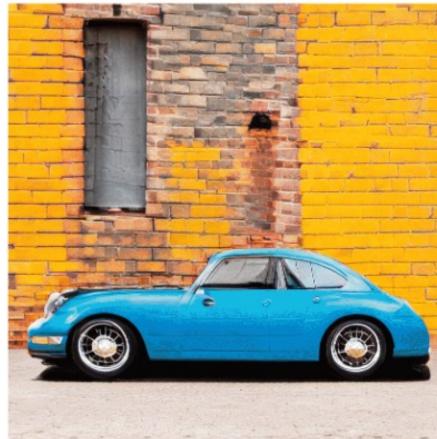


A living room with a fireplace at a wood cabin. Interior design.



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



Eiffel Tower, landscape photography

Lecture 13: Text-to-Image Synthesis Jun-Yan Zhu 16-726 Spring 2023

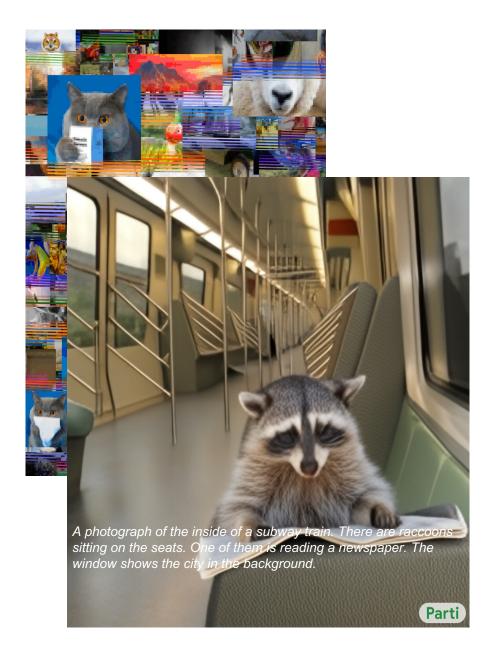
Slides credit: many slides are from Robin Rombach, Karsten Kreis, Ruigi Gao, Arash Vahdat, etc.

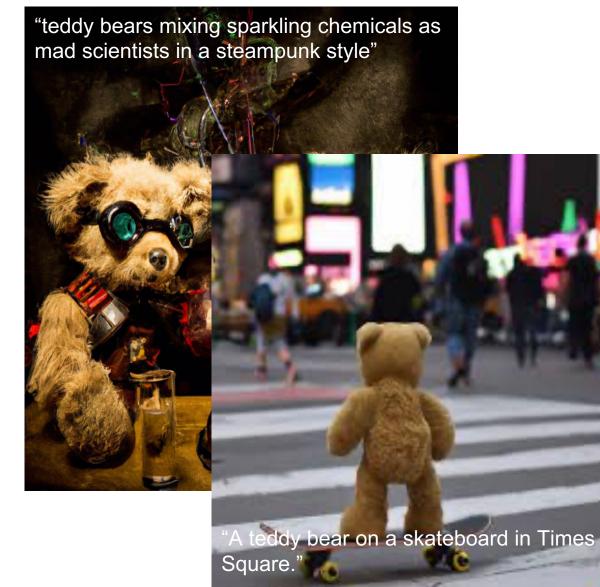


A painting of a majestic royal tall ship in Age of Discovery.

Photo credit: Minguk Kang et al.

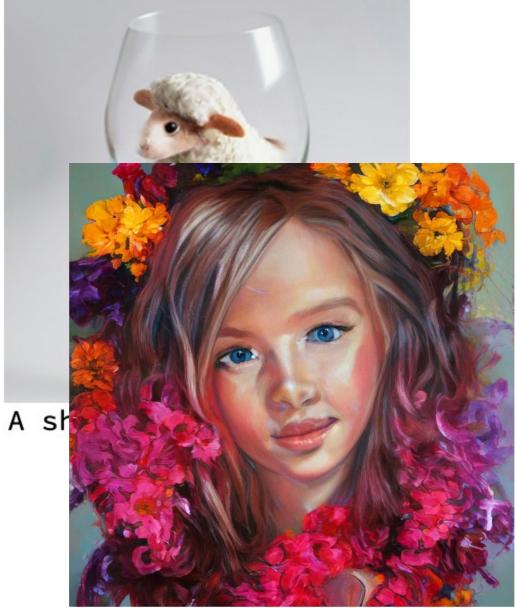
Text-to-Image Everywhere





Autoregressive models (Image GPT, Parti)

Diffusion models (DALL-E 2, Imagen)



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

GANs, Masked GIT (GigaGAN, MUSE)

Text-to-Image Everywhere

Scott Lighthiser @LighthiserScott · Sep 18 .@StableDiffusion Img2Img x #ebsynth Creature Test

#stablediffusion #Alart



Scott Lighthiser @LighthiserS
 @StableDiffusion Img2Img x #ebsynth x @koe_recast TEST

#stablediffusion #Alart



Matt Reed @mcreed · Sep 9 I am at a loss for everything #stablediffusion #aiart Show this thread





Few comments about the Midjourney/@D_ID_n Video wondering why this means we will soon be able to create our own personalised digital assistants. Here's a vision of a personalised digital assistant to explain. #midjourney #Midjourneyai #Alart #Digitalart #animated



Replicate @replicatehq · Sep 9
The Stable Diffusion innovation just doesn't stop!

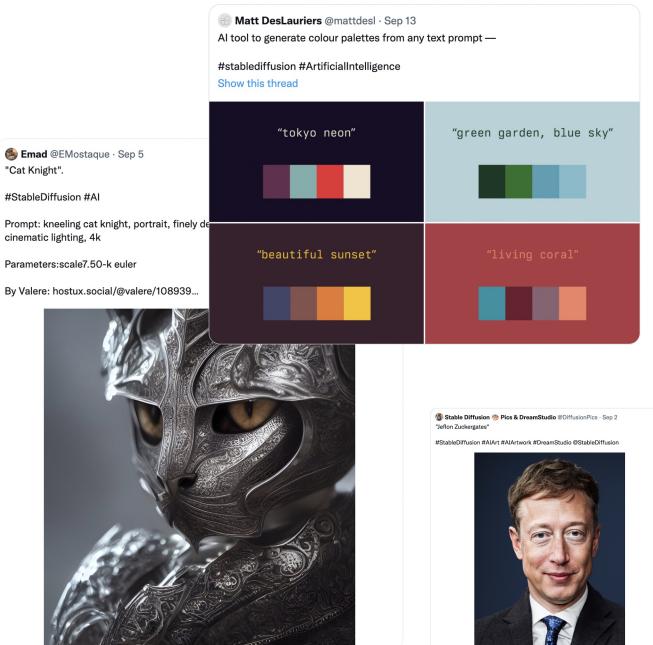
Here's a new open-source model from the @monaverse that produces seamless tiling

images: replicate.com/tommoore515/ma... Show this thread





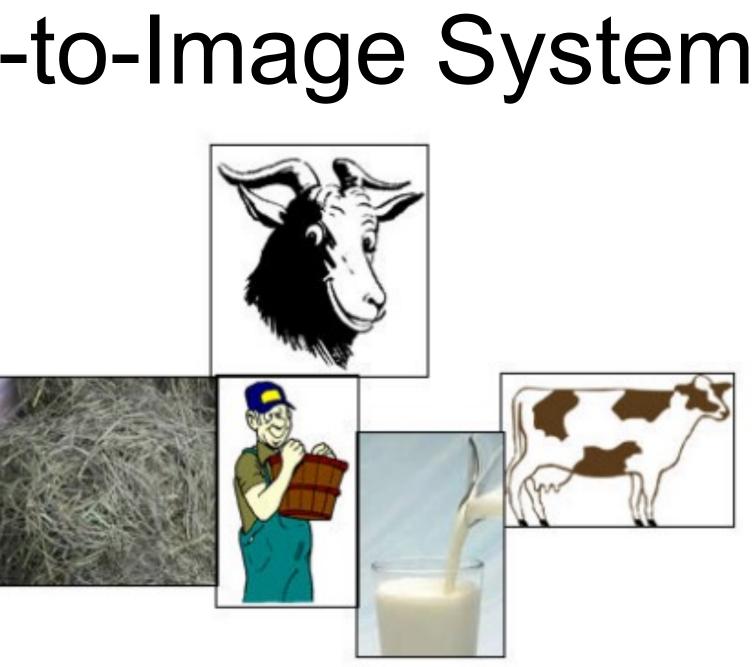
Slides credit: Robin Rombach



Where/when did it start?

First Text-to-Image System

First the farmer gives hay to the goat. Then the farmer gets milk from the COW.



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 A herd of elephants flyblue skies. ing 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

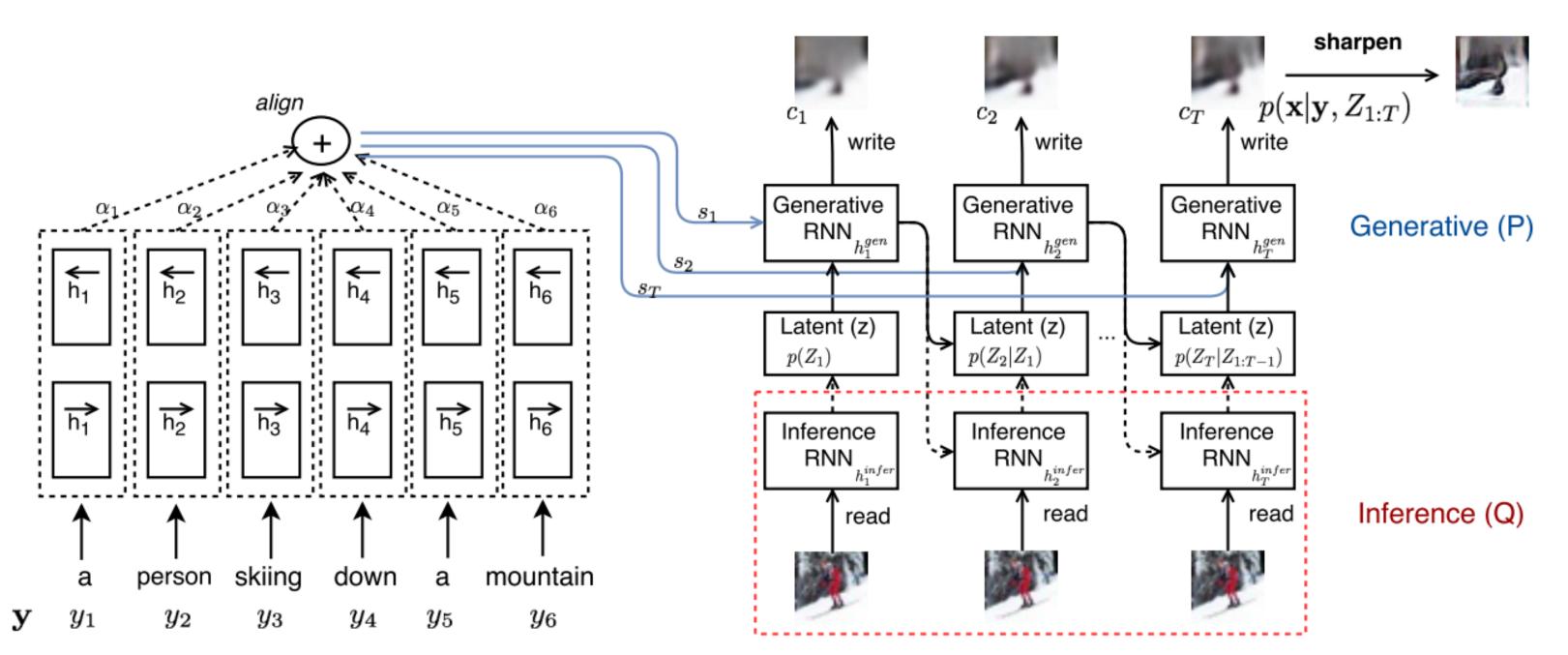


A toilet seat sits open in A person skiing on sand the grass field. Clad vast desert.

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



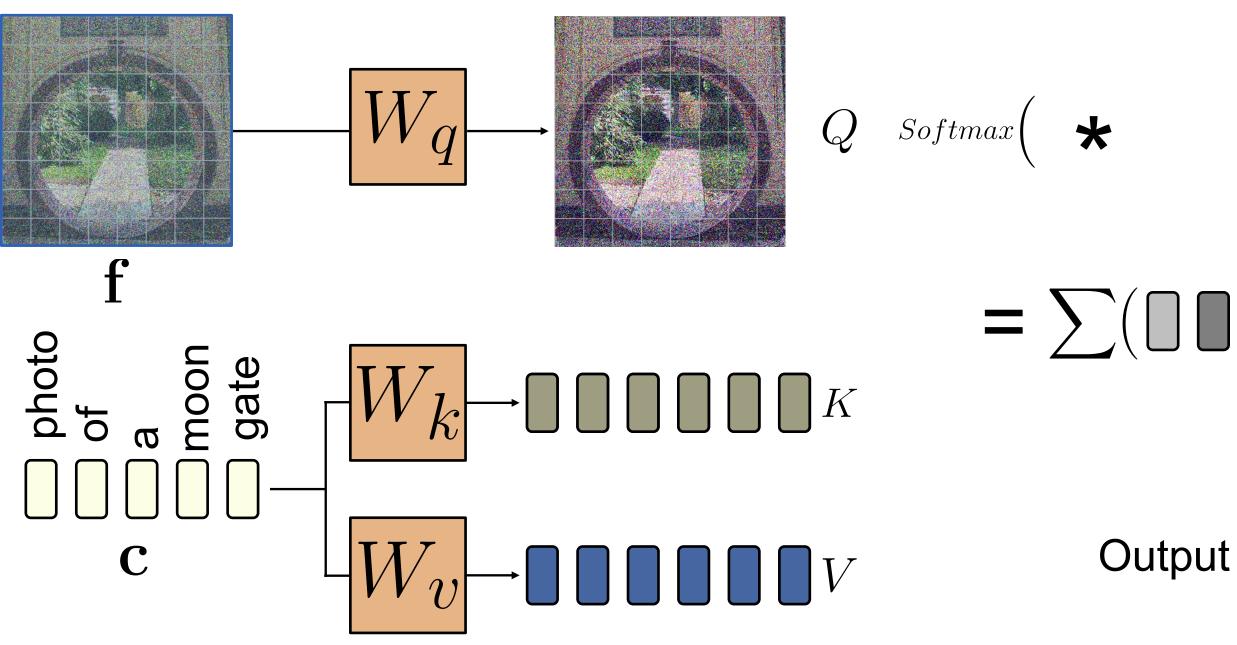
First Deep Learning Work



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



Output = 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

this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.





