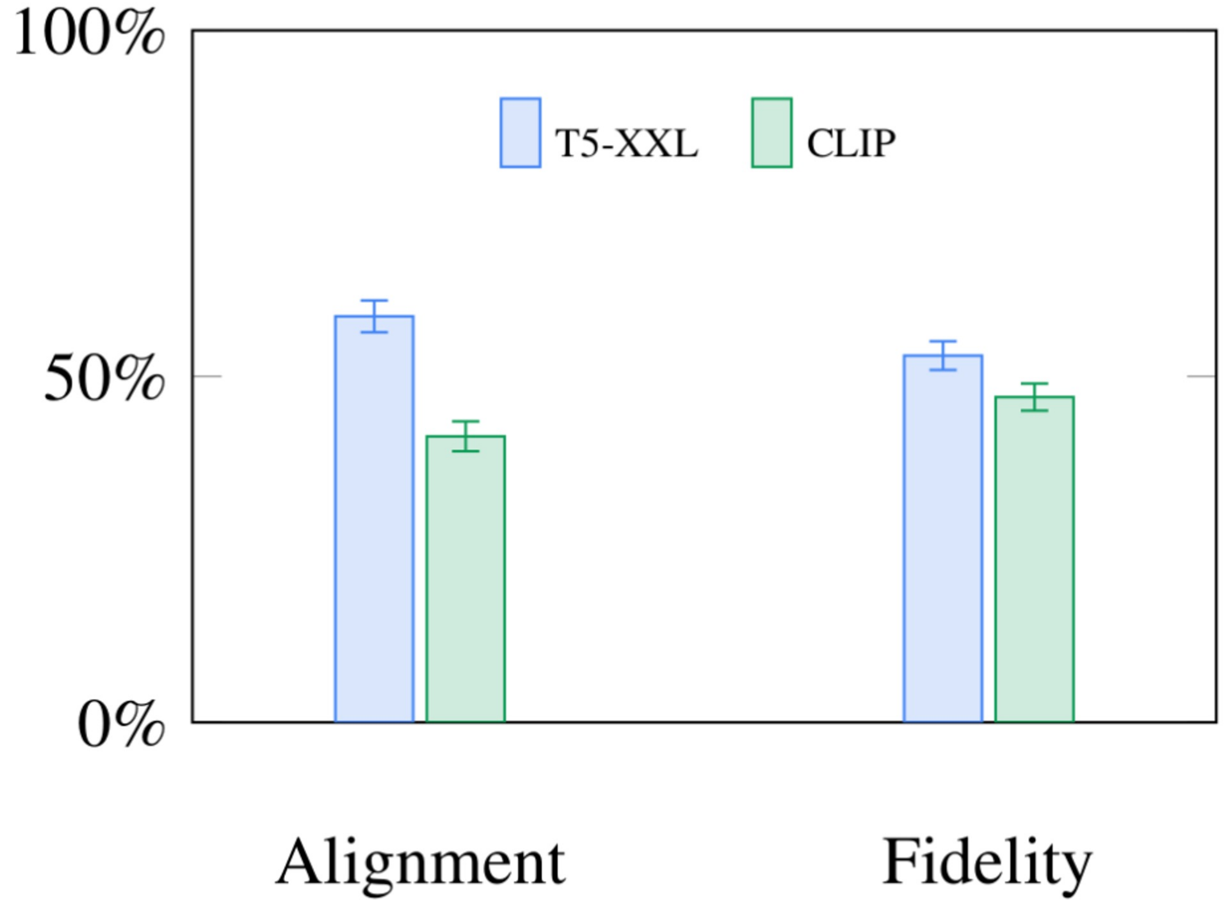
Latent Diffusion ++

From Latent to Stable Diffusion

- goal: achieve a small model that people can actually run locally on “small” GPUs (~10GB VRAM)
- progressive training: pretrain on 256x256, then continue on 512x512
- fix text encoder (as in Imagen)
- → choose CLIP (ViT-L/14) since performance/size tradeoff seems significant



(a) Pareto curves comparing various text encoders.



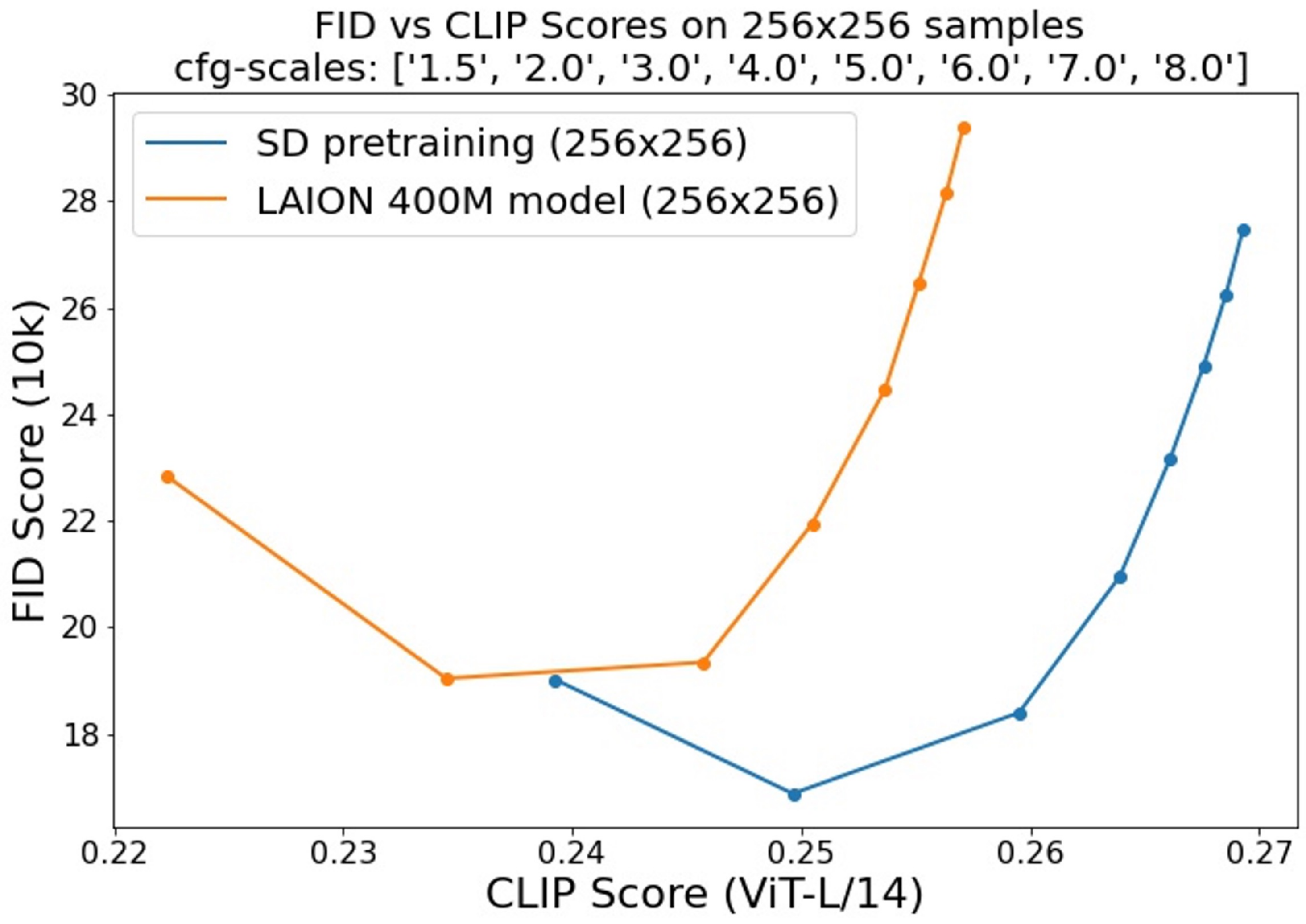
(b) Comparing T5-XXL and CLIP on DrawBench.

