Lightricks

The Text2Image Magic

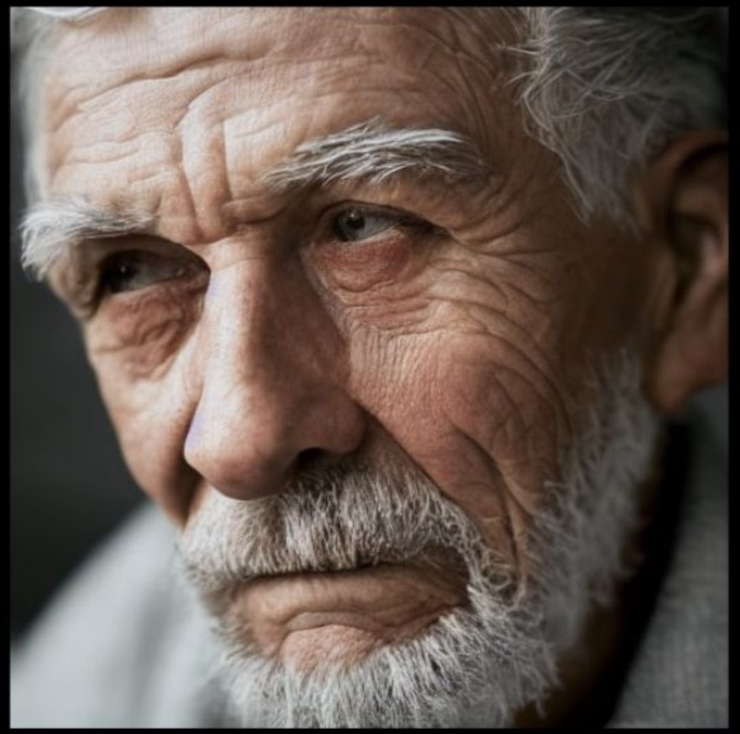
A high level overview of the technology's building blocks

Naomi Ken Korem
Researcher

MIDJOURNEY

DALL-E 2

STABLEDIFFUSION



film still, portrait of an old man, wrinkles, dignified look, grey silver hair, peculiar nose, wise, eternal wisdom and beauty, incredible lighting and camera work, depth of field, bokeh, screenshot from a hollywood movie

LAION
@laion_ai

Guiding Stable Diffusion with our CLIP H:
"Professional HDR photo of a polar bear holding a lollipop on a rooftop in Hong Kong looking up at a UFO in the night sky. A UFO flies above the polar bear. The polar bear holds a lollipop on a rooftop. The background shows Hong Kong."

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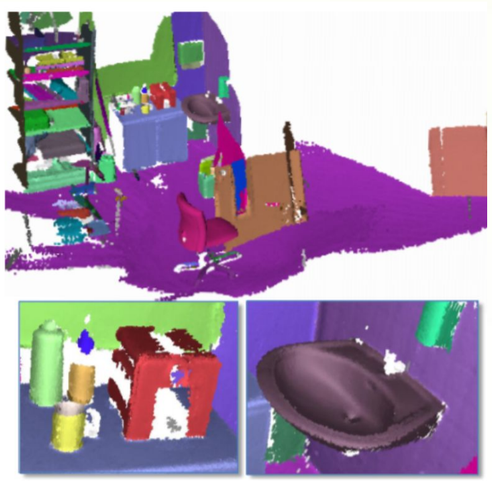