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

GANs-based Text-to-Image

the flower has petals that are bright pinkish purple with white stigma

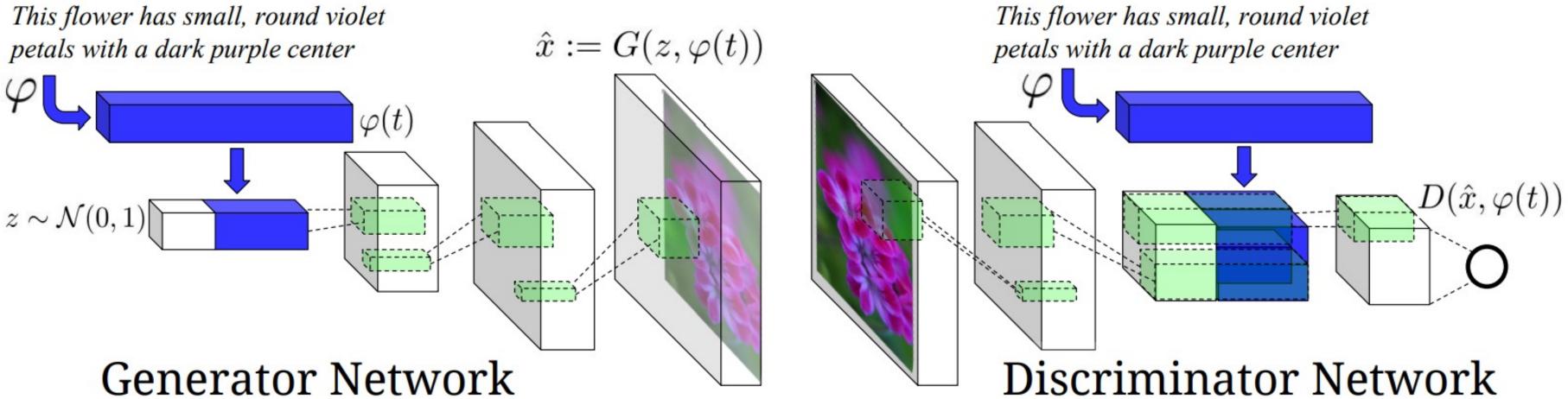




Generative Adversarial Text to Image Synthesis Scott Reed et al., ICML 2016

this white and yellow flower have thin white petals and a round yellow stamen

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?

This bird has a

yellow belly and

with some black on tarsus, grey back, wings, and brown its head and wings, and has a long throat, nape with of short yellow orange beak a black face filaments

This bird is white

(a) StackGAN Stage-I 64x64 images

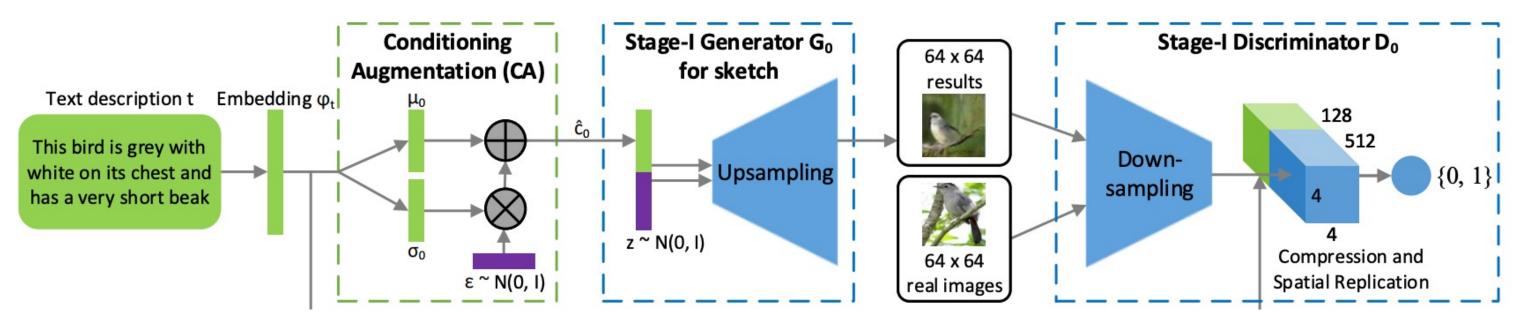
(b) StackGAN Stage-II 256x256 images

(c) Vanilla GAN 256x256 images

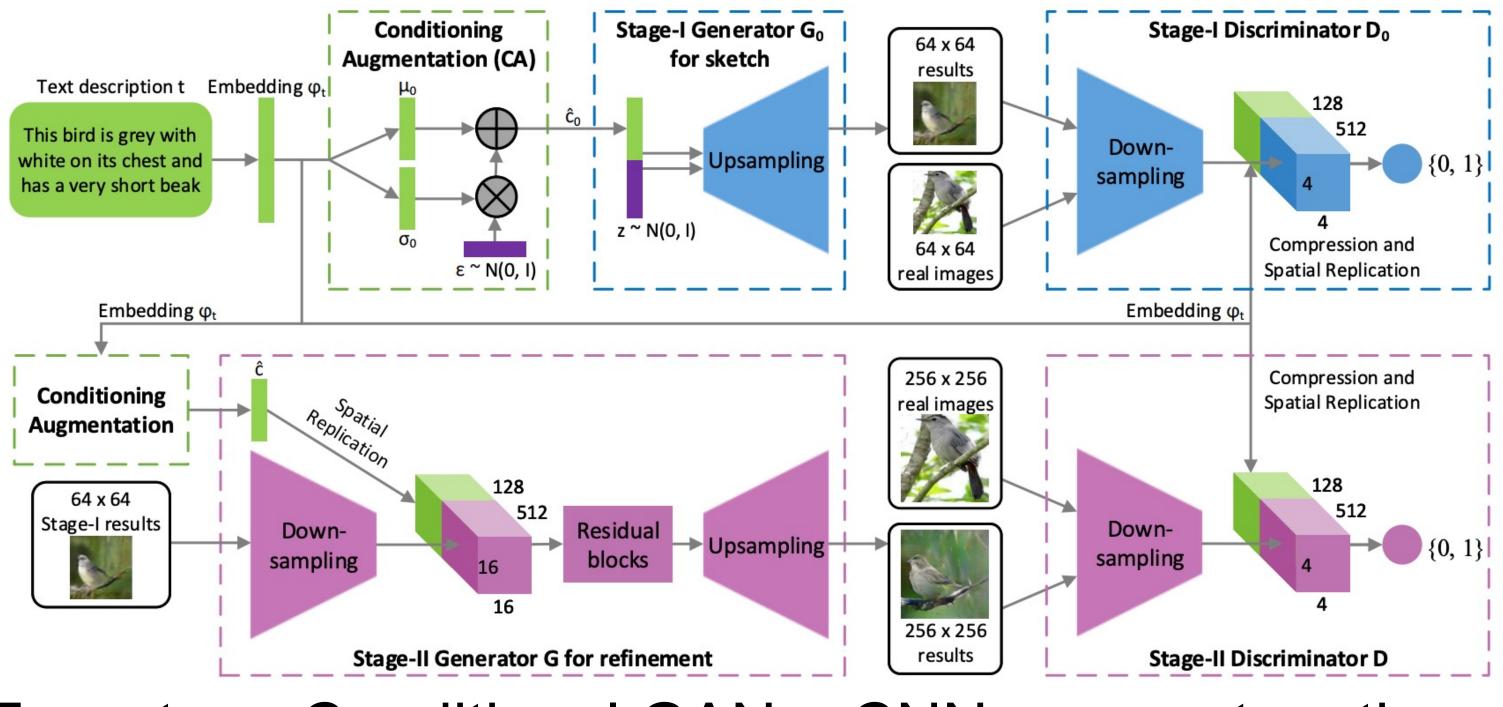
Two-stage Conditional GAN + CNN + concatenation StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks Han Zhang et al., ICCV 2017

This flower has overlapping pink pointed petals surrounding a ring



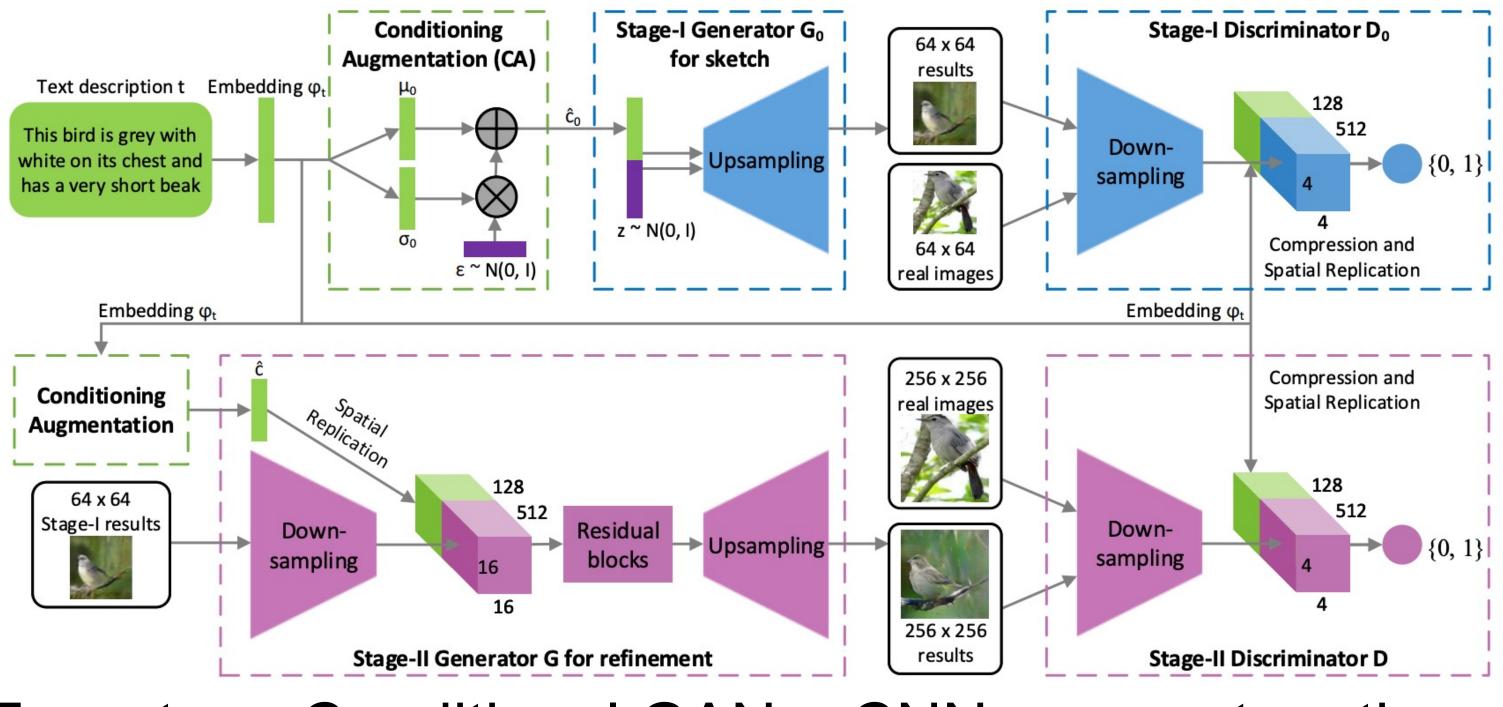


Two-stage Conditional GAN + CNN + concatenation StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks Han Zhang et al., ICCV 2017



Two-stage Conditional GAN + CNN + concatenation

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



Two-stage Conditional GAN + CNN + concatenation

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

Text description

This flower has a lot of small purple petals in a dome-like configuration This flower is pink, white, and yellow in color, and has petals that are striped This flower has petals that are dark pink with white edges and pink stamen



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

This flower is white and yellow in color, with petals that are wavy and smooth

Text description A picture of a very clean living room

A group of people on skis stand in the snow

Eggs fruit candy nuts and meat served on white dish



64x64 GAN-INT-CLS

> 256x256 StackGAN

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

A street sign on a stoplight pole in the middle of a day



+ Cross-attention to connect Text and Image

this bird is red with white and has a very short beak



3:red 10:short

11:beak

9:very



5:white 1:bird 3:red 10:short

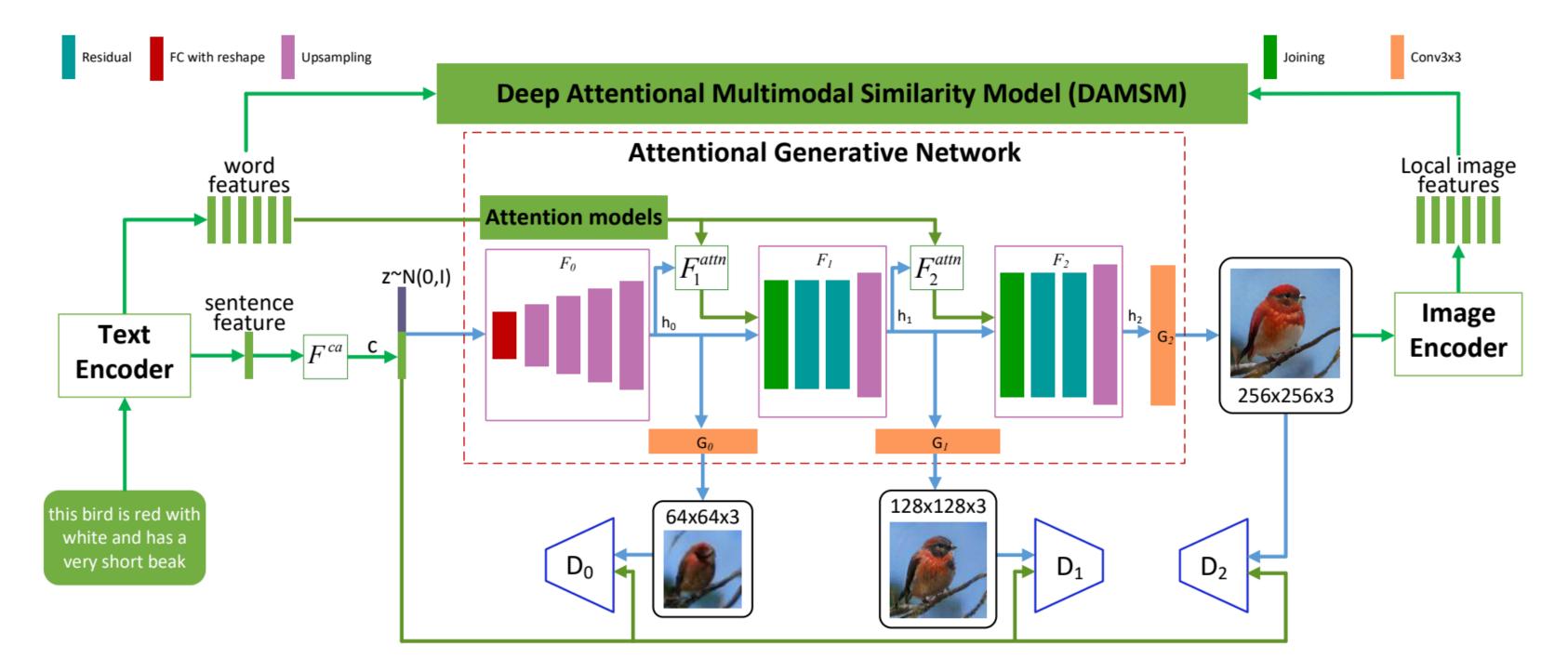
AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks Tao Xu et al., CVPR 2018