Figure from Imagen, https://arxiv.org/abs/2205.11487

From Latent Diffusion to Stable Diffusion

Stage 1: Pretraining @256x256

- 237k steps at resolution 256x256 on LAION 2B(en)
- batch-size = 2048
- ~ 64 A100 GPUs



10k random COCO val captions / 50 decoding steps

From Latent Diffusion to Stable Diffusion

Stage 2: Training @512x512. batch-size=2048, #gpus=256

part 1 (v1.1):

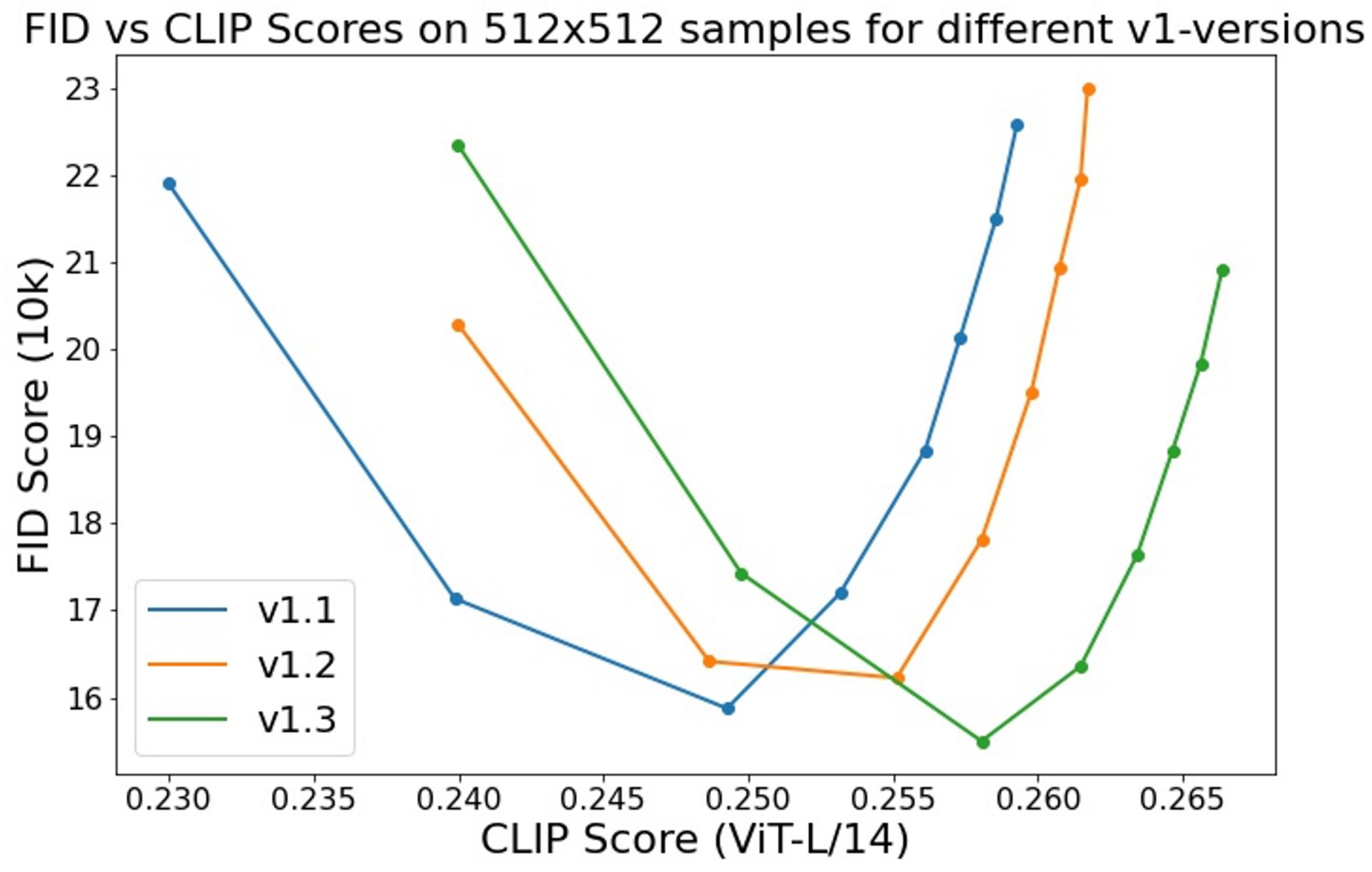
- 194k steps at resolution 512x512 on laion-high-resolution (170M examples from LAION-5B with resolution >= 1024x1024).

part 2 (v1.2):

- 515k steps at resolution 512x512 on "laion-improved-aesthetics" (a subset of laion2B-en, filtered to images with an original size >= 512x512, estimated aesthetics score > 5.0, and an estimated watermark probability < 0.5

part 3/4 (v1.3/v1.4):

- 195k/225k steps at resolution 512x512 on "laion-improved-aesthetics" and 10% dropping of the text-conditioning

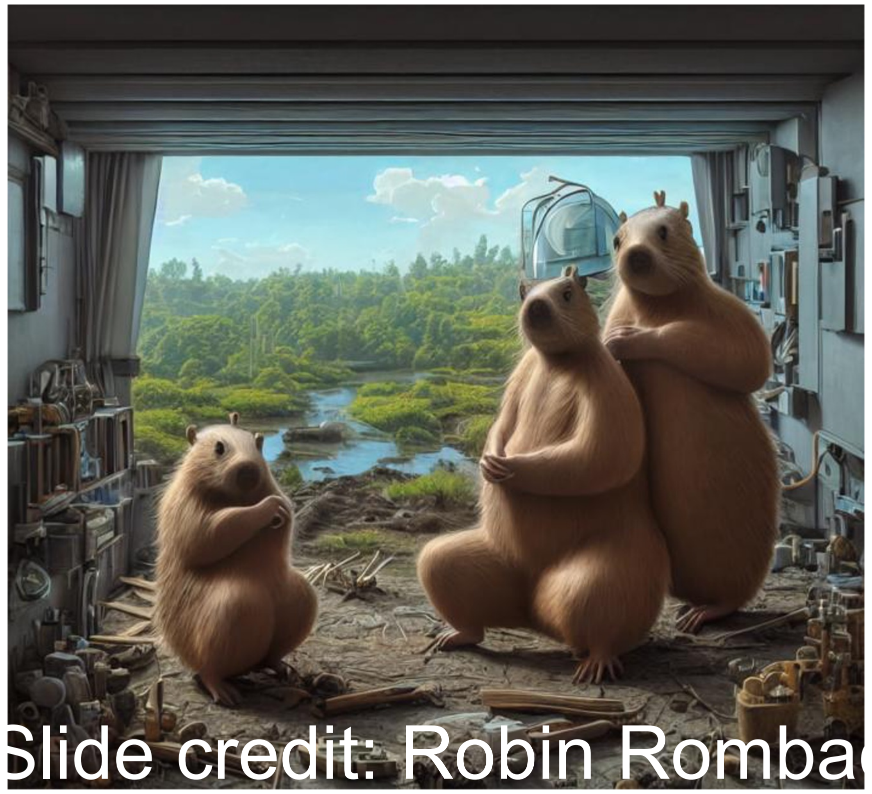


10k random COCO val captions / 50 decoding steps

→ 4.2 GB checkpoint (EMA only, fp32)







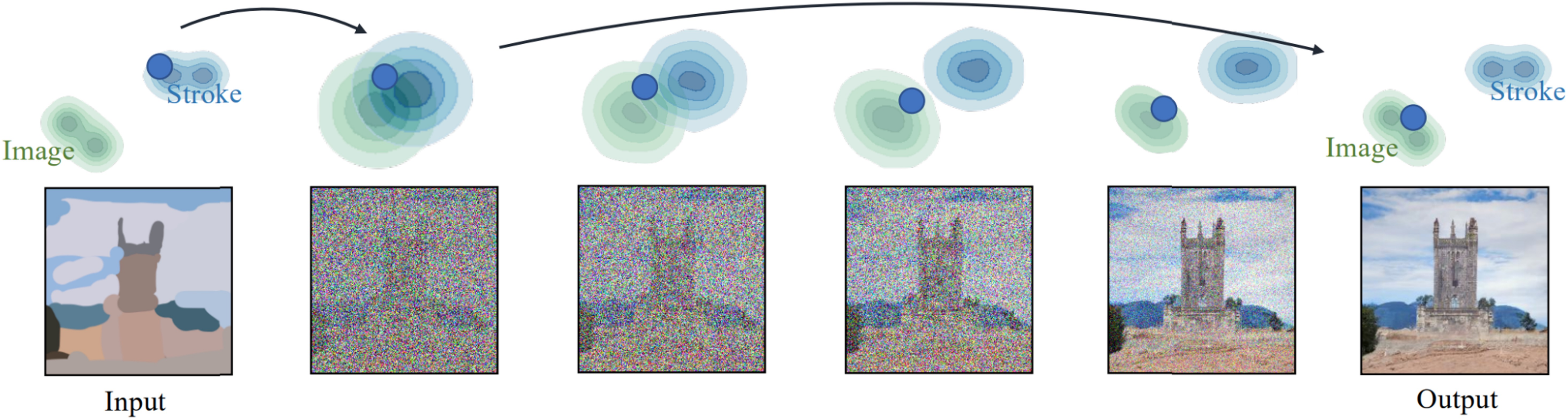

Slide credit: Robin Rombach

Text-Guided Image-to-Image

SDEdit (https://arxiv.org/abs/2108.01073) recipe: diffuse → denoise

Adding noises (diffuse)