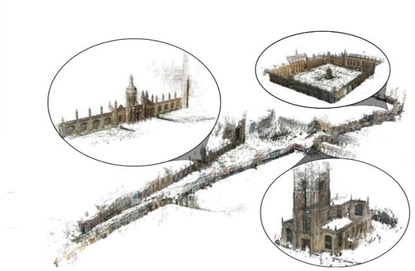

Naomi Ken Korem

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Lightricks Team

Harel Cain

AJ Bruce

Shaked Dunsky

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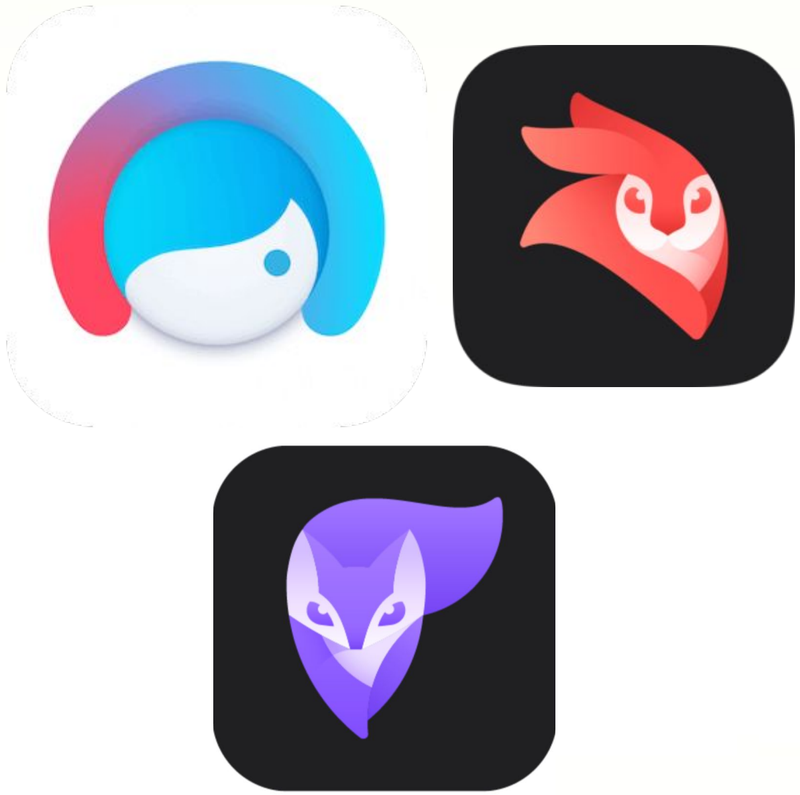
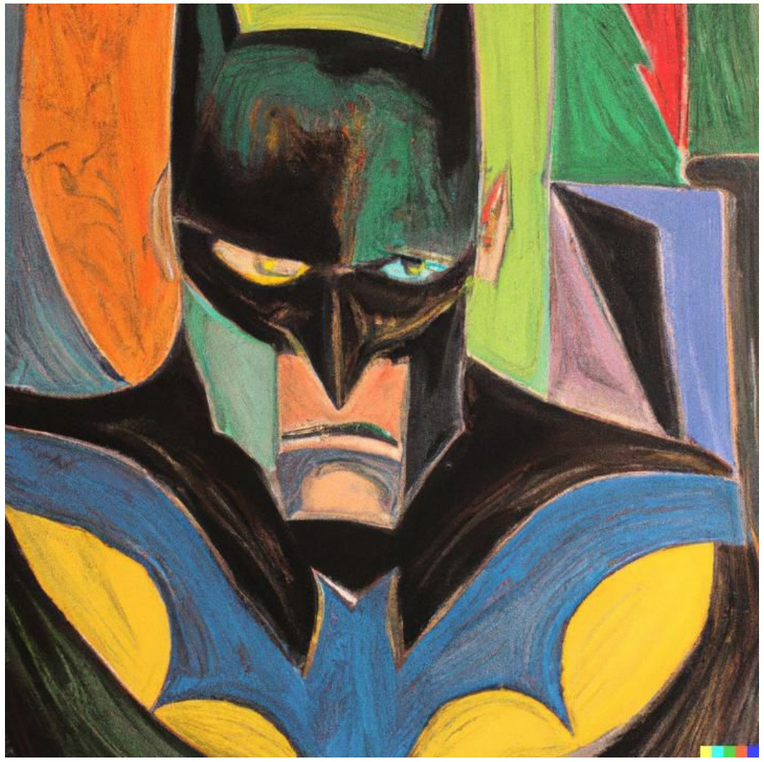
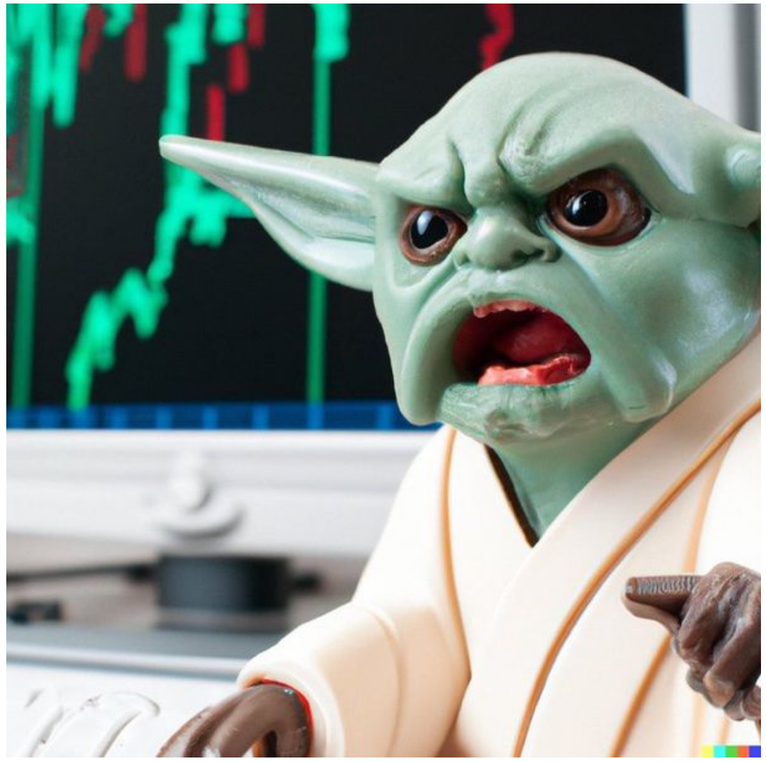