8:a



+ 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)

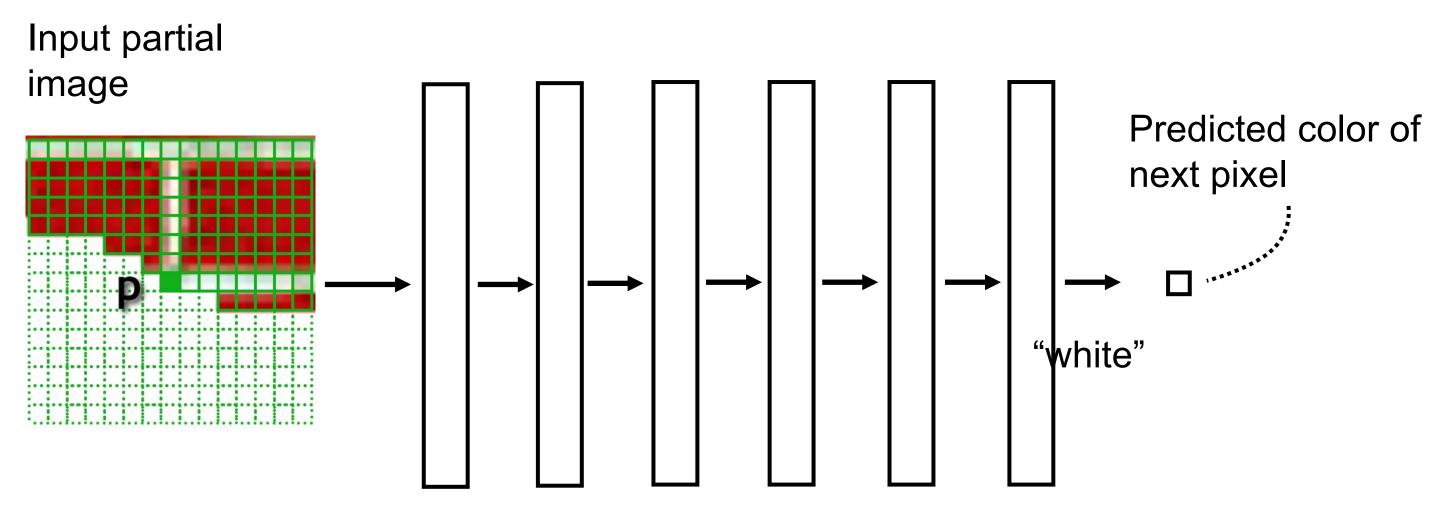
Who shall we blame?

- 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.

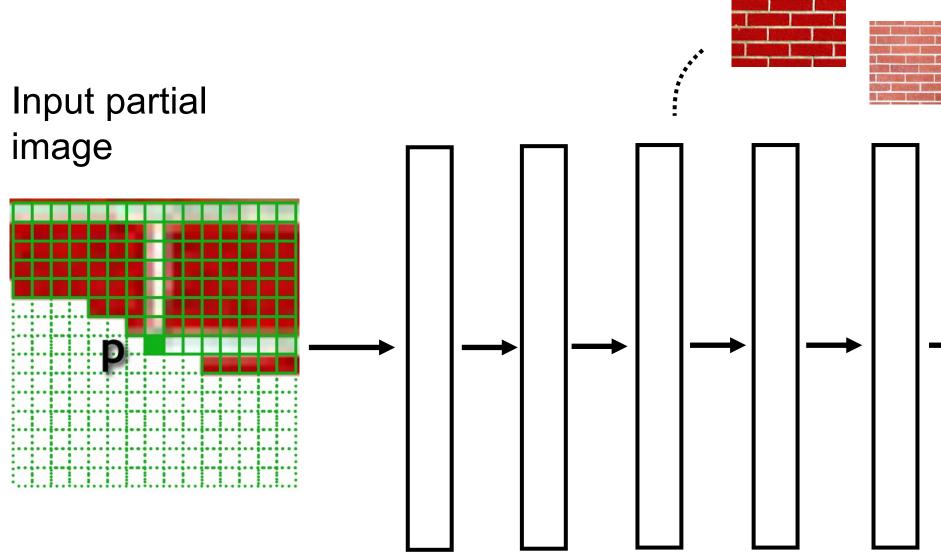
How could we synthesize images beyond single or a few categories

Taming Transformers for High-Resolution Image Synthesis Björn Ommer Heidelberg Collaboratory for Image Processing, IWR, Heidelberg University, Germany *Both authors contributed equally to this work 2021 Jun 23 Figure 1. Our approach enables transformers to synthesize high-resolution images like this one, which contains 1280x460 pixels. N U and are increasingly adapted in other areas such as audio [cs. [12] and vision [8, 16]. In contrast to the predominant vision architecture, convolutional neural networks (CNNs), Abstract the transformer architecture contains no built-in inductive 033 interactions on sequential the locality of interactions and is therefore free

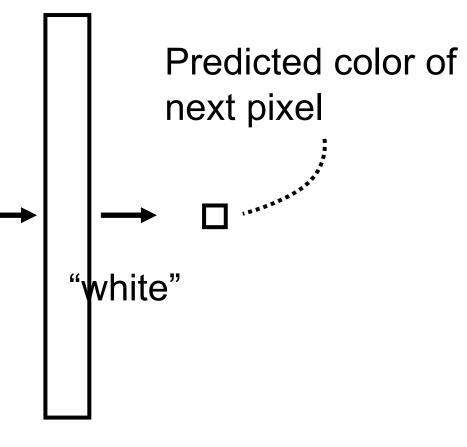
Autoregressive (AR) image synthesis



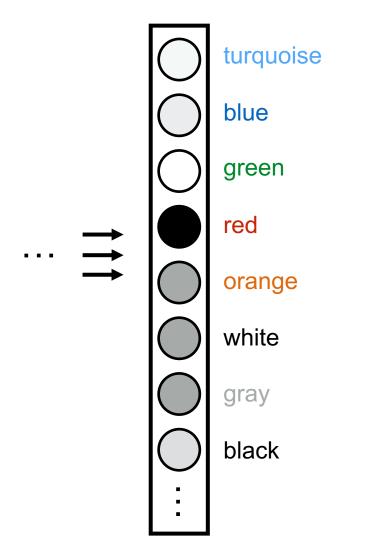
[PixelRNN, PixelCNN, van der Oord et al. 2016]





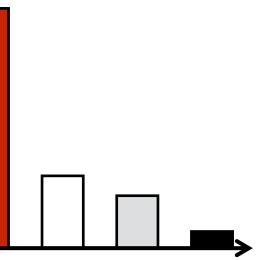


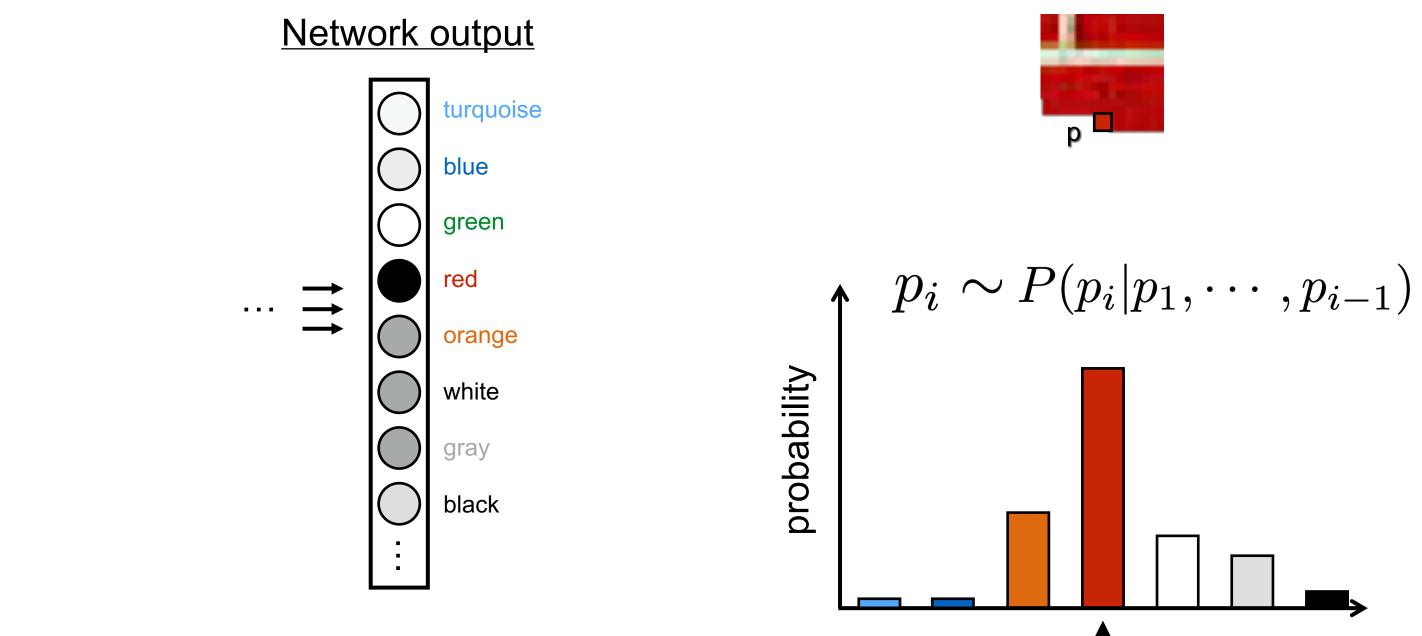
[PixelRNN, PixelCNN, van der Oord et al. 2016]