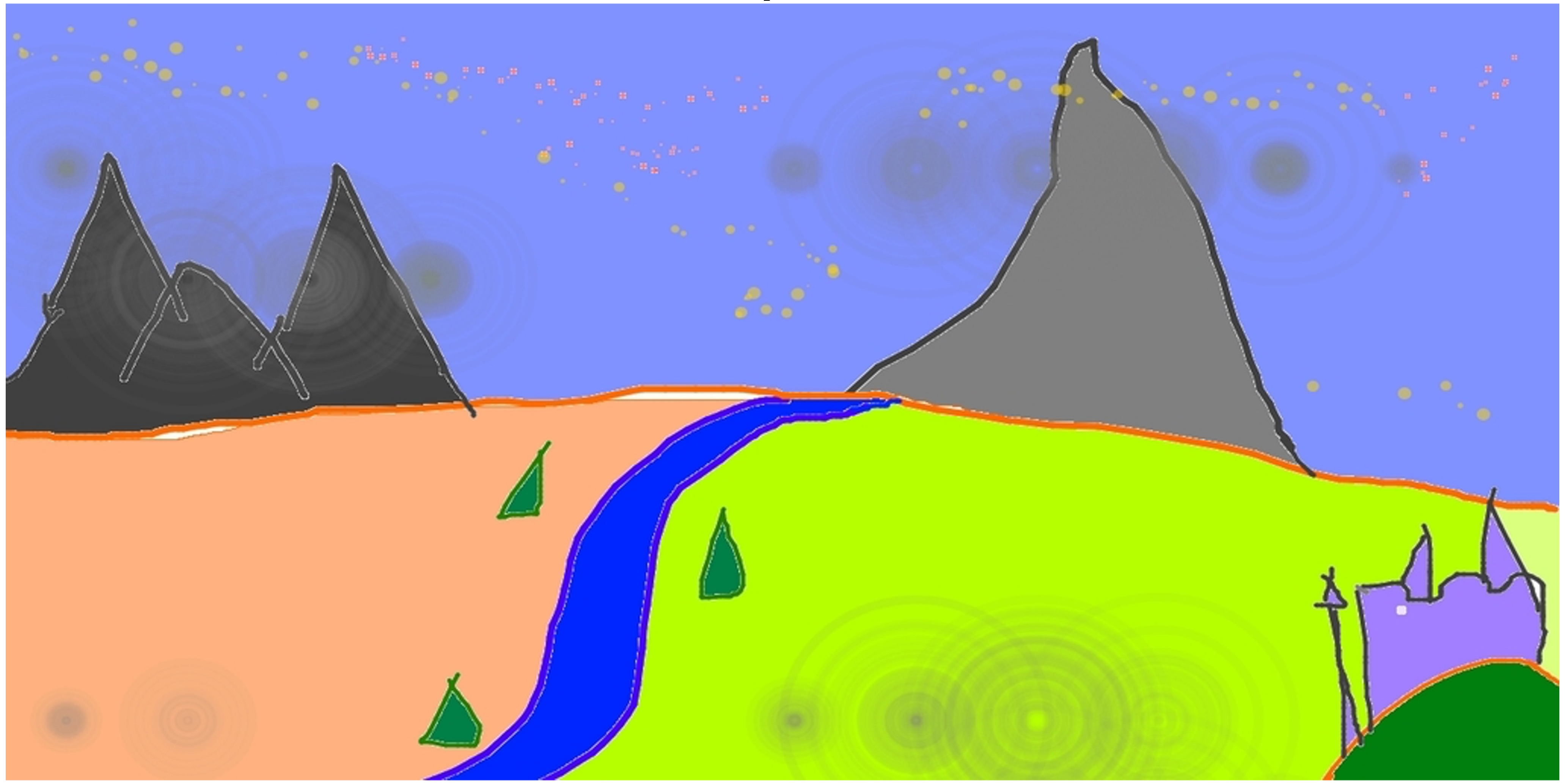
Denoise



Slide credit: Robin Rombach

Text-Guided Image-to-Image

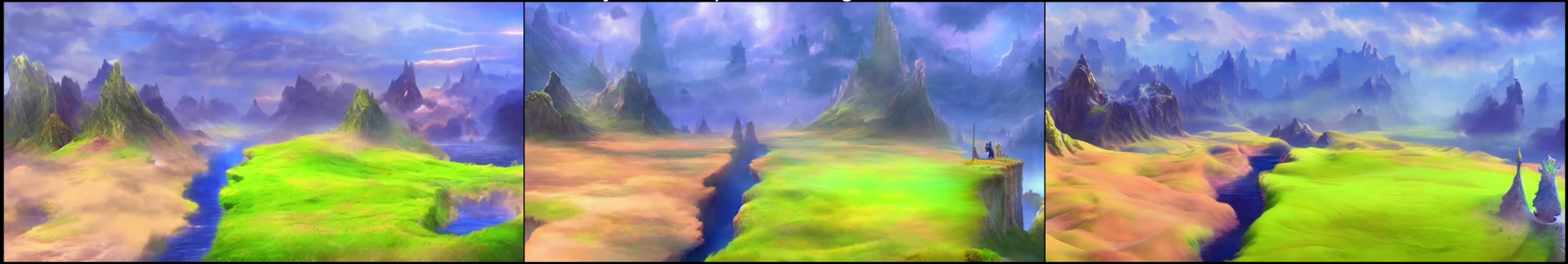
input



Slide credit: Robin Rombach

“a fantasy landscape, watercolor painting”

“a fantasy landscape, trending on artstation”