DALLE v2 (Apr 2022)

Academic researcher before a deadline, as painted by Edvard Munch.



Batman, as painted by Picasso.



Yoda angry at having lost money in the stock market.

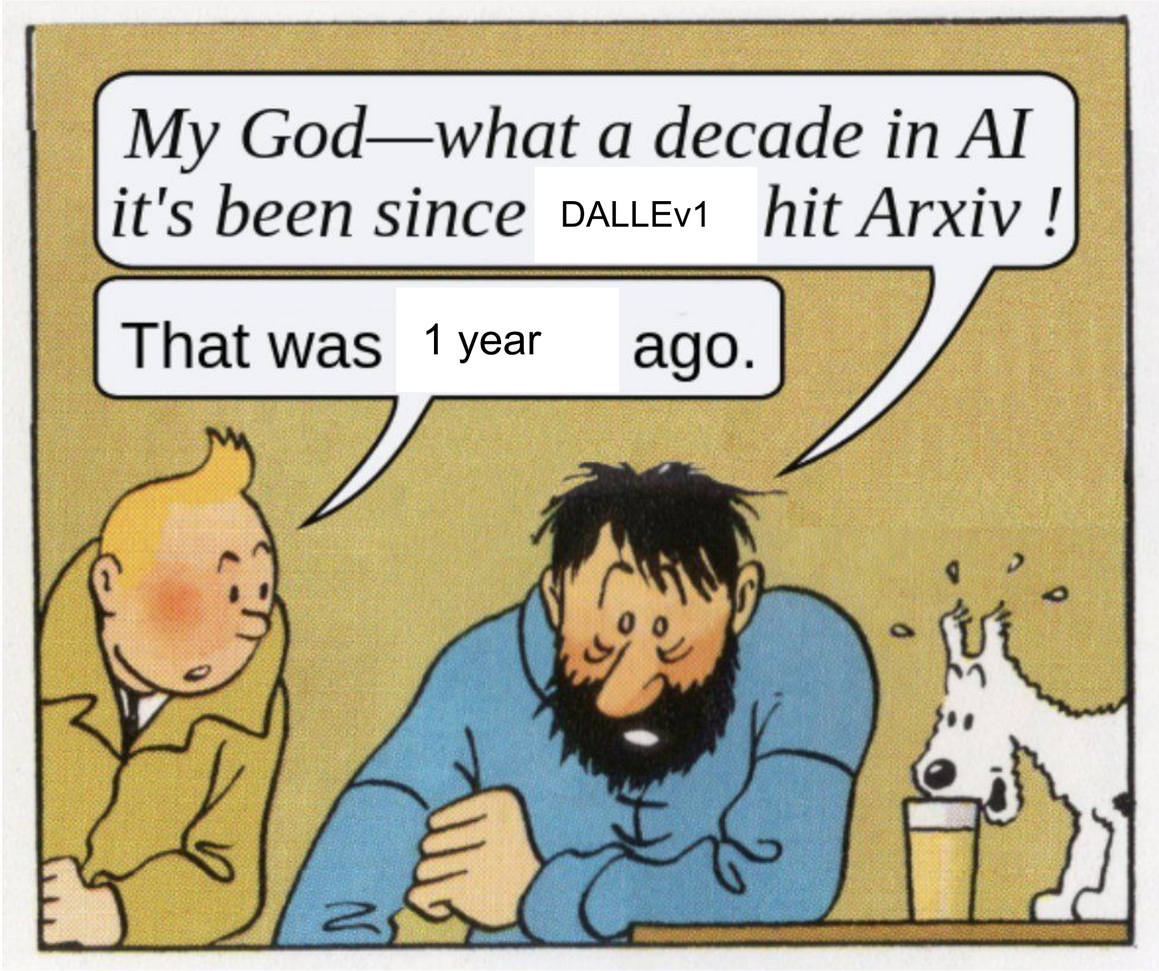
Imagen (May 2022)