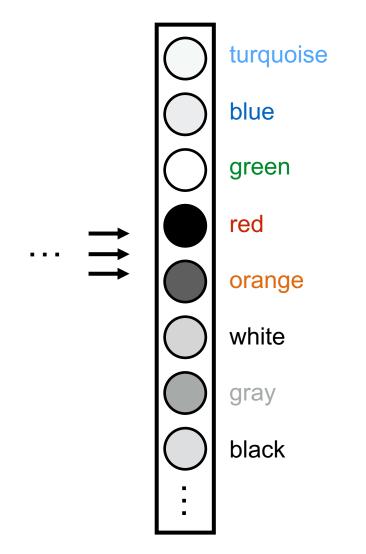


P(next pixel | previous pixels) $P(p_i|p_1,\cdots,p_{i-1})$ probability









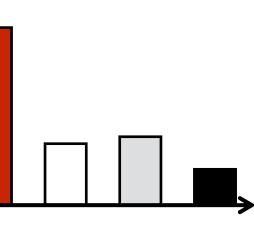


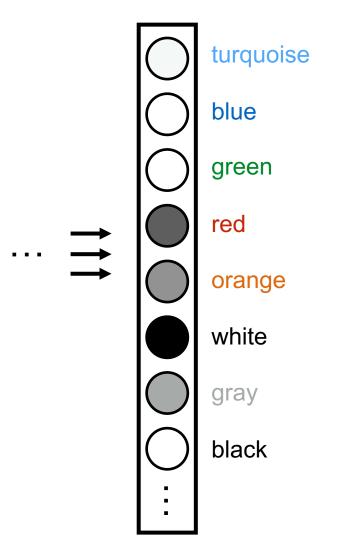
 $p_i \sim P(p_i$

probability



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





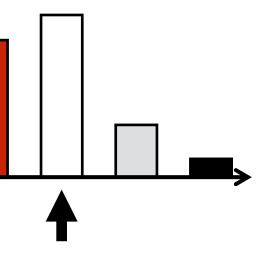


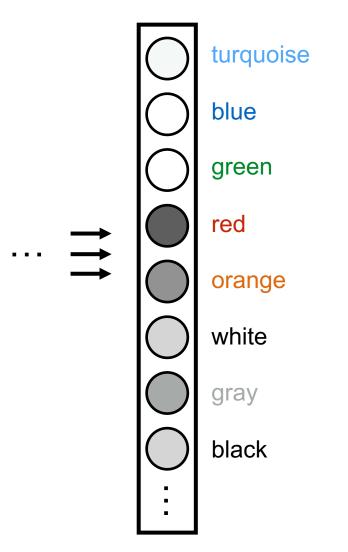
 $p_i \sim P(p_i$

probability



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



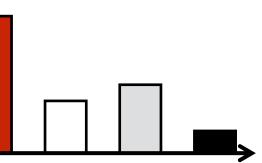




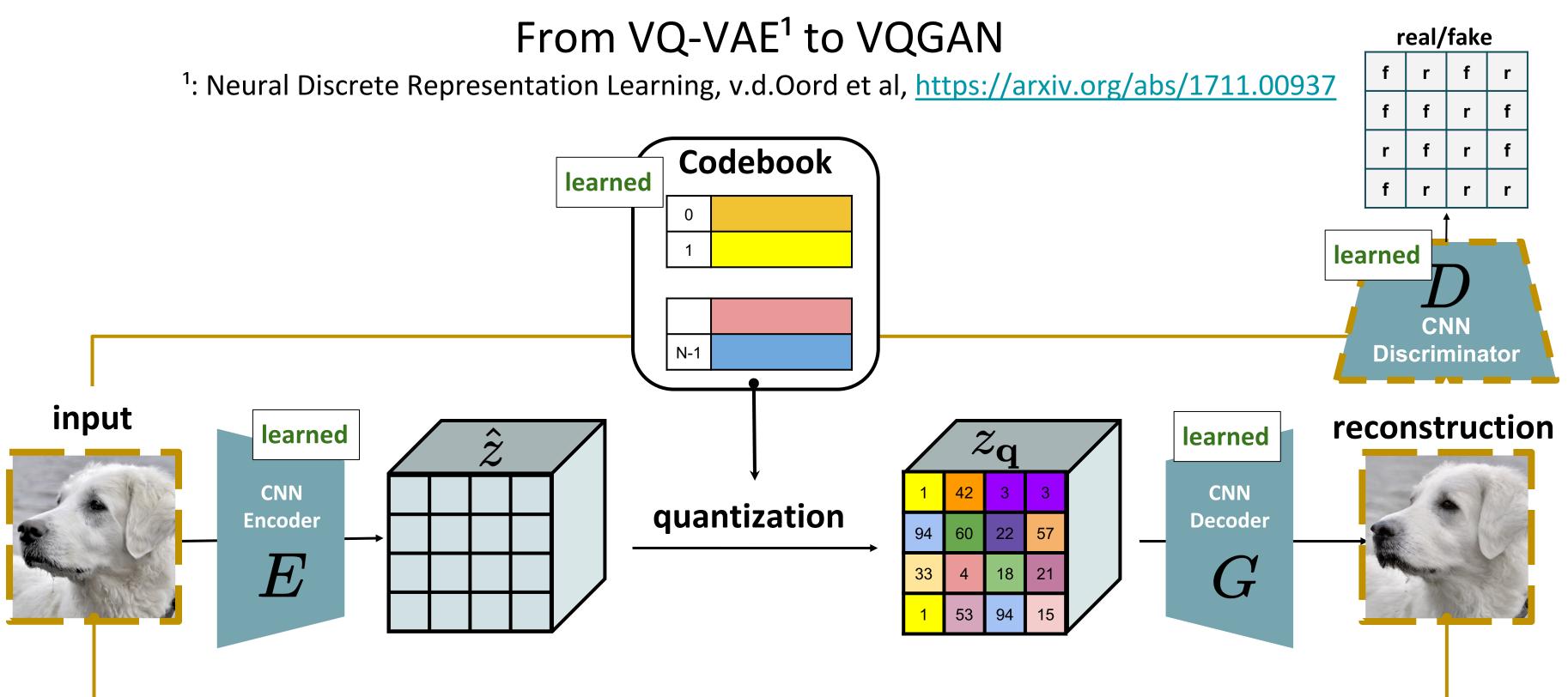
brobability $p_i \sim P(p_i$



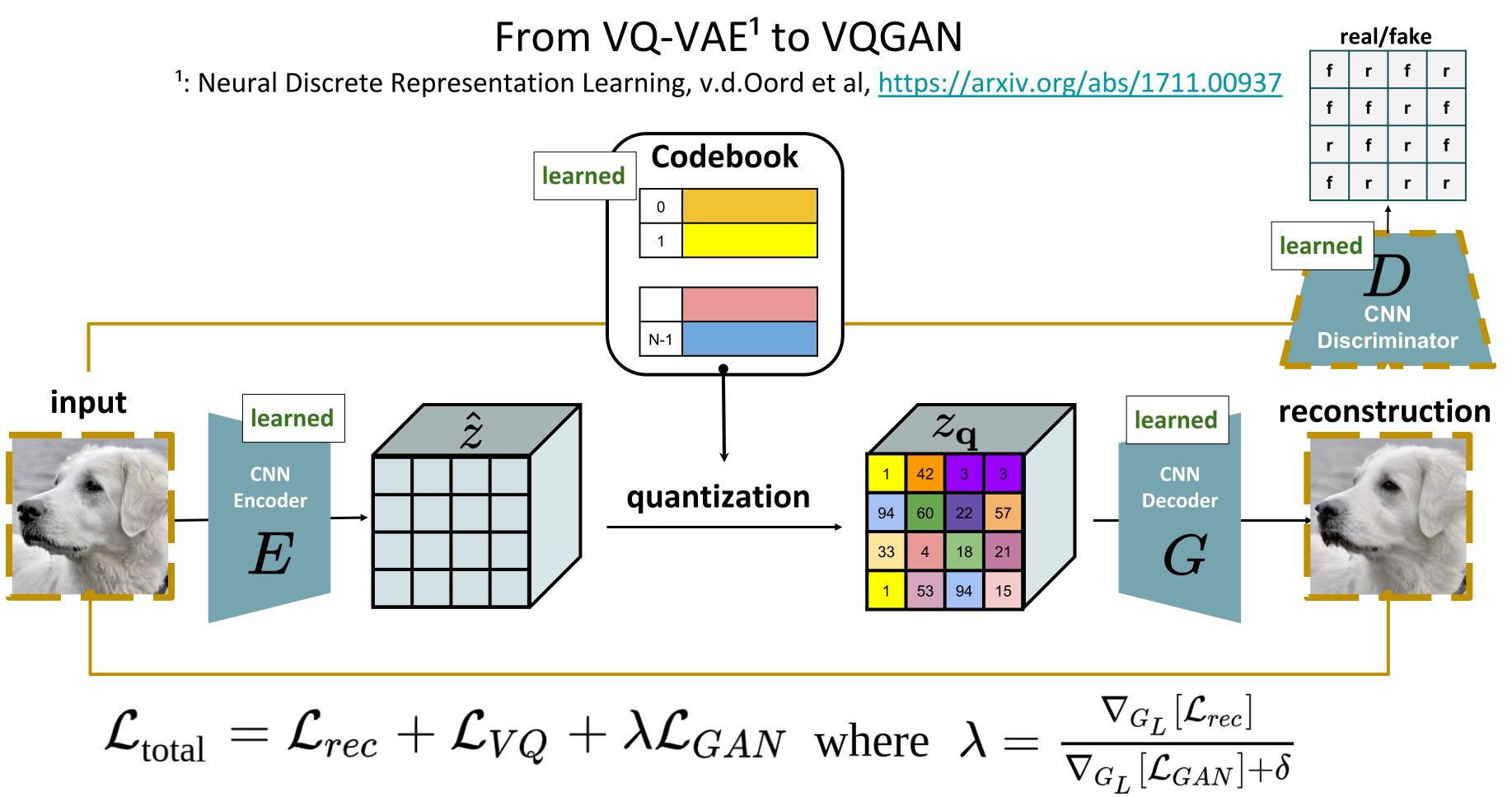
$p_i \sim P(p_i | p_1, \cdots, p_{i-1})$



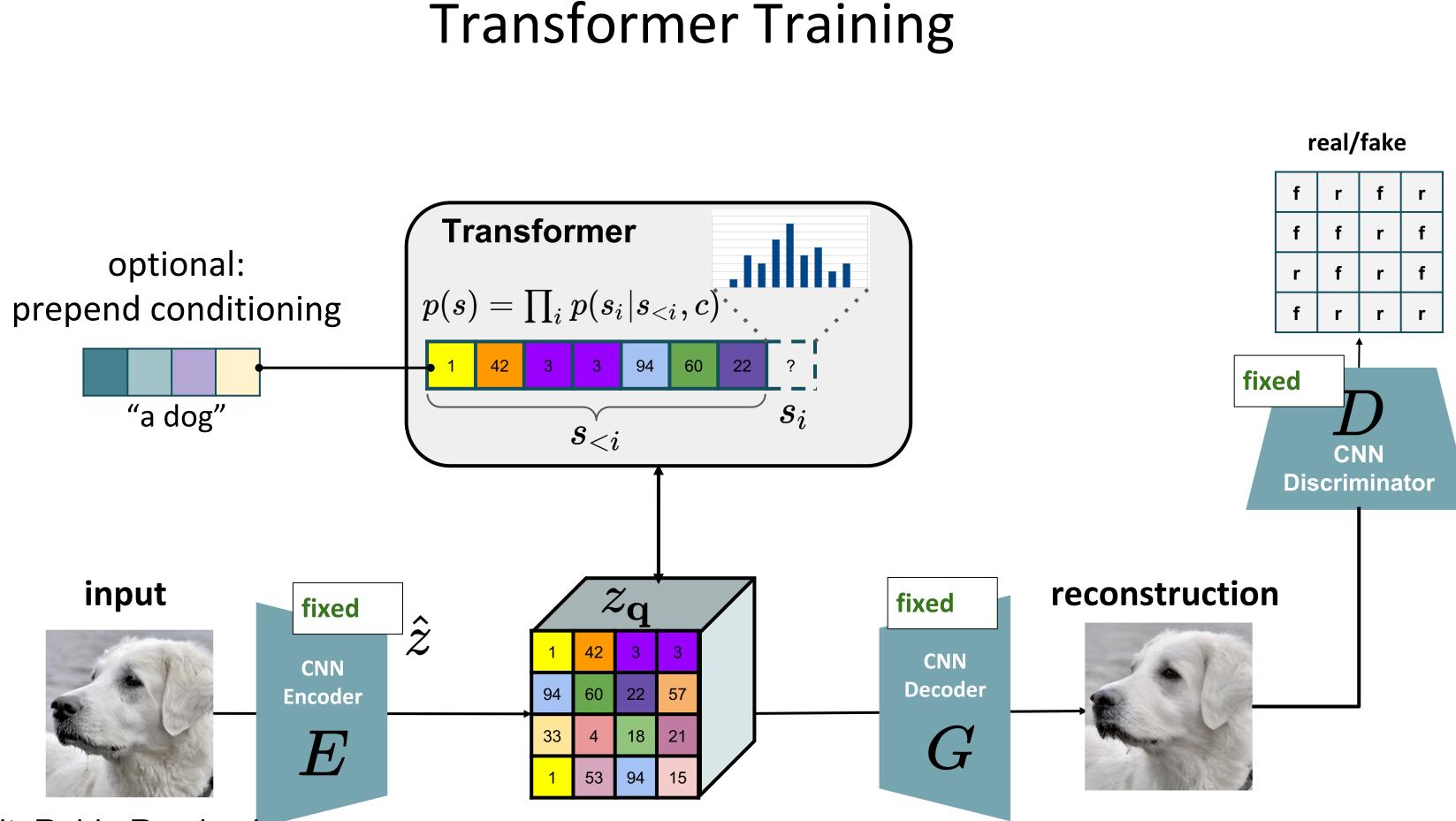
Generation is super slow? What should we do?



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



$$\mathcal{L}_{\text{total}} = \mathcal{L}_{rec} + \mathcal{L}_{VQ} + \lambda \mathcal{L}_{GAN}$$
 where







Scaling VQGAN for Text-to-Image!

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

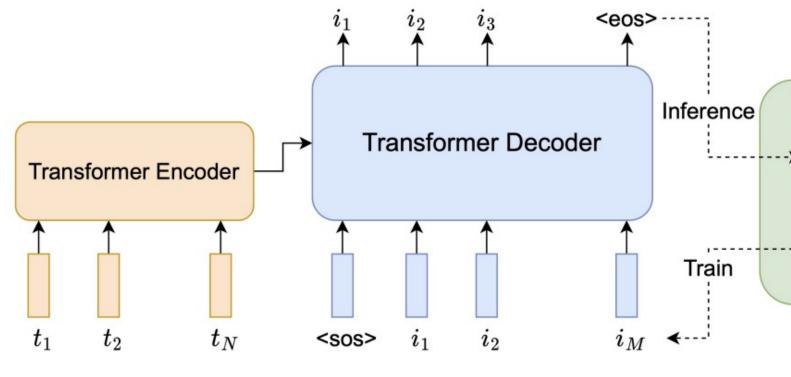


A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!



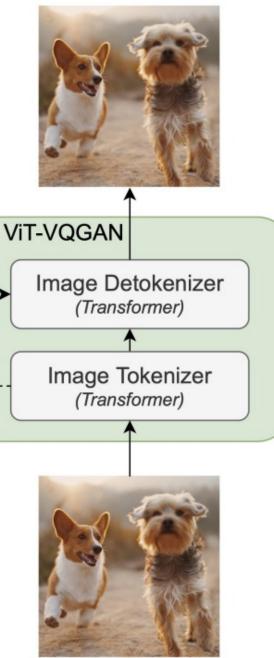
Scaling VQGAN for Text-to-Image!

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



Two dogs running in a field

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

... but very expensive :(

Slide credit: Robin Rombach

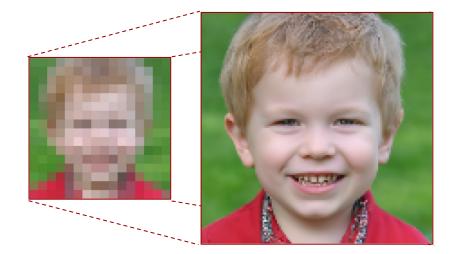
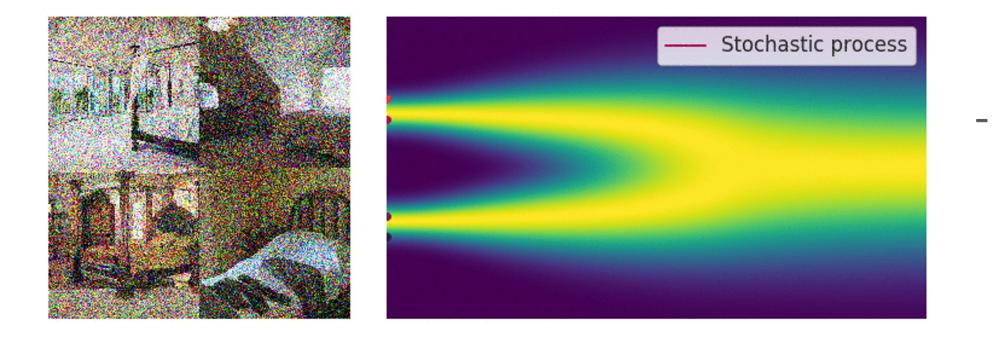


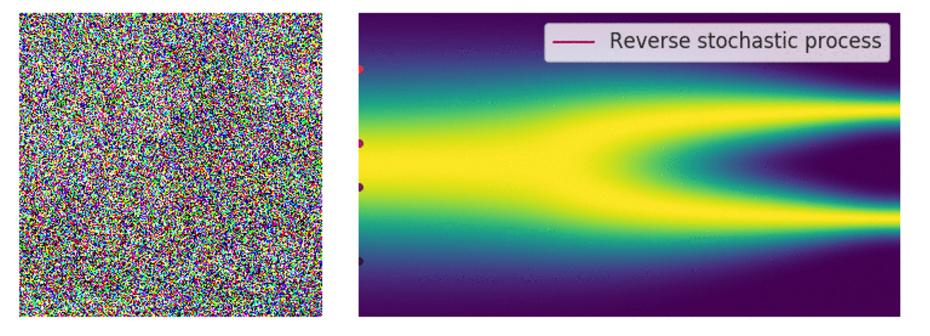
Image Super-Resolution via Iterative Refinement

Chitwan Saharia, et al

https://arxiv.org/abs/2104.07636

Brief Overview of Diffusion Models





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

"destroy" the data by gradually adding small amounts of gaussian noise

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

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)





Reverse denoising process (generative)