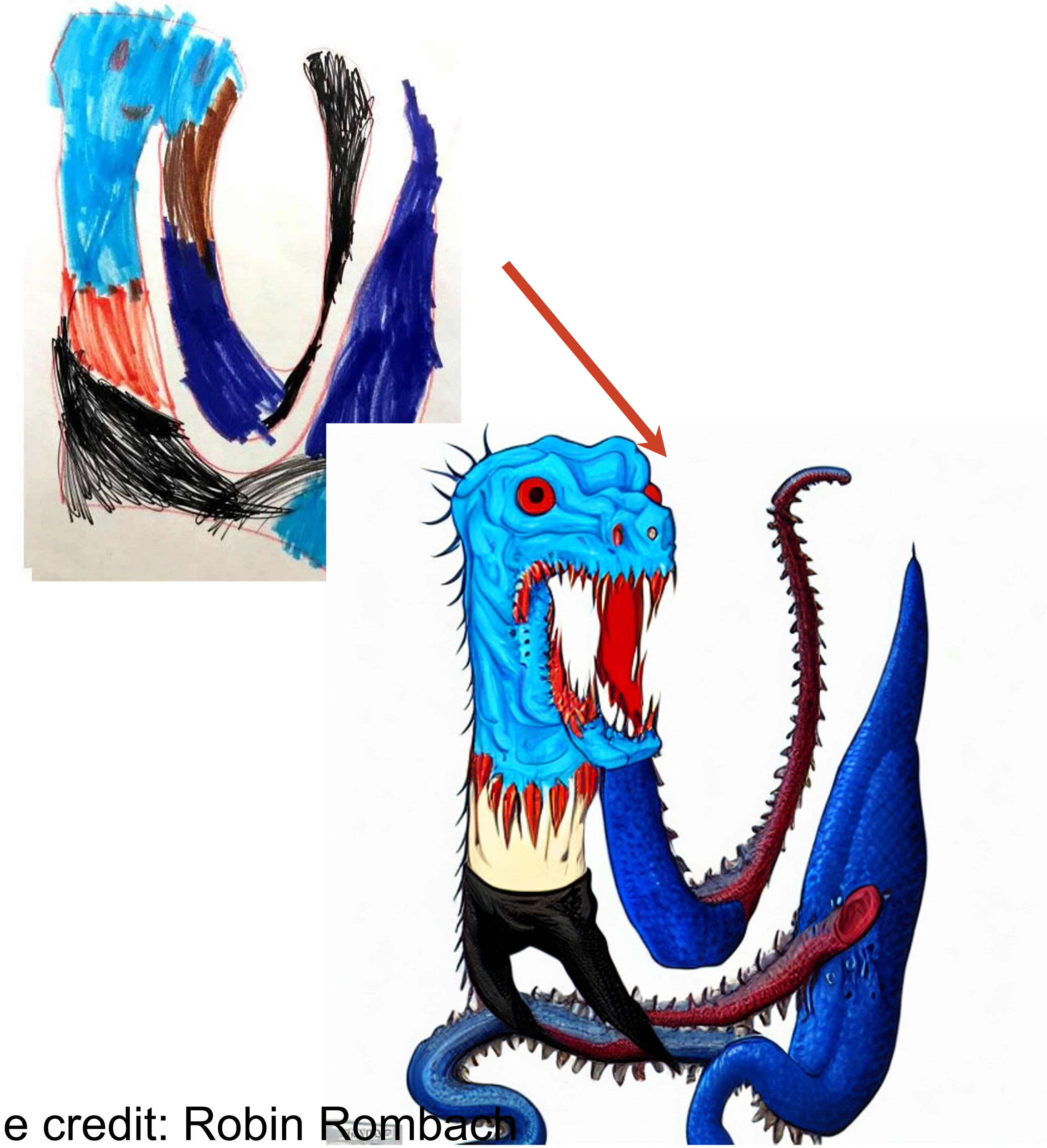


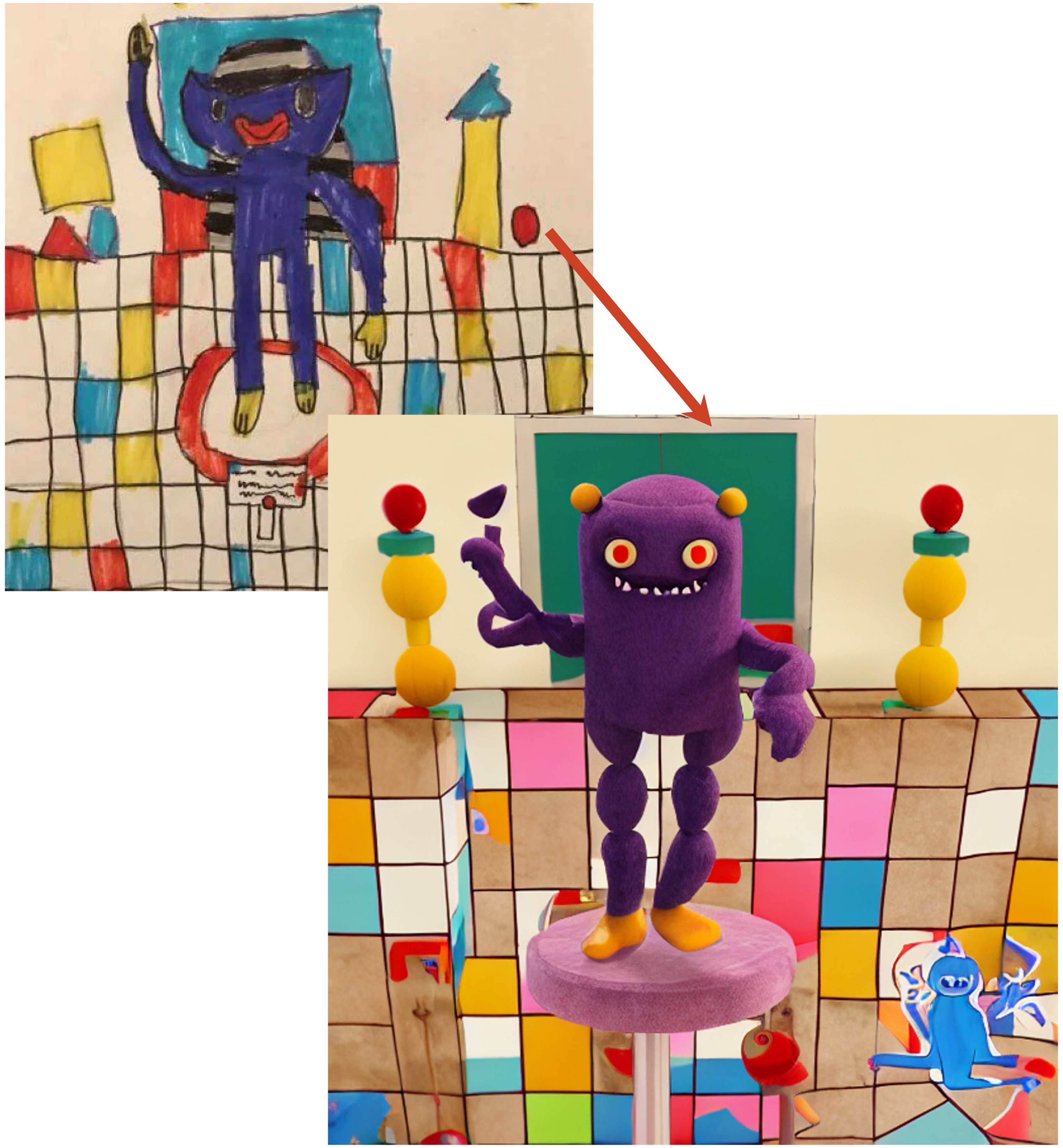
“a fantasy landscape, by Simon Stalenhag”

Slide credit: Robin Rombach

“Upgrade” your child’s artwork

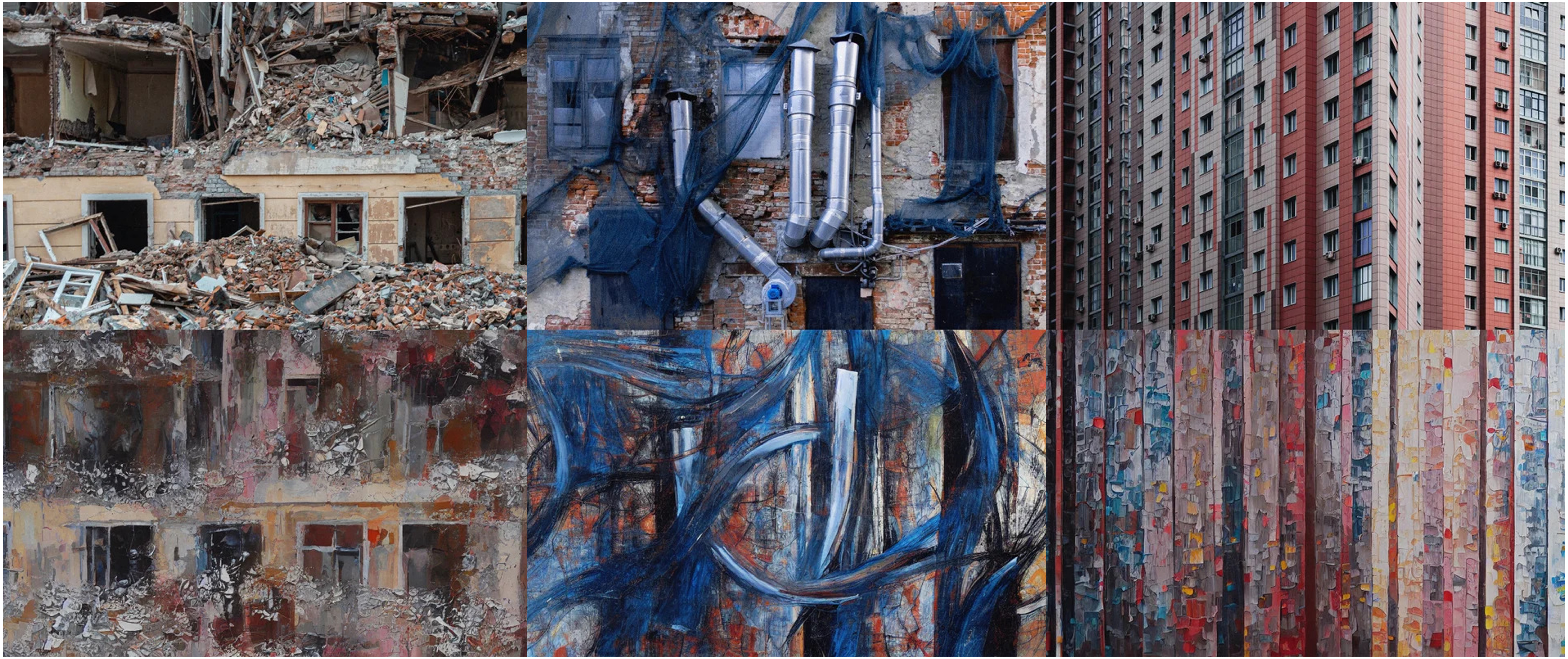
original post: https://www.reddit.com/r/StableDiffusion/comments/wyq04v/using_img2img_to_upgrade_my_sons_artwork/





Slide credit: Robin Rombach

abstract art from photos



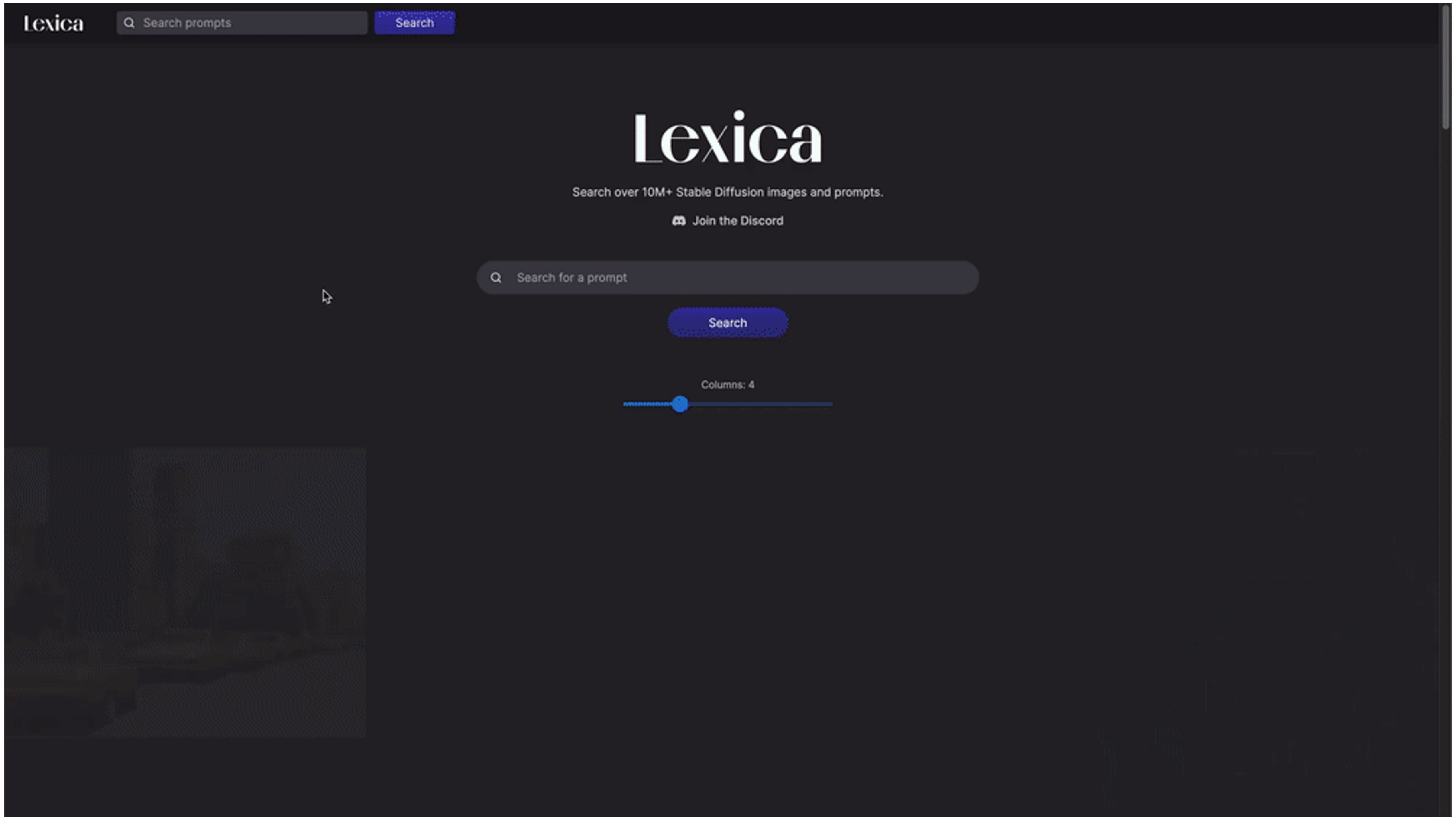
original post by u/Pereulkov
https://www.reddit.com/r/StableDiffusion/comments/xhhyad/i_made_abstract_art_from_my_photos/