Android mascot made of bamboo.

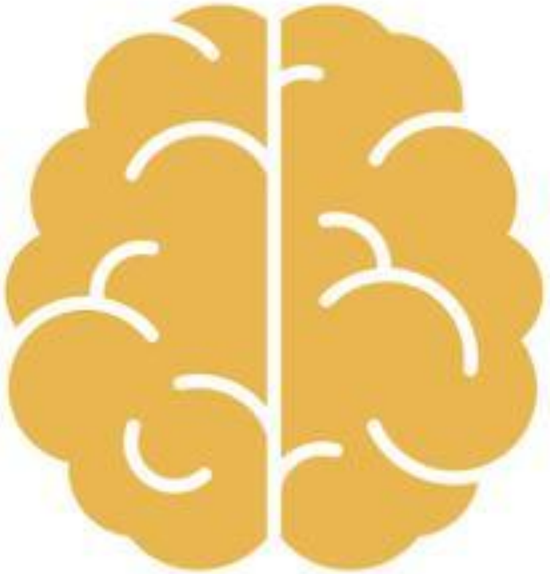
A dog looking curiously in the mirror, seeing a cat.

A chrome-plated duck with a golden beak arguing with an angry turtle in a forest.

It all happened so fast



System 1



Fast, intuitive and emotional

System 2

Slow, conscious and effortful

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Timeline

Neural style transfer and related domains and StyleGAN.

OpenAI publish DALL-E paper and open source CLIP model

Diffusion models and Gans using CLIP

DALLE-2 is published by OpenAI and hype hits mainstream media

Google Brain releases Imagen

Stability.ai releases Stable Diffusion, open license

Pre 2021

1-2021

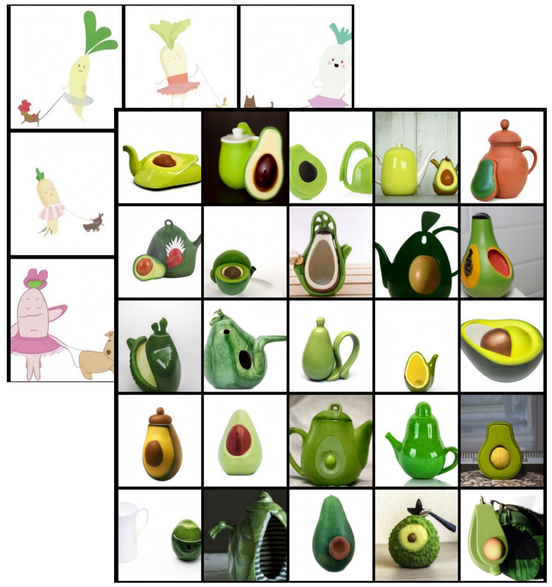
2021-2022

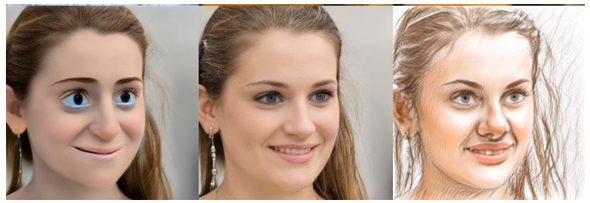
04-2022

5-2022

8-2022

Neural style transfer (2016)





What cause this fast progress?