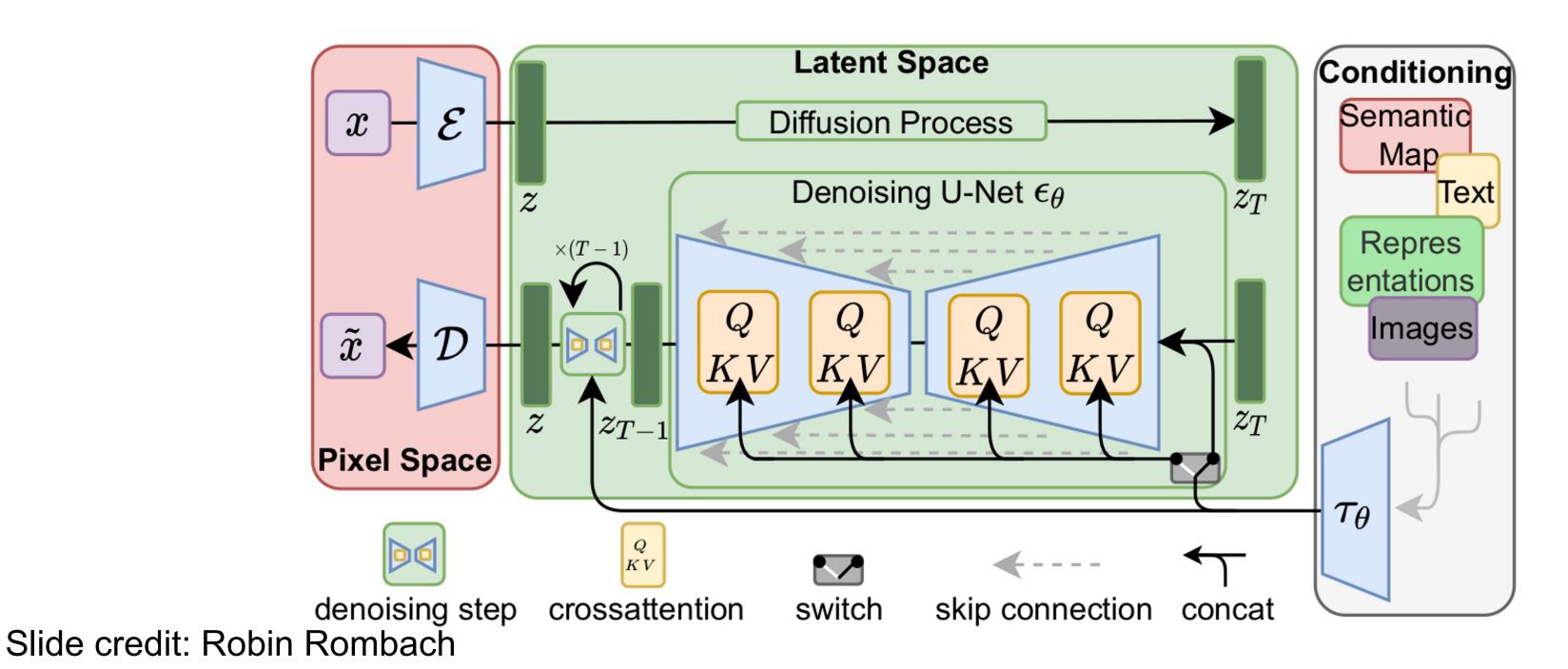
Sohl-Dickstein et al., Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML 2015 Ho et al., Denoising Diffusion Probabilistic Models, NeurIPS 2020 Song et al., Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021

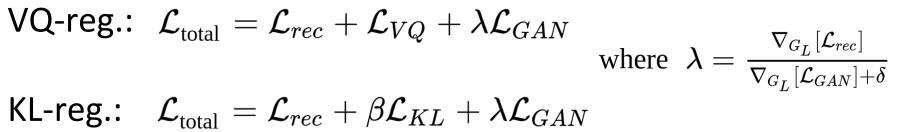
Noise

Slide credit: Karsten Kreis et al.

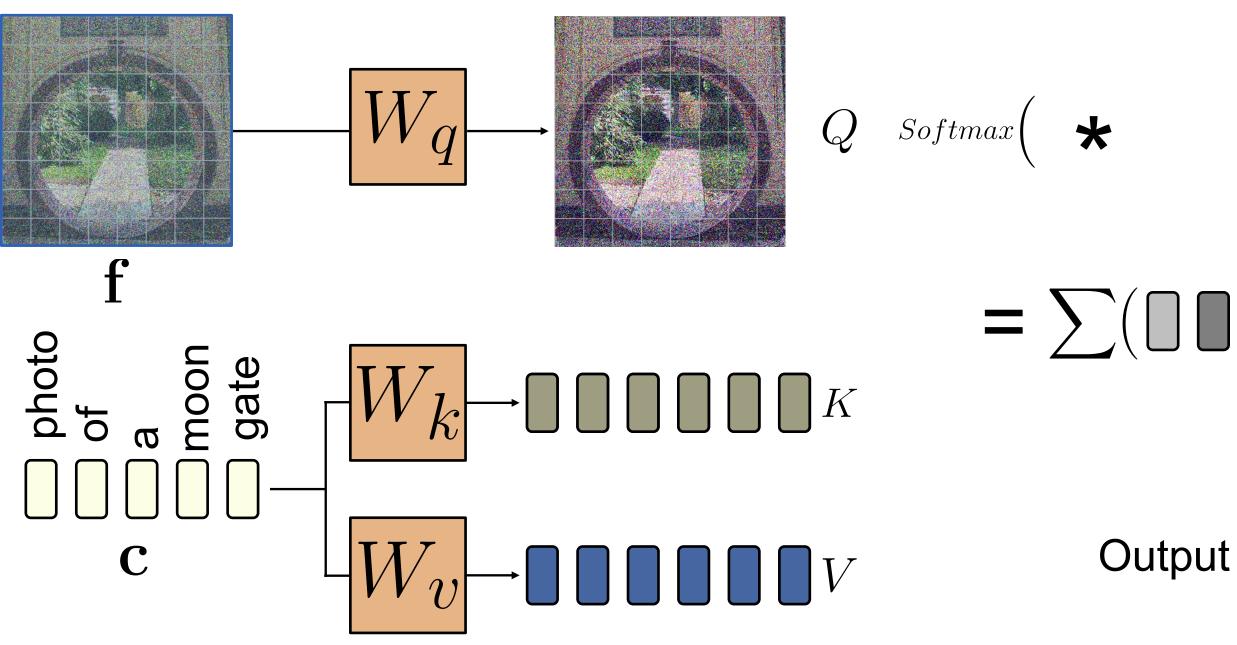
Latent Diffusion Modeling: Architecture

Autoencoder with KL or VQ regularization.





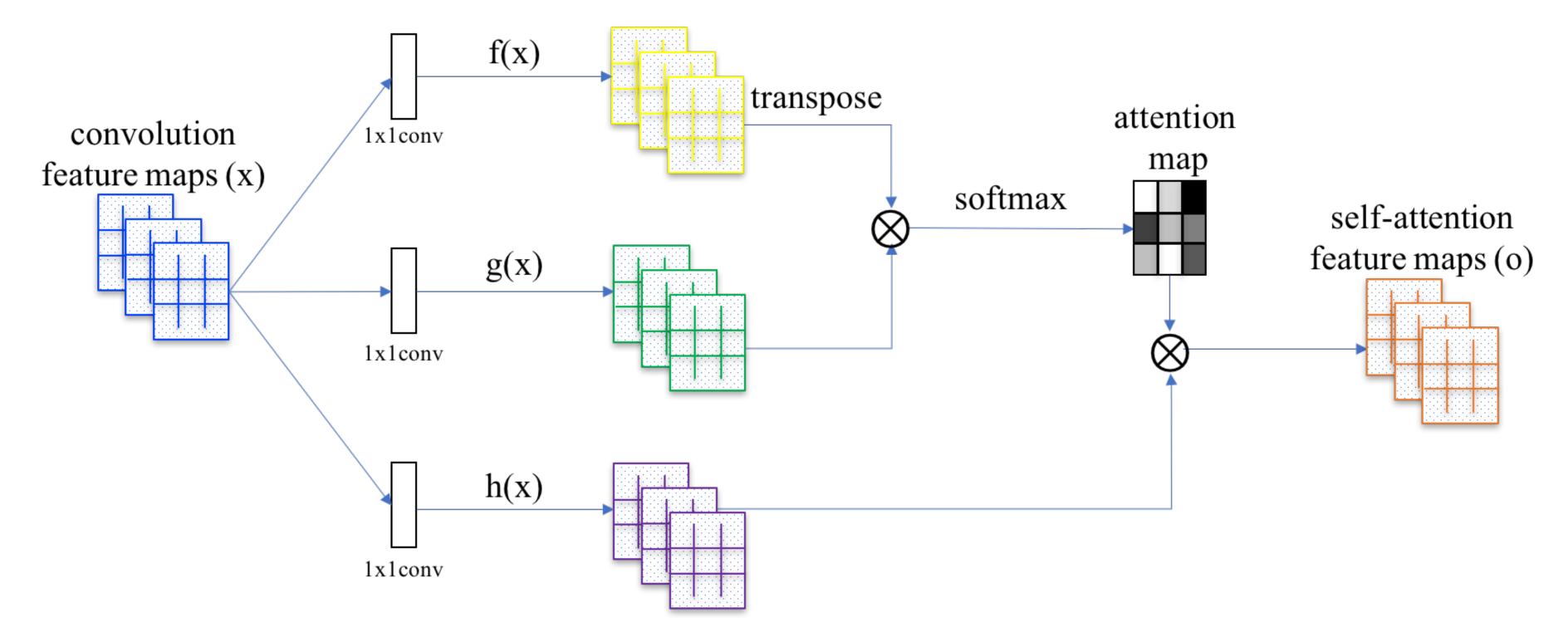
Text-Image Cross-Attention



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

Slides from [Kumari et al., CVPR 2023]

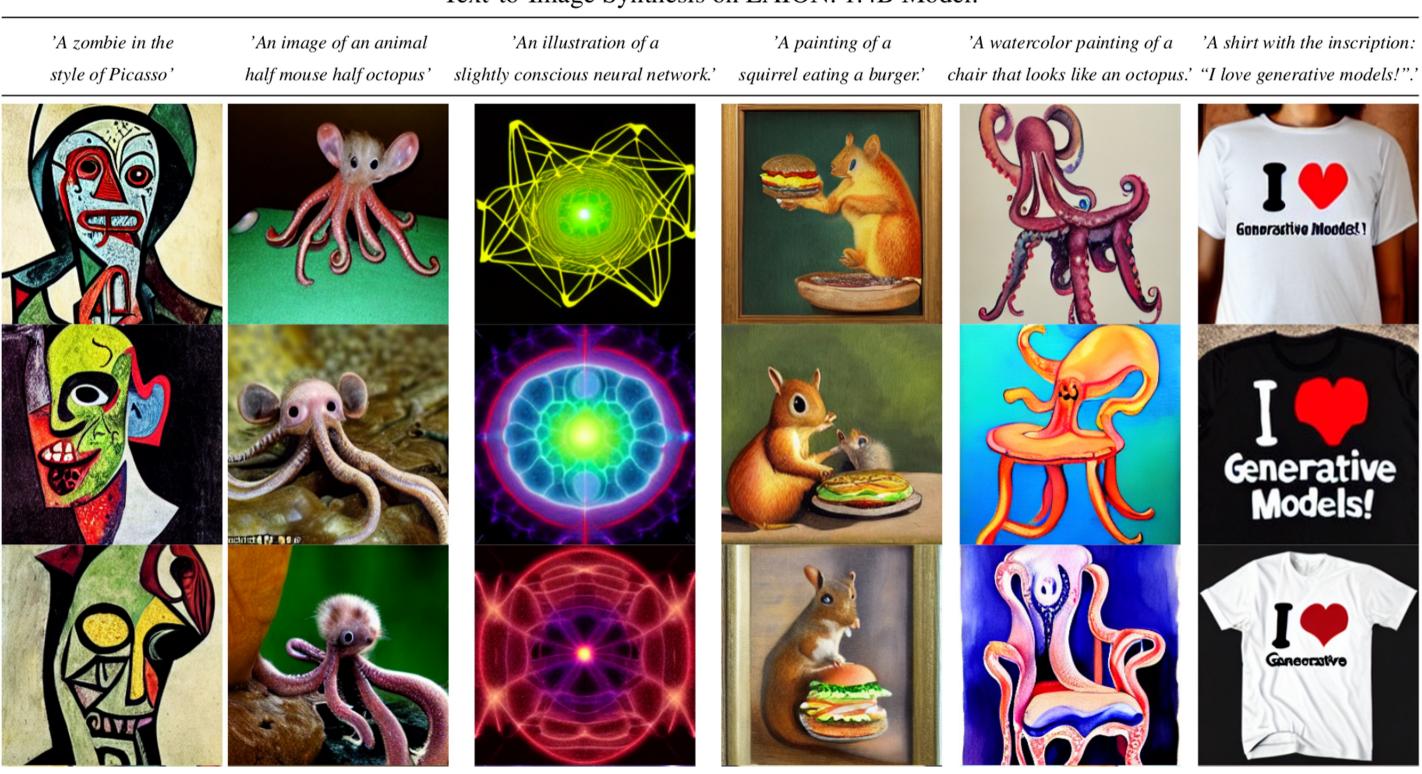
(Spatial) Self-attention Layer



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 -



Slide credit: Robin Rombach

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

LDMs for Text-to-Image Synthesis

convolutional sampling (train on 256², generate on >256²)

"A sunset over a mountain range, vector image"



"Cheat Code": Classifier-Free Diffusion Guidance

Jonathan Ho, Tim Salimans

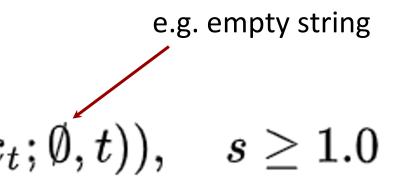
- see https://arxiv.org/abs/2207.12598
- works very well for conditional image generation:

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

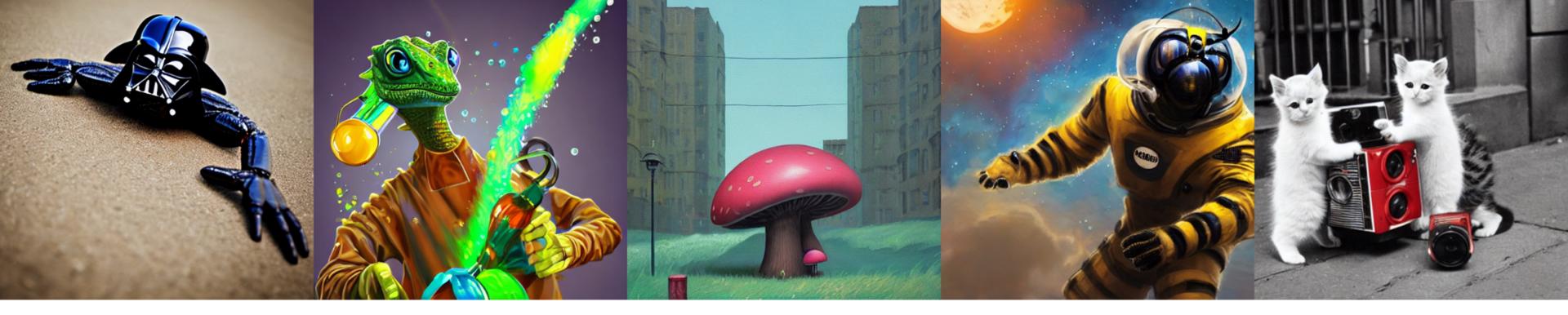
$$s = 1.0$$







s = 7.5

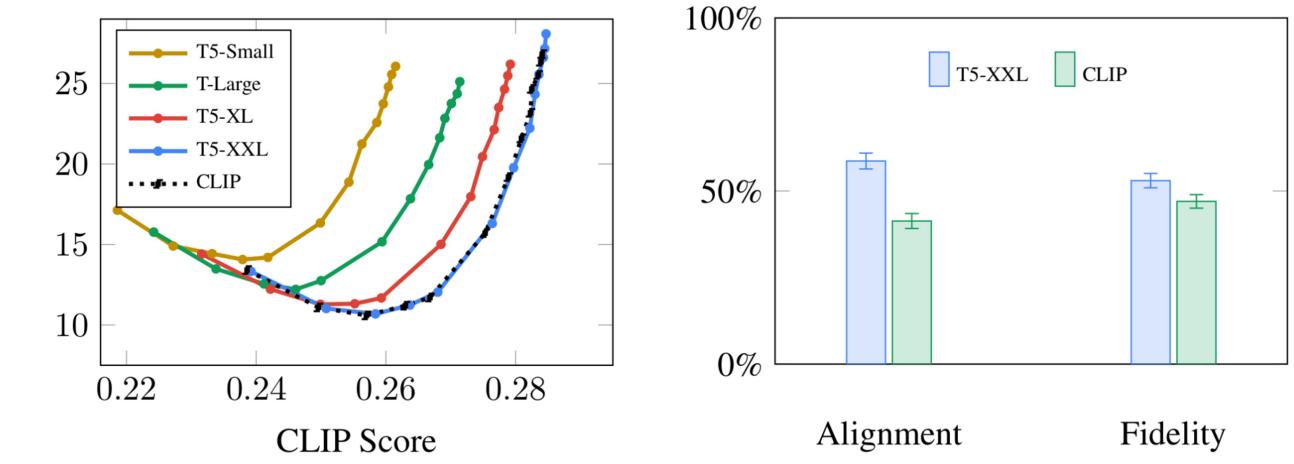


Stable Diffusion Latent Diffusion ++



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)
- \rightarrow choose CLIP (ViT-L/14) since performance/size tradeoff seems significant _



(a) Pareto curves comparing various text encoders.