Video Synthesis

Stable Diffusion (img2img) + EBSynth by Scott Lightsier:
https://twitter.com/LighthiserScott/status/1567355079228887041?t=kXXCAVtuO5lJCGcro3Ma3A&s=19

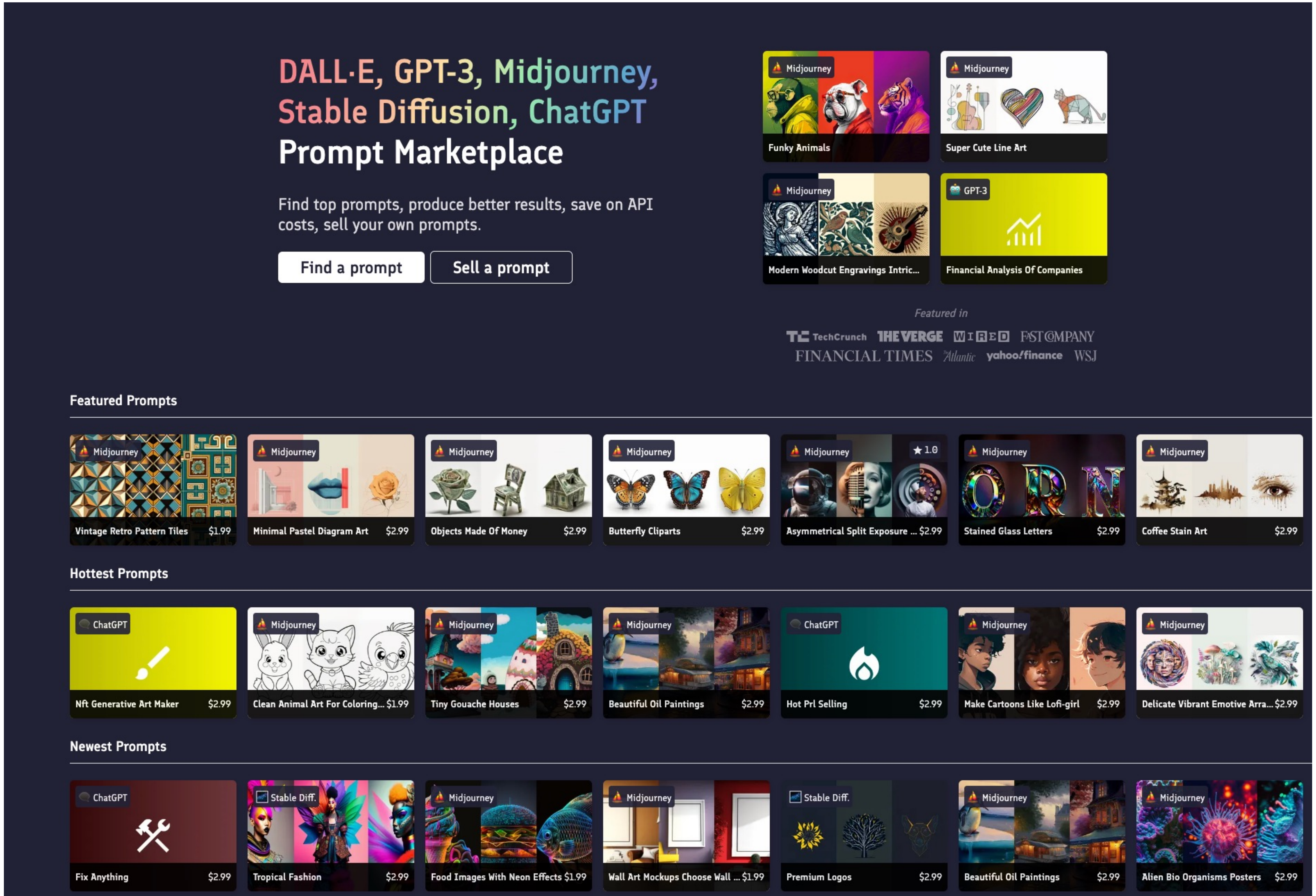
EBSynth: single-frame video stylization app: https://ebsynth.com/

Prompt Search Engine (lexica.art)