FID-10K

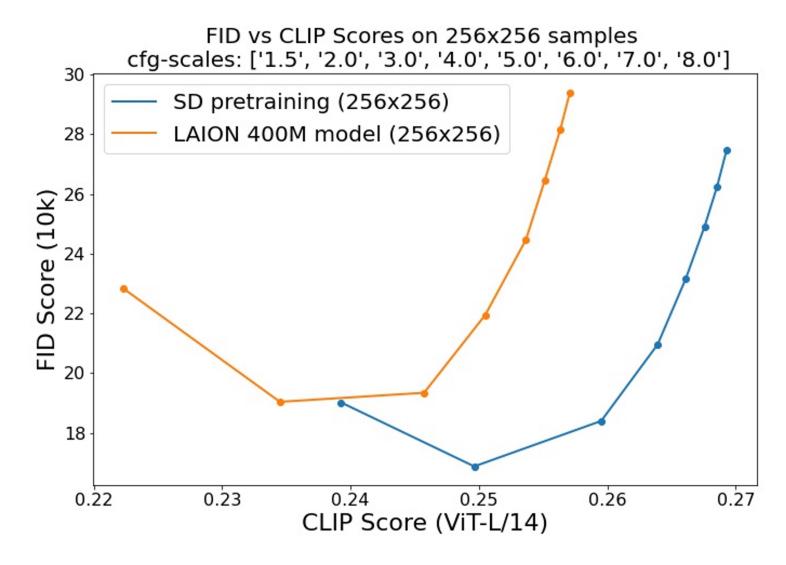
(b) Comparing T5-XXL and CLIP on DrawBench.

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 <u>laion-high-resolution</u> (170M examples from LAION-5B with resolution >= 1024x1024).

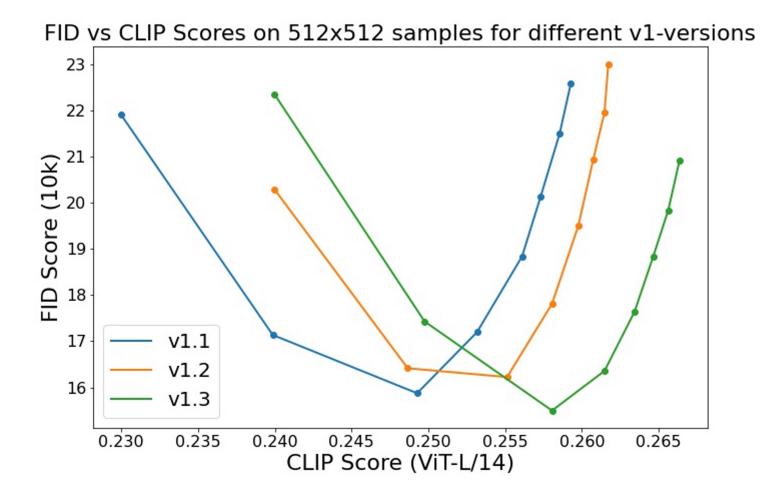
part 2 (v1.2):

 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):

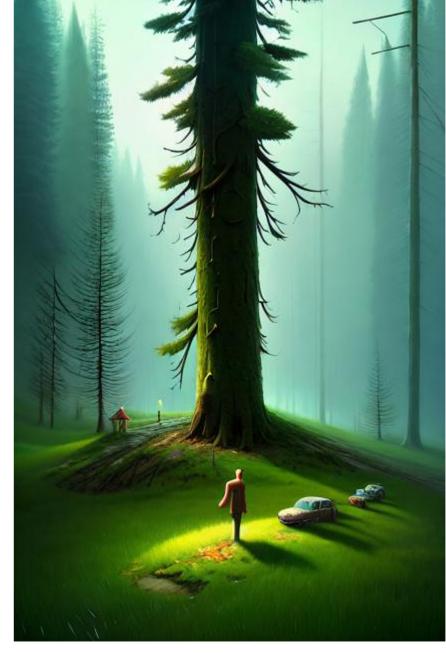
- 195k/225k steps at resolution 512x512 on "laion-improvedaesthetics" and 10% dropping of the text-conditioning

→ 4.2 GB checkpoint (EMA only, fp32)



10k random COCO val captions / 50 decoding steps







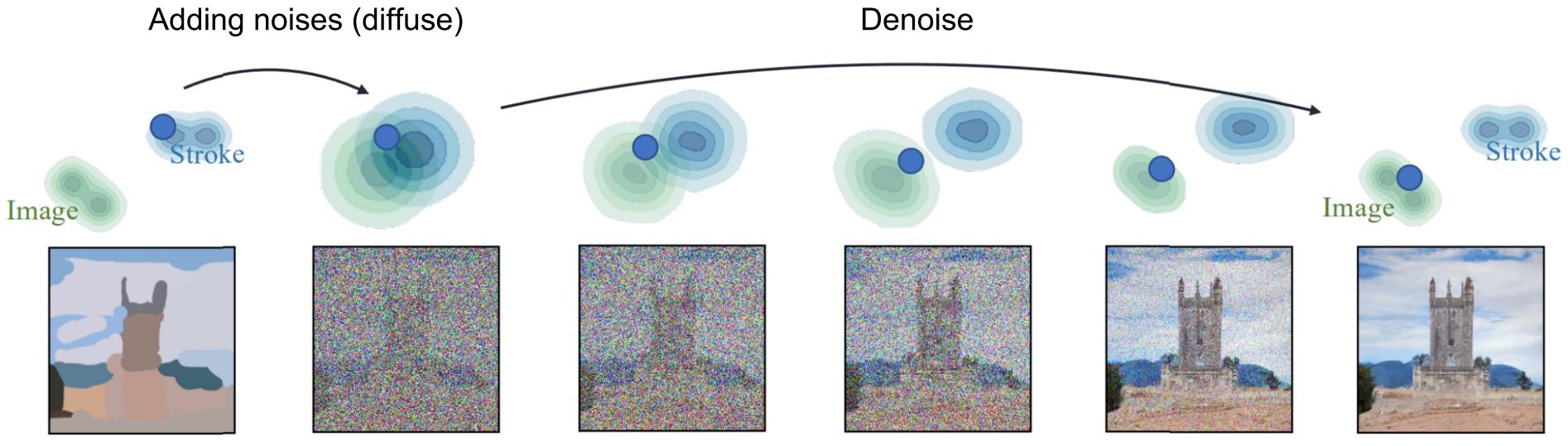






Text-Guided Image-to-Image

SDEdit (<u>https://arxiv.org/abs/2108.01073</u>) recipe: diffuse \rightarrow denoise

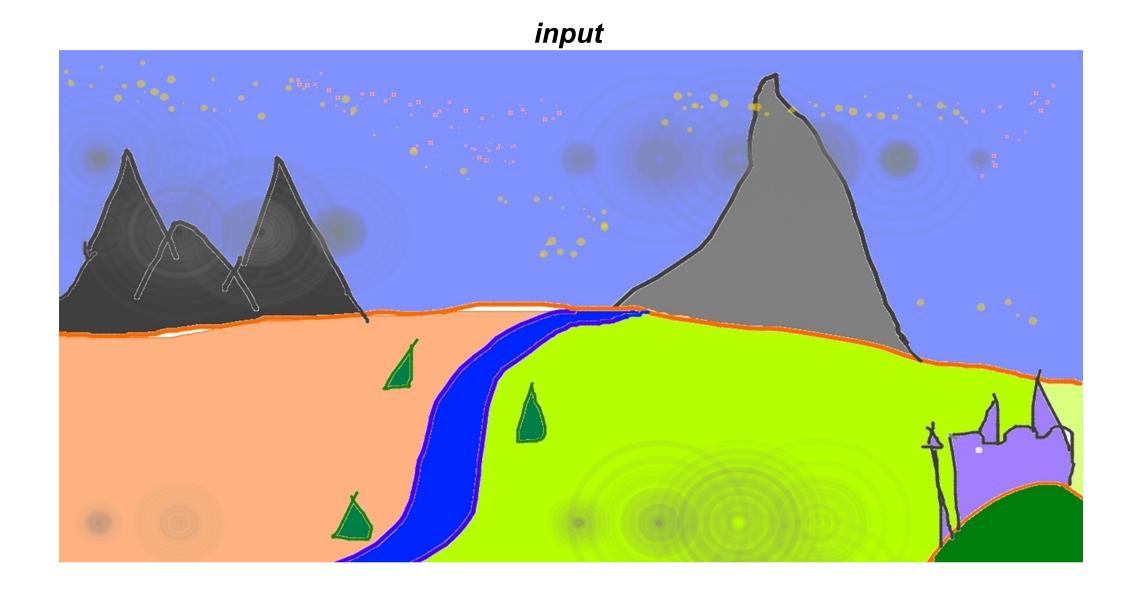


Input

Slide credit: Robin Rombach

Output

Text-Guided Image-to-Image



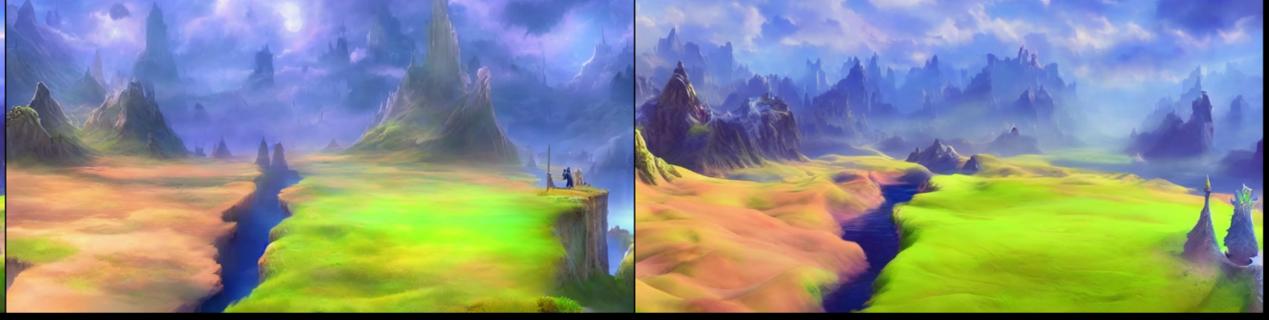
"a fantasy landscape, watercolor painting"





"a fantasy landscape, trending on artstation"





"a fantasy landscape, by Simon Stalenhag"