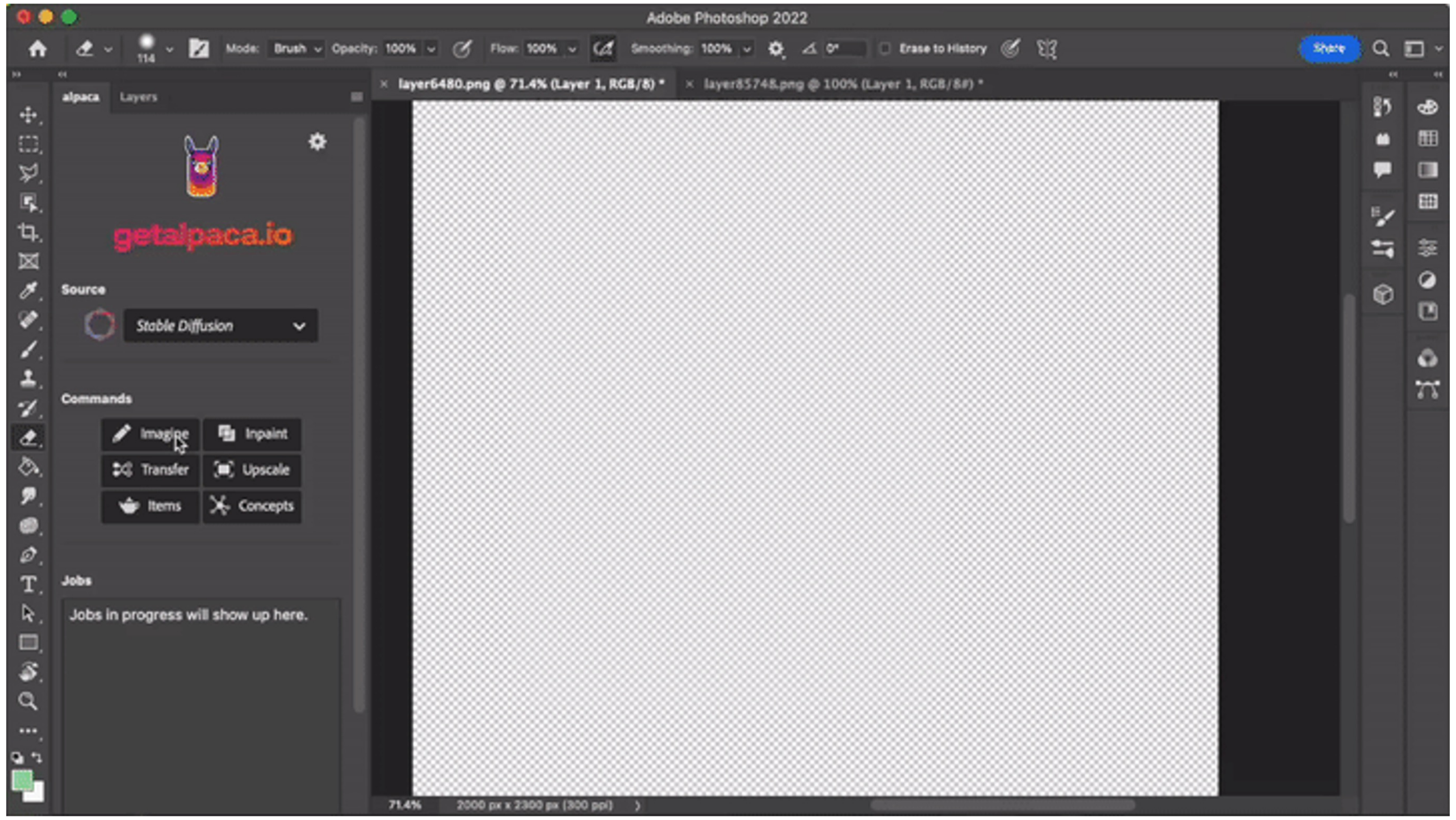


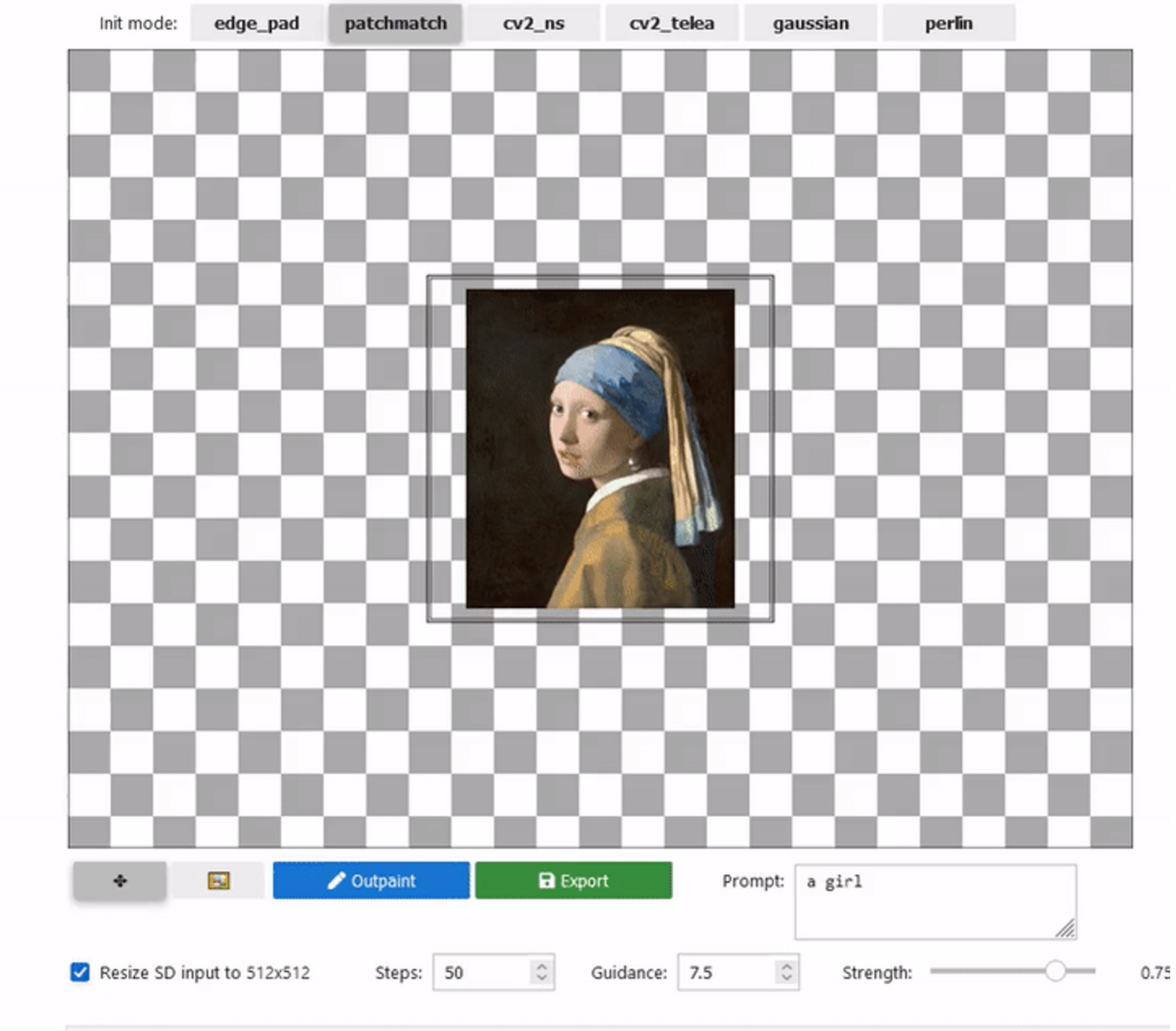
Slide credit: Robin Rombach

Prompt Marketplace (promptbase.com)



UIs / Plug-Ins for Photoshop, GIMP etc





https://twitter.com/wbuchw/status/1563162131024920576

https://github.com/lkwq007/stablediffusion-infinity

Slide credit: Robin Rombach

What if you have 1,000+ GPUs/TPUs

DALL·E 2, Imagen

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

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.

Teddy bears swimming at the Olympics 400m Butter-fly event.

A cute corgi lives in a house made out of sushi.

A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

- Pixel-based Diffusion (No encoder-decoder)
- pre-trained text encoder (CLIP, t5)
- Diffusion model + classifier-free guidance
- Cascaded models: 64->128->512

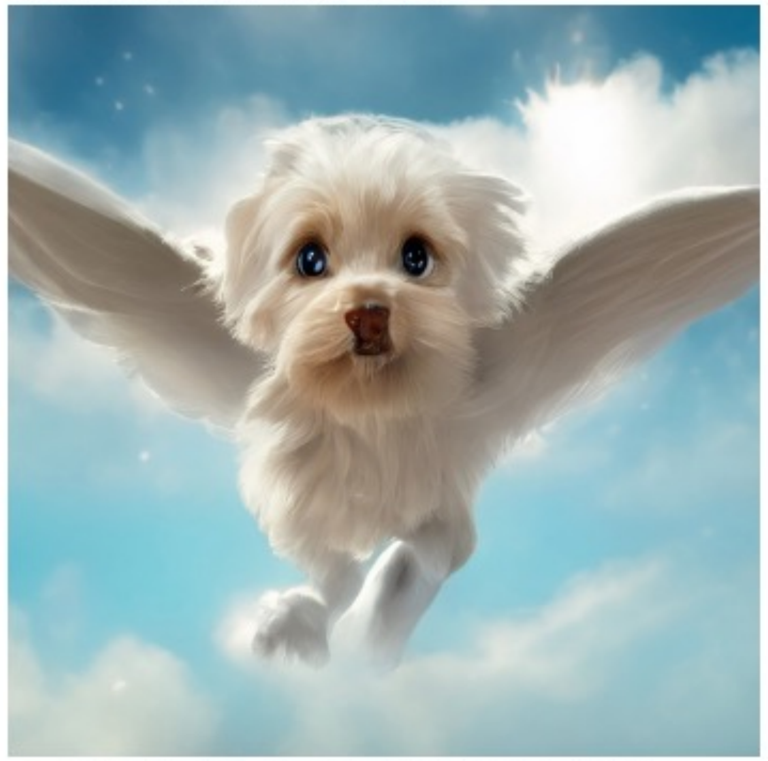
https://cdn.openai.com/papers/dall-e-2.pdf
https://arxiv.org/abs/2205.11487

Diffusion vs. Autoregressive vs. GANs

GigaGAN: Scaling up GANs

A portrait of a human growing colorful flowers from her hair. Hyperrealistic oil painting. Intricate details.

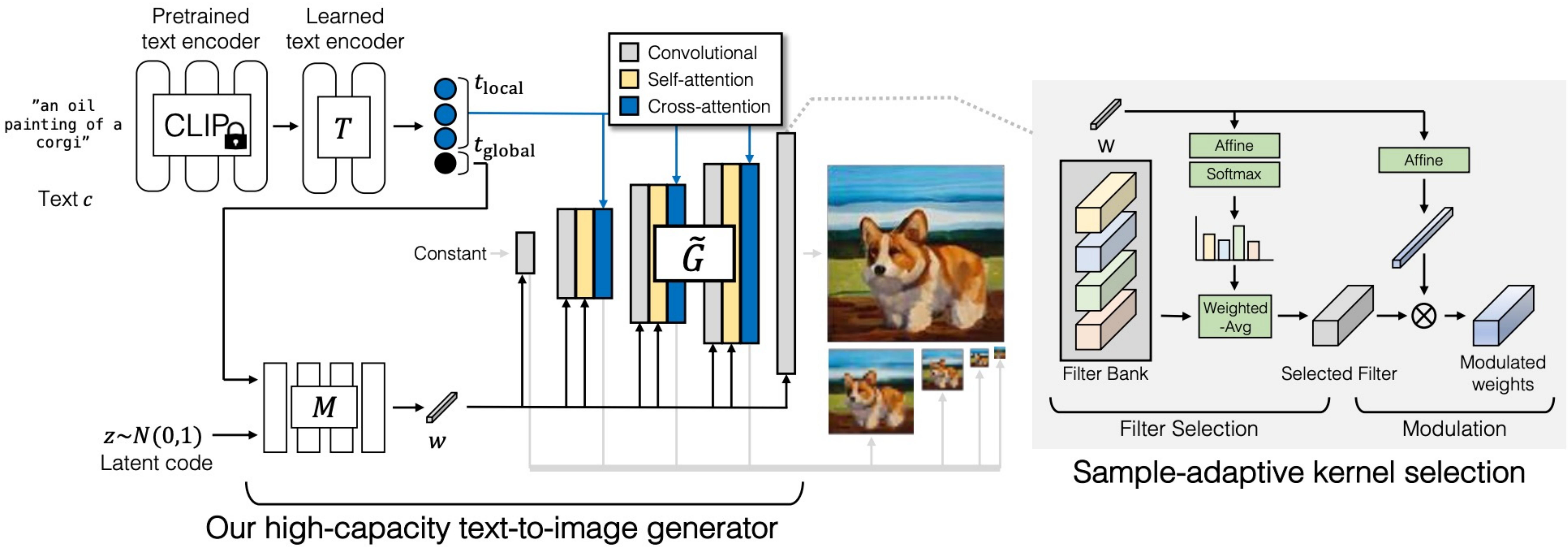
A golden luxury motorcycle parked at the King's palace. 35mm f/4.5.