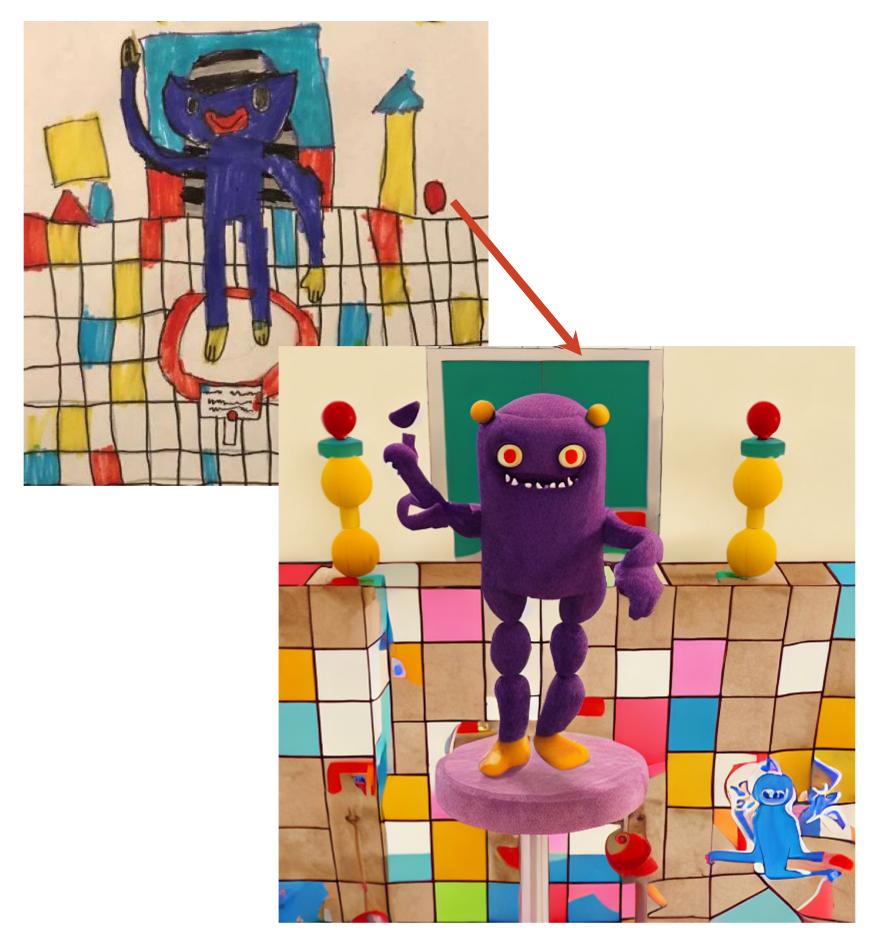




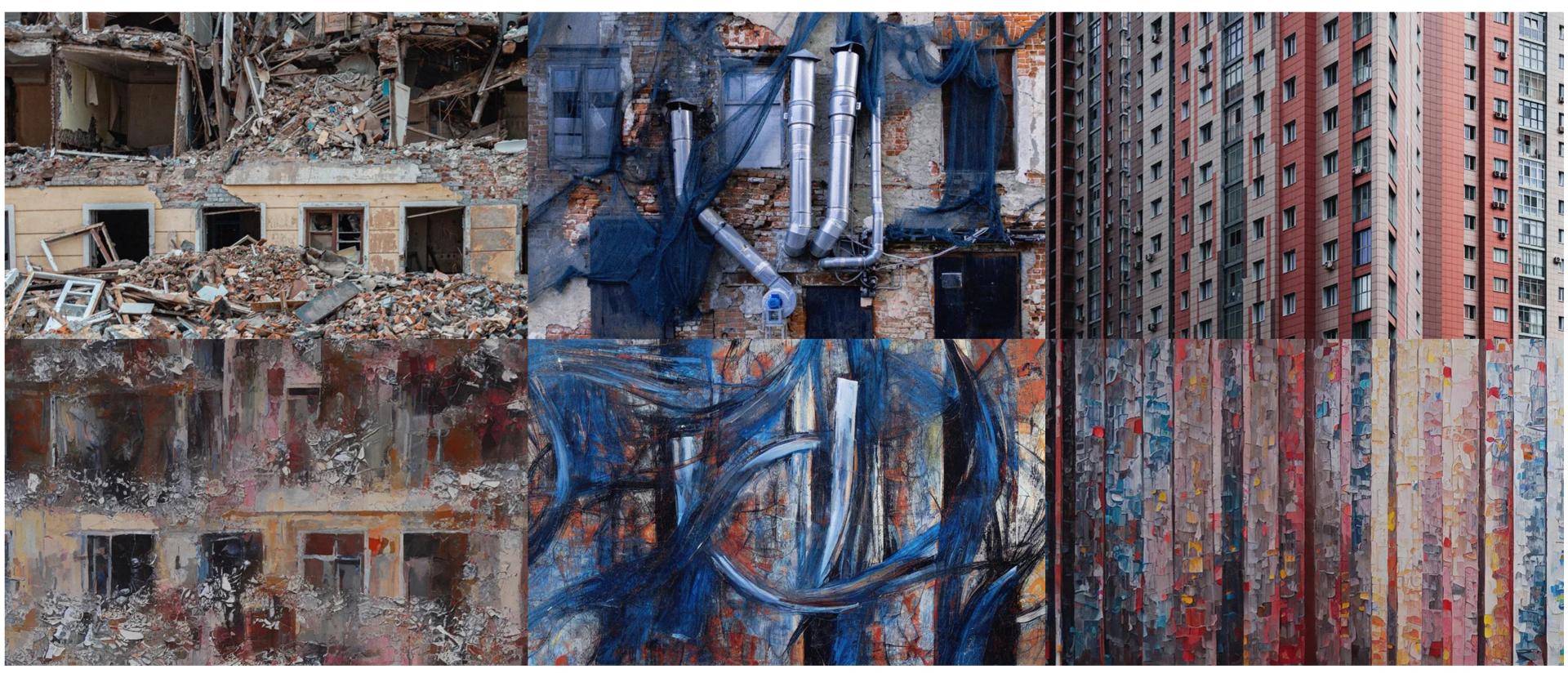
"Upgrade" your child's artwork

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





abstract art from photos



original post by <u>u/Pereulkov</u> <u>https://www.reddit.com/r/StableDiffusion/comments/xhhyad/i_made_abstract_art_from_my_photos/</u>⁶¹

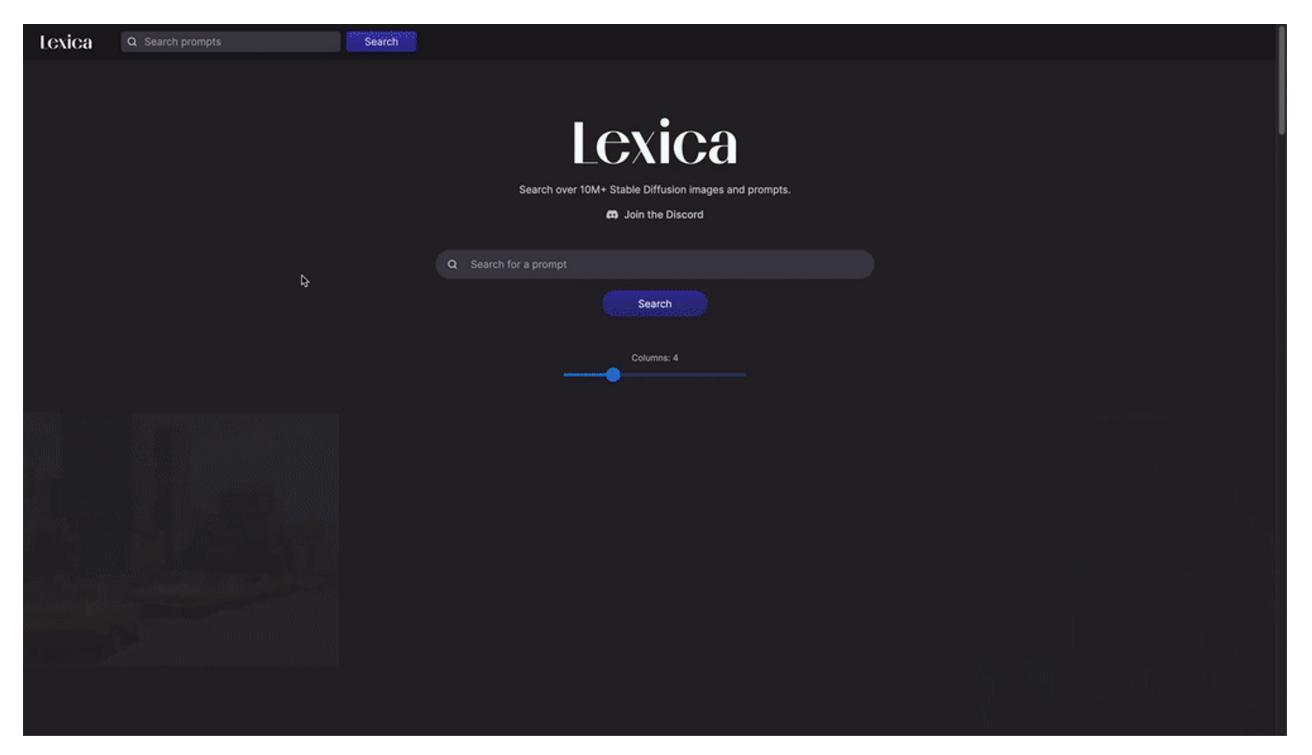
Video Synthesis



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)

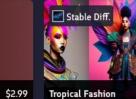


Prompt Marketplace (promptbase.com)

DALL·E, GPT-3, Midjourney, Stable Diffusion, ChatGPT **Prompt Marketplace** Funky Animals Find top prompts, produce better results, save on API costs, sell your own prompts. Sell a prompt Find a prompt Modern Woodcut Engravings Intric... Featured Prompts - <u>-</u> C Midiourne \$2.99 Butterfly Cliparts Vintage Retro Pattern Tiles \$1.99 Minimal Pastel Diagram Art \$2.99 Objects Made Of Money \$2.99 Asymmetrical Split Exposure ... \$2.99 Hottest Prompts ChatGPT ChatGPT 0 \$2.99 Beautiful Oil Paintings Hot Prl Selling Nft Generative Art Maker \$2.99 Clean Animal Art For Coloring... \$1.99 Tiny Gouache Houses \$2.99 Newest Prompts ChatGPT Stable Diff.

Premium Logos

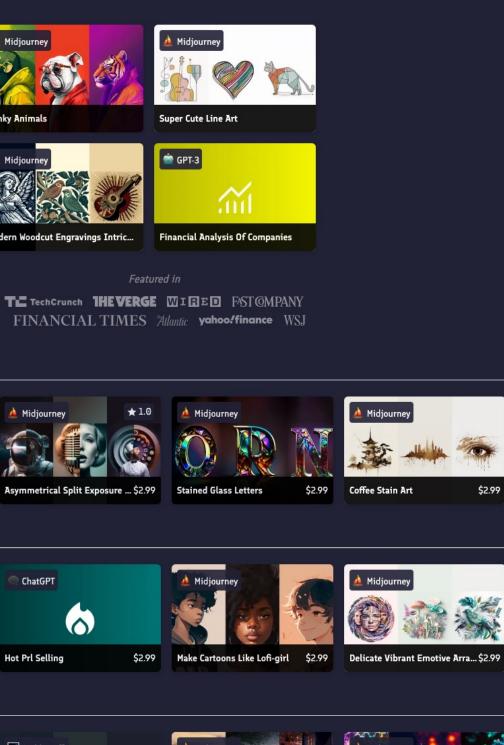




\$2.99

Food Images With Neon Effects \$1.99

Wall Art Mockups Choose Wall ... \$1.99



Alien Bio Organisms Posters \$2.99

\$2.99

Beautiful Oil Paintings

\$2.99

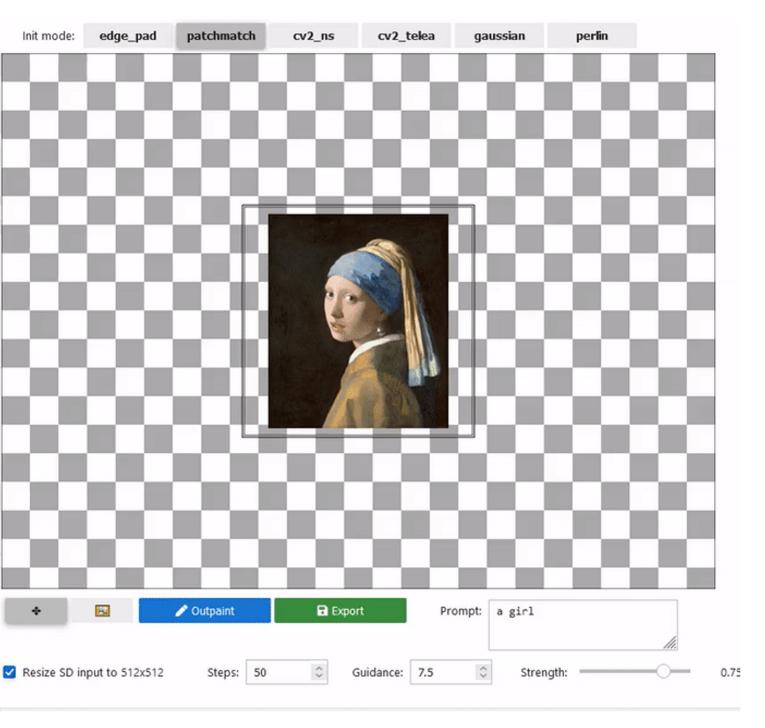
Uls / Plug-Ins for Photoshop, GIMP etc

	Adobe Photoshop 2022		tait as a day	a da a
🛃 v 📲 v 🔯 Mode: Brush v Oper	achy: 100% v 🧭 Flow: 100% v 🕼 Smoothing: 100% v 🎝 🗠 0* 🛛 Erase to History 🖉 💱	🤒 Q 🖬 -	init mode:	eage_
Imaging Imaging Imaging Imaging Imaging Imaging	acity: 100% v 🧭 Flow: 100% v 🕼 Smoothing: 100% v 🎝 🗠 0* 🛛 Erase to History 🖉 💱		Init mode:	
	71.4% 2000 px x 2300 px (300 ppi))			þ
	Imaging Imaging	I was will show up here.	Image: Image: Ima	

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

20

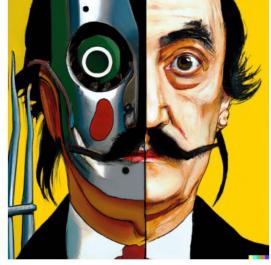
Slide credit: Robin Rombach



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

What if you have 1,000+ GPUs/TPUs

DALL·E 2, Imagen



ting 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





fly event.

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

Sprouts in the shape of text 'Imagen' coming out of a A photo of a Shiba Inu dog with a backpack riding a A high contrast portrait of a very happy fuzzy panda fairytale book. A photo of a Shiba Inu dog with a backpack riding a 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- A cute corgi lives in a house made out of sushi.

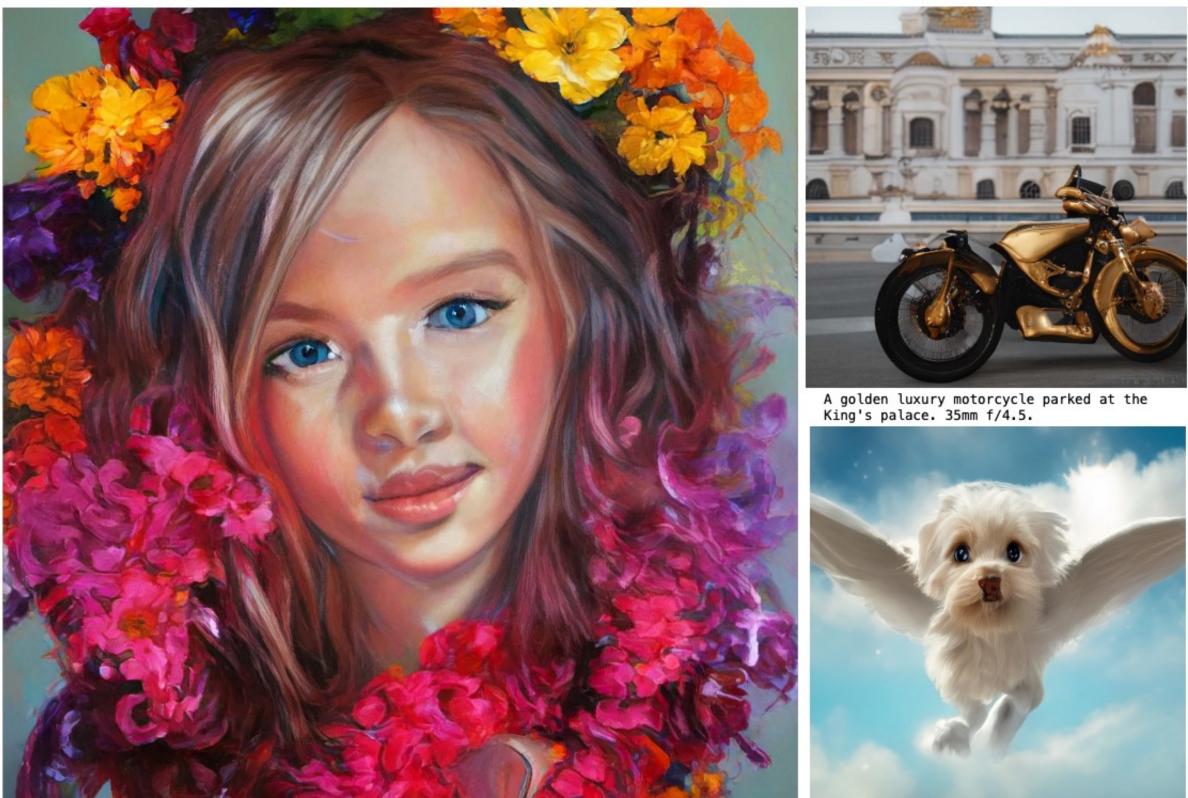


A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

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

Diffusion vs. Autoregressive vs. GANs

GigaGAN: Scaling up GANs

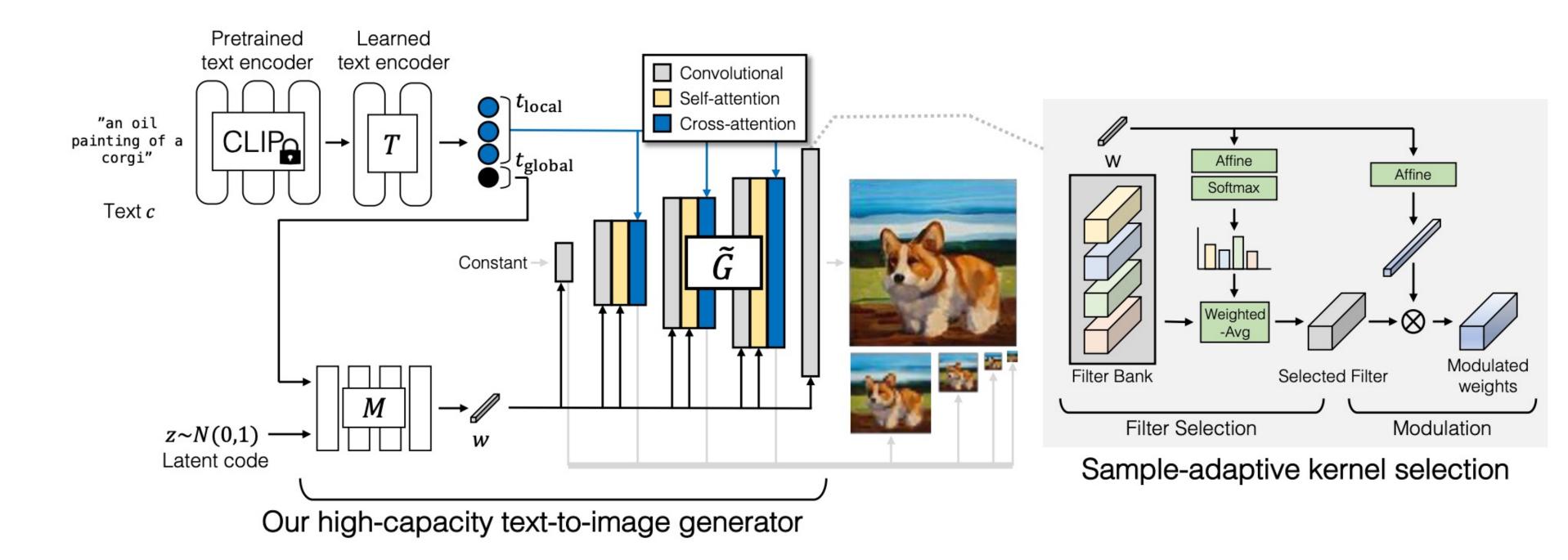


A portrait of a human growing colorful flowers from her hair. Hyperrealistic oil painting. Intricate details.

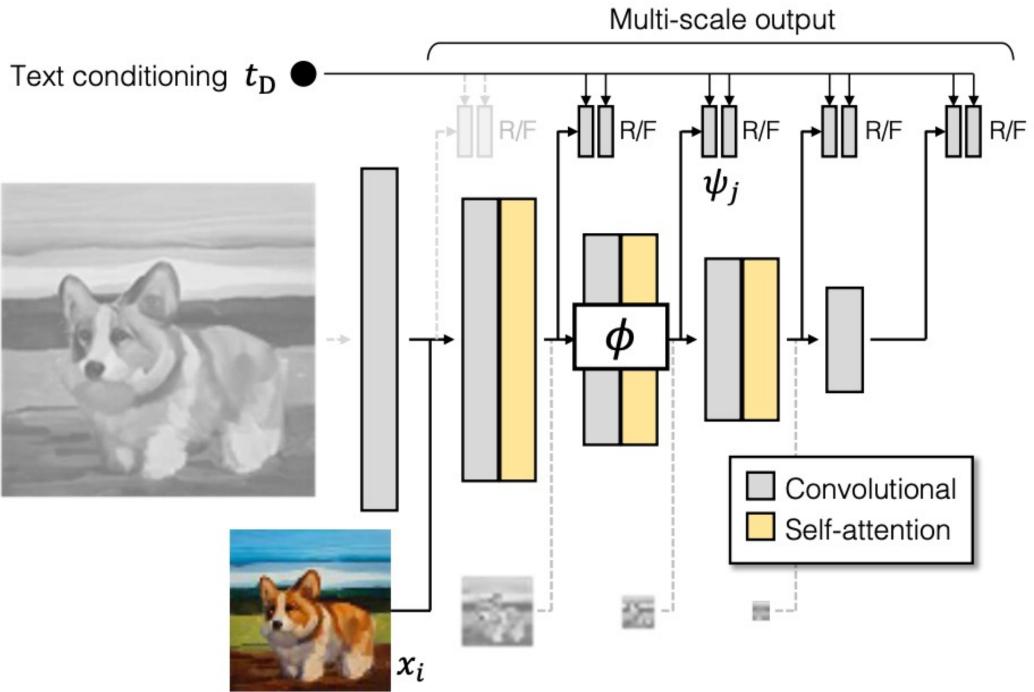


a cute magical flying maltipoo at light speed, fantasy concept art, bokeh, wide sky

GigaGAN Generator



GigaGAN Discriminator



Sweep through multi-scale input

Style Mixing



"A Toy sport sedan, CG art."

Coarse styles



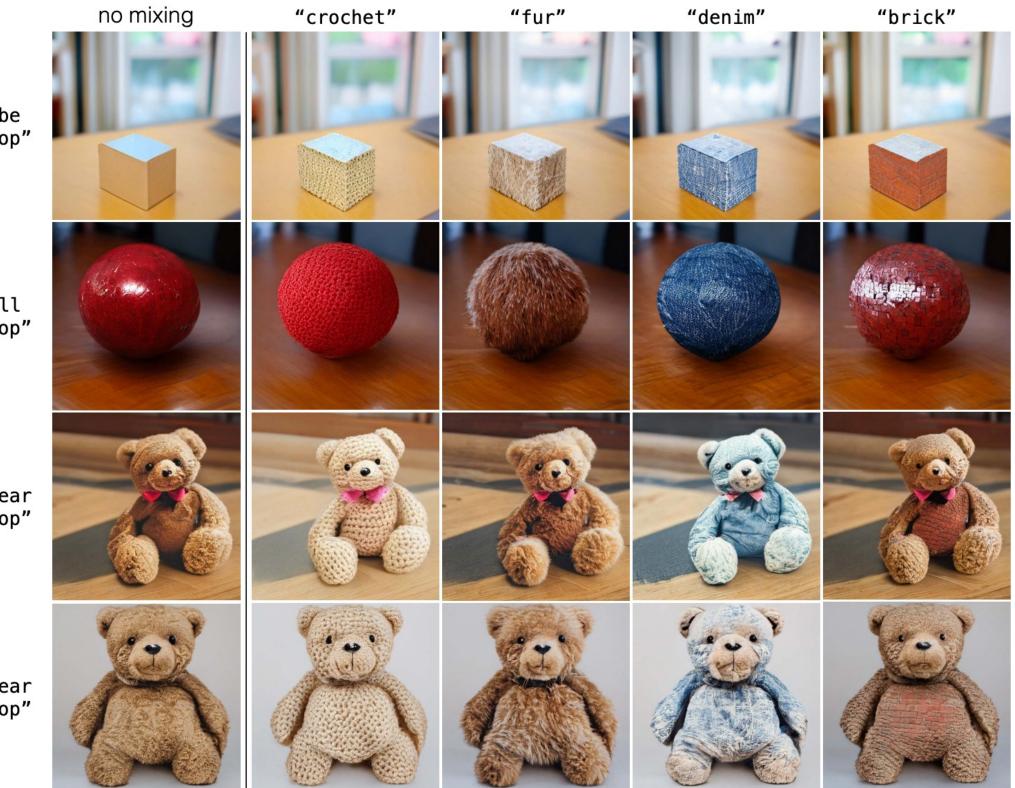




[Kang et al., CVPR 2023]

72

Prompt Mixing



"a cube on tabletop"

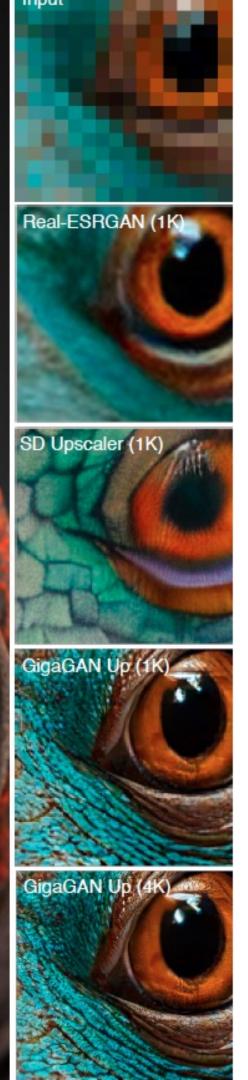
"a ball on tabletop"

"a teddy bear on tabletop"

"a teddy bear on tabletop"







Comparison between Different Models

<i>U</i>		L		L	
Model	Туре	# Param.	# Images	FID-30k \downarrow	Inf. time
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	-
DALL·E 2 [74] Solution [80] Solution [5]	Diff	3.0B	15.36B	7.27	9.1s
a 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
SD-v1.5* [78]	Diff	0.9B	3.16B	9.62	2.9s
$\frac{10}{5}$ Muse-3B [10]	AR	3.0B	0.51B	7.88	1.3s
GigaGAN	GAN	1.0B	0.98B	9.09	0.13s

Comparison between Different Models



Ours (512px, 0.14s / img, truncation $\psi = 0.8$)

N 1 2 N



LDM (256px, 9.4s / img, 250 steps, guidance=6.0)



Stable Diffusion v1.5 (512px, 2.9s / img, 50 steps, guidance=7.5)



DALL·E 2 (1024px)











LDM (256px, 9.4s / img, 250 steps, guidance=6.0)

Stable Diffusion v1.5 (512px, 2.9s / img, 50 steps, guidance=7.5)

DALL·E 2 (1024px)

StyleGAN-T



A painting of a fox in the style of starry night.

Beautiful landscape of an ocean. Mountain in the background. Sun is setting.



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



Surrealist dream-like oil painting by Salvador Dali of a cat playing checkers



Panda mad scientist mixing sparkling chemicals, artstation

Fall landscape with a small cottage next to a lake.

77 [Sauer et al., ArXiv 2023]

StyleGAN-T



A painting of a fox in the style of starry night.

Beautiful landscape of an ocean. Mountain in the background. Sun is setting.



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



Surrealist dream-like oil painting by Salvador Dali of a cat playing checkers

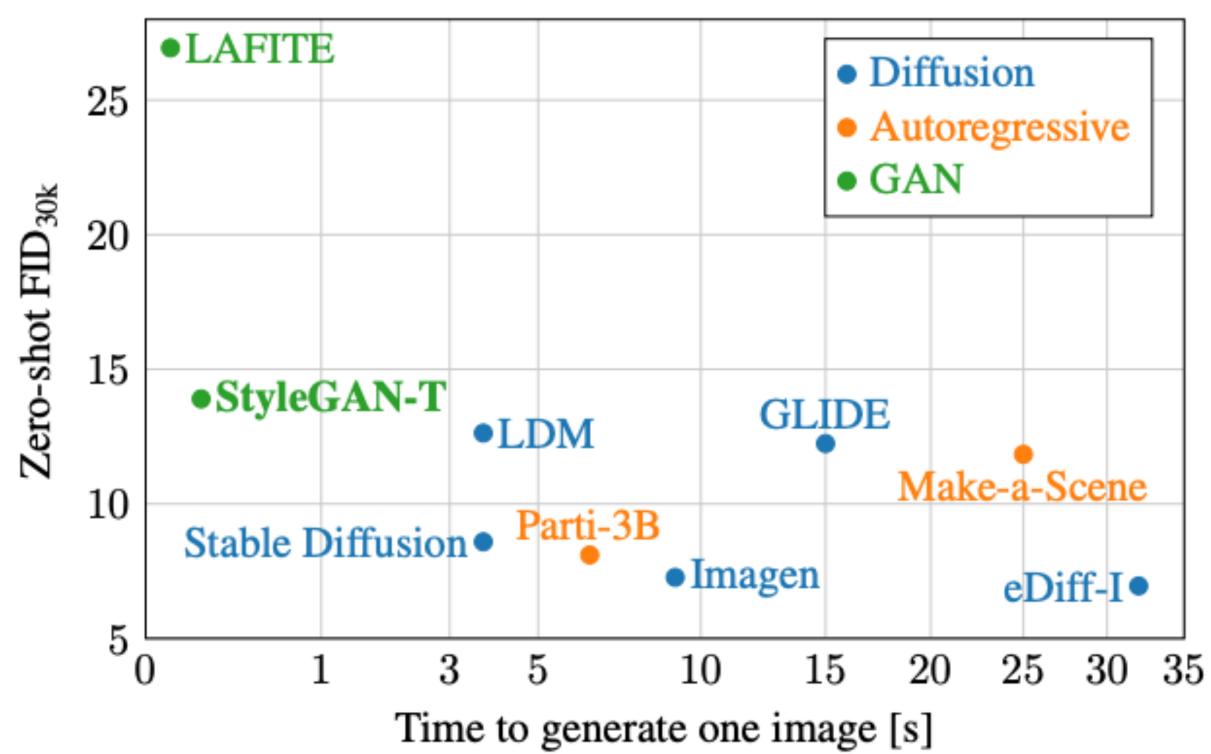


Panda mad scientist mixing sparkling chemicals, artstation

Fall landscape with a small cottage next to a lake.

78 [Sauer et al., ArXiv 2023]

StyleGAN-T



79 [Sauer et al., ArXiv 2023]

How could we improve it?

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

ls, diffusion, AR, Hybrid CLIP, T5) -> CNN + Transformer on -> AdaIN -> cross-attentio 100.