a cute magical flying maltipoo at light speed, fantasy concept art, bokeh, wide sky

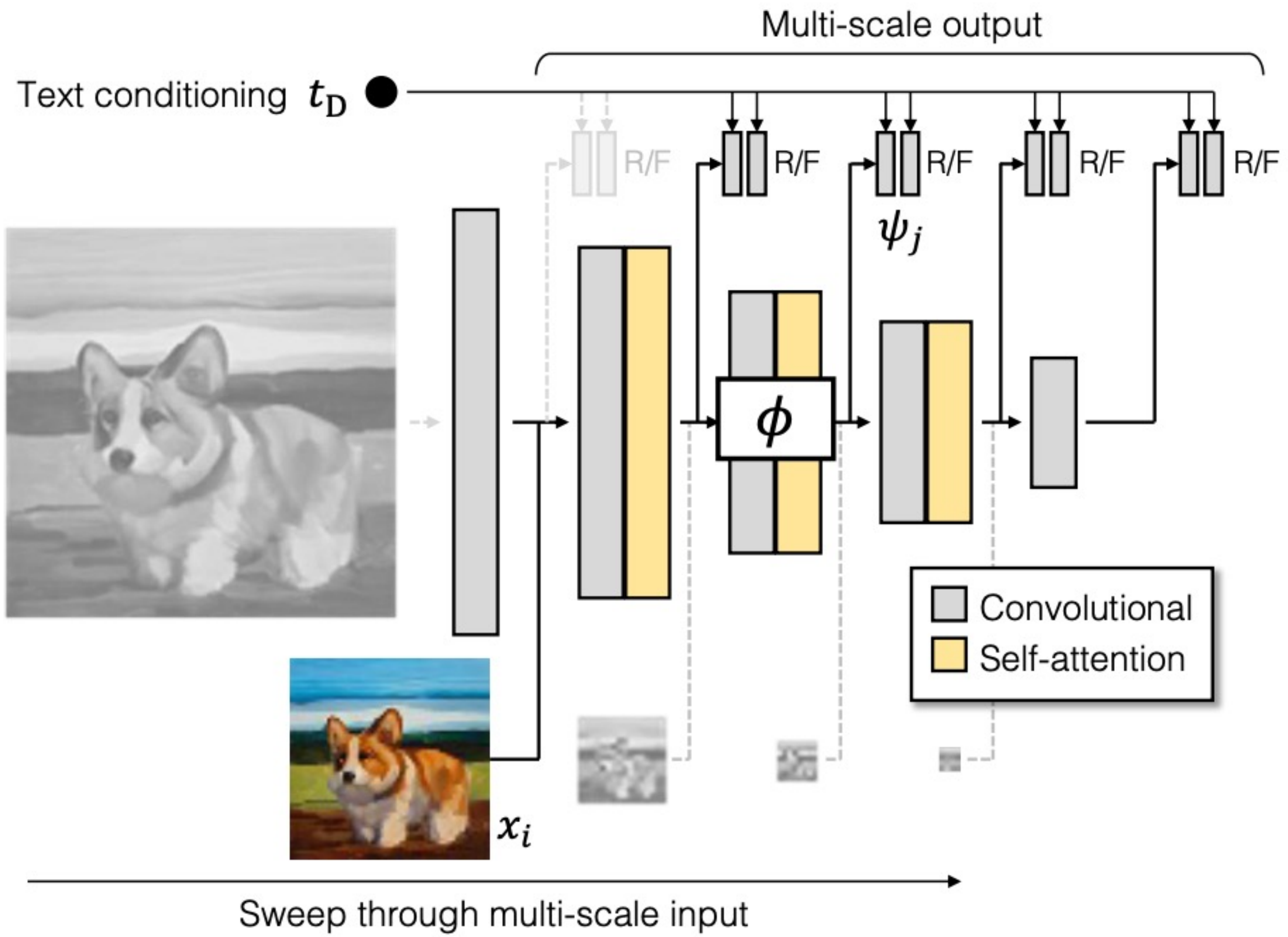
[Kang et al., CVPR 2023]

GigaGAN Generator



[Kang et al., CVPR 2023]

GigaGAN Discriminator

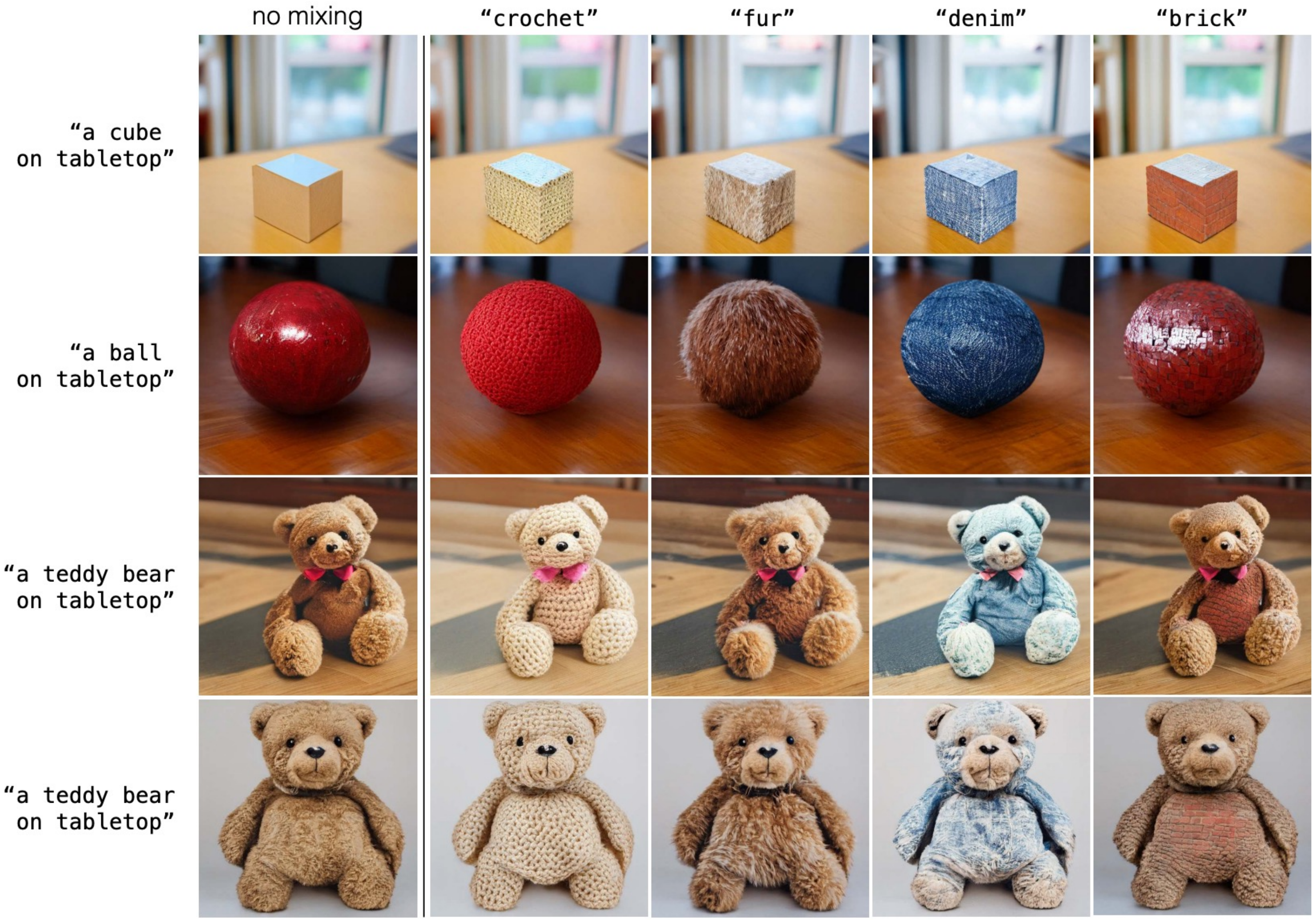


[Kang et al., CVPR 2023]

Style Mixing

[Kang et al., CVPR 2023]

Prompt Mixing



[Kang et al., CVPR 2023]


Input
Real-ESRGAN (1K)
SD Upscaler (1K)
GigaGAN Up (1K)
GigaGAN Up (4K)
GigaGAN Upsampler (4096px, 16Mpix, 3.66s)

Comparison between Different Models

	Model	Type	# Param.	# Images	FID-30k ↓	Inf. time
256	DALL·E [75]	Diff	12.0B	1.54B	27.50	-
	GLIDE [63]	Diff	5.0B	5.94B	12.24	15.0s
	LDM [79]	Diff	1.5B	0.27B	12.63	9.4s
	DALL·E 2 [74]	Diff	5.5B	5.63B	10.39	-
	Imagen [80]	Diff	3.0B	15.36B	7.27	9.1s
	eDiff-I [5]	Diff	9.1B	11.47B	6.95	32.0s
	Parti-750M [101]	AR	750M	3.69B	10.71	-
	Parti-3B [101]	AR	3.0B	3.69B	8.10	6.4s
	Parti-20B [101]	AR	20.0B	3.69B	7.23	-
	LAFITE [108]	GAN	75M	-	26.94	0.02s
512	SD-v1.5* [78]	Diff	0.9B	3.16B	9.62	2.9s
	Muse-3B [10]	AR	3.0B	0.51B	7.88	1.3s
	GigaGAN	GAN	1.0B	0.98B	9.09	0.13s

[Kang et al., CVPR 2023]

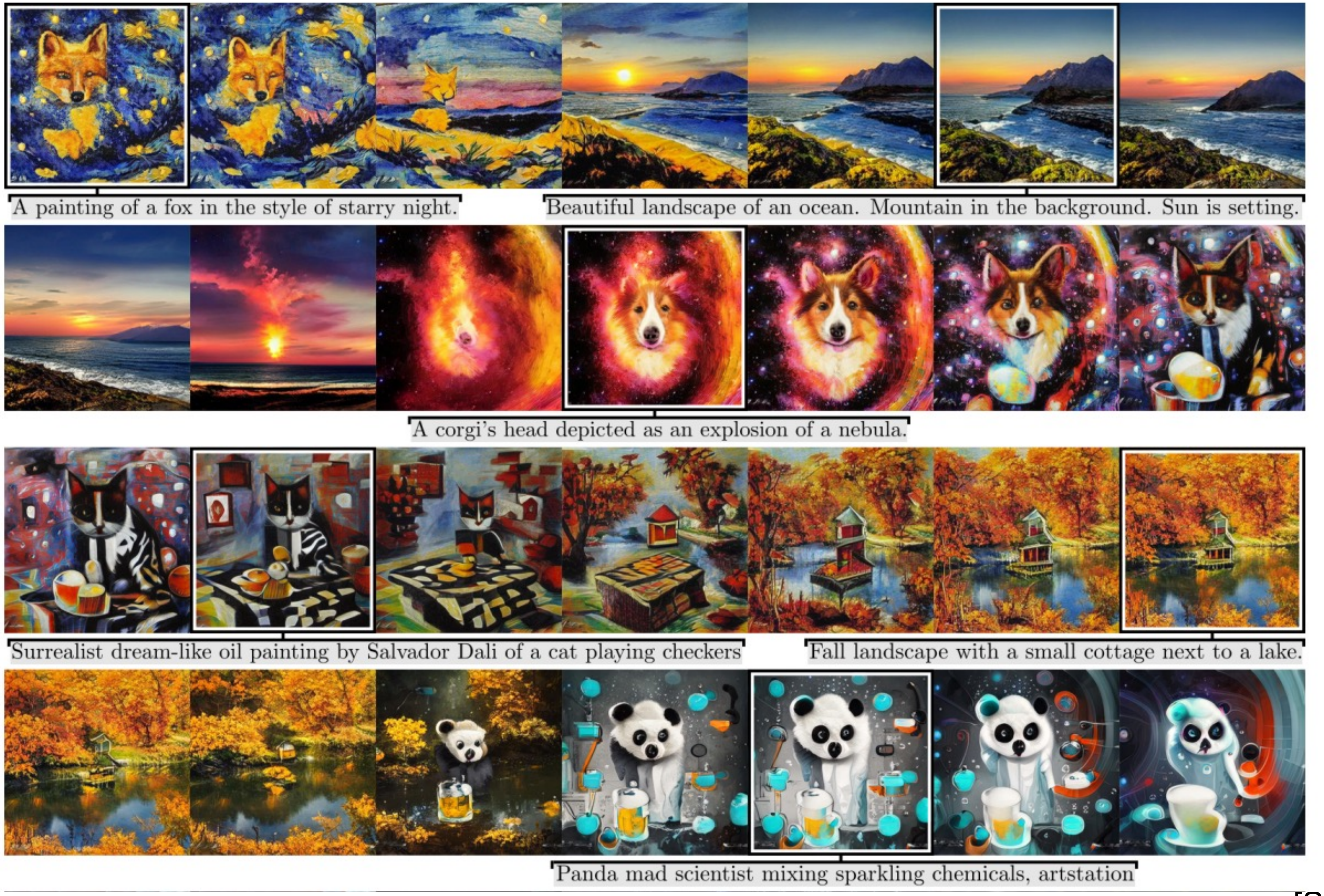
Comparison between Different Models

[Kang et al., CVPR 2023]

StyleGAN-T

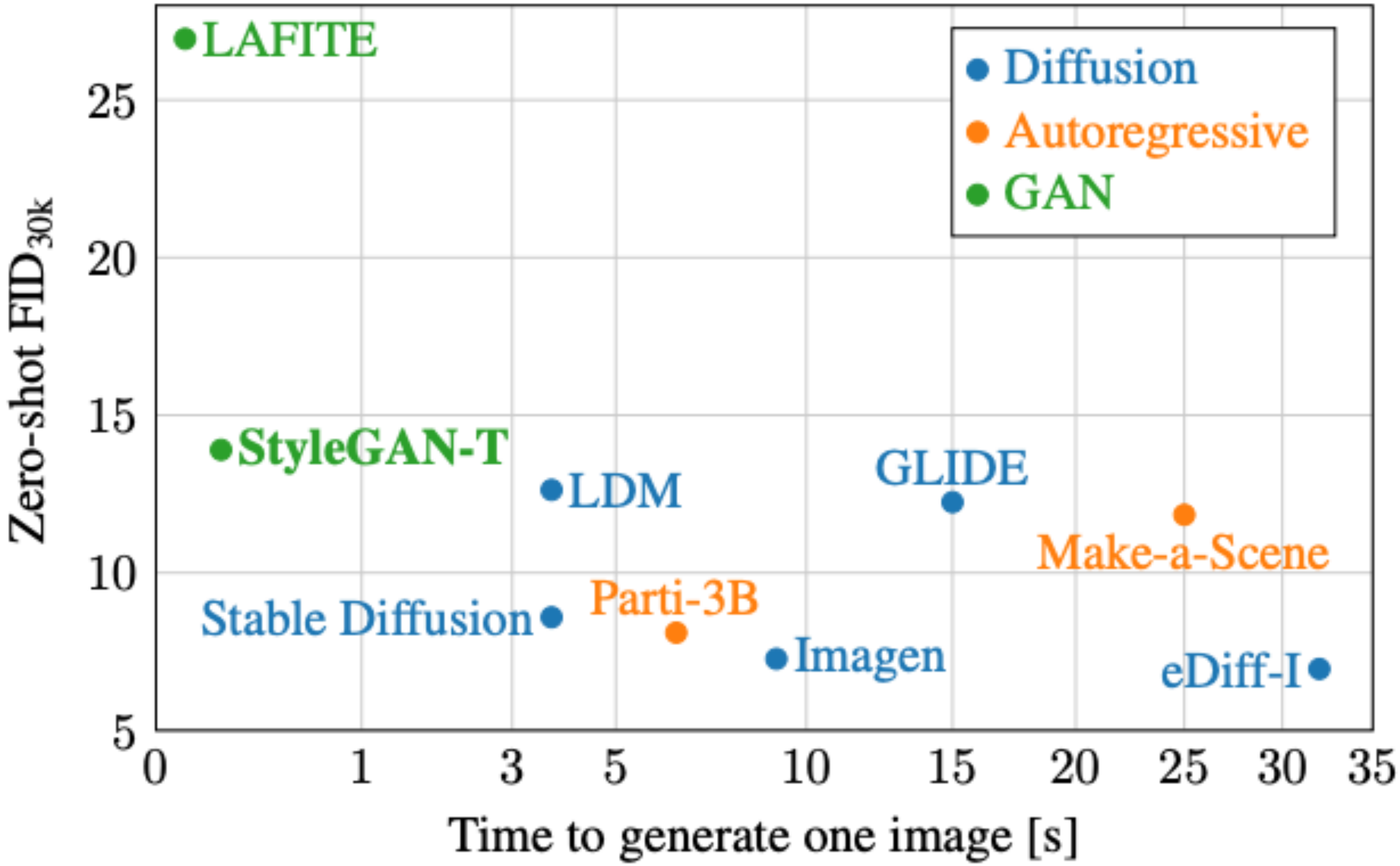
[Sauer et al., ArXiv 2023]

StyleGAN-T



[Sauer et al., ArXiv 2023]

StyleGAN-T



[Sauer et al., ArXiv 2023]

How could we improve it?

- Better generative modeling techniques: VAEs, GANs, diffusion, AR, Hybrid
- Better text encoders: RNN/LSTM -> Transformers (CLIP, T5)
- Better generator architectures: RNN/LSTM -> CNN -> CNN + Transformer
- Better ways to connect text and image: concatenation -> AdaIN -> cross-attention
- More data + GPU/TPU computing: a few hundred A100.
- Bigger model sizes: 1B-20B.