1. **DATA**

   5 Billion image, text pairs!

2. **Parallel training in scale** -

   2.5M training steps of batch size 2048 in very short time. (256 TPU-v4 chips)

3. **Multi domain connections**

   New architectures, layers (Bert, GPT3, StyleGAN, ViT)

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The building blocks that got us there -

our agenda for this workshop

1. Generators and StyleGAN
2. Diffusion models
3. Text conditioned diffusion models (Dalle2, glide)
4. Stable Diffusion

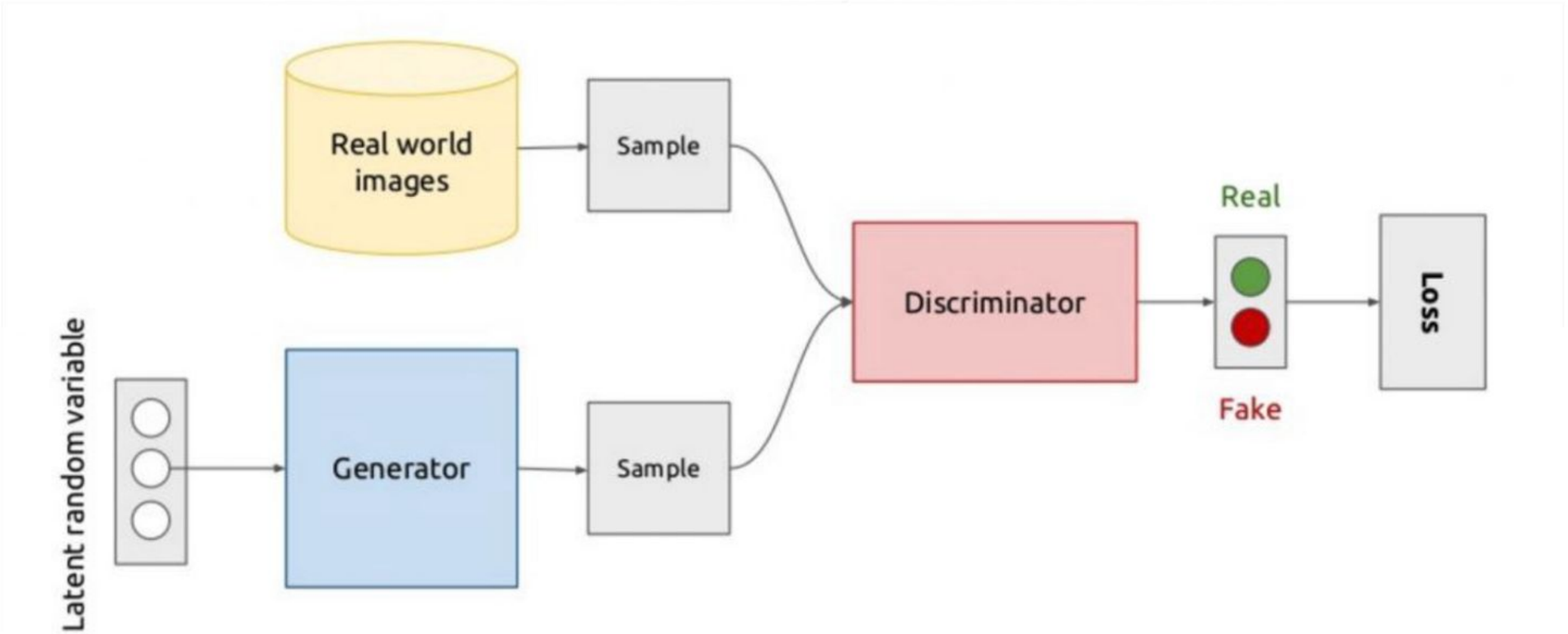
Generative Adversarial Network

Input: random noise vector (dimensions - 1xd)

Output: Image (dimensions wxhx3)

GAN

(Generative adversarial network)



Generative Adversarial Networks

StyleGAN

Nvidia, 2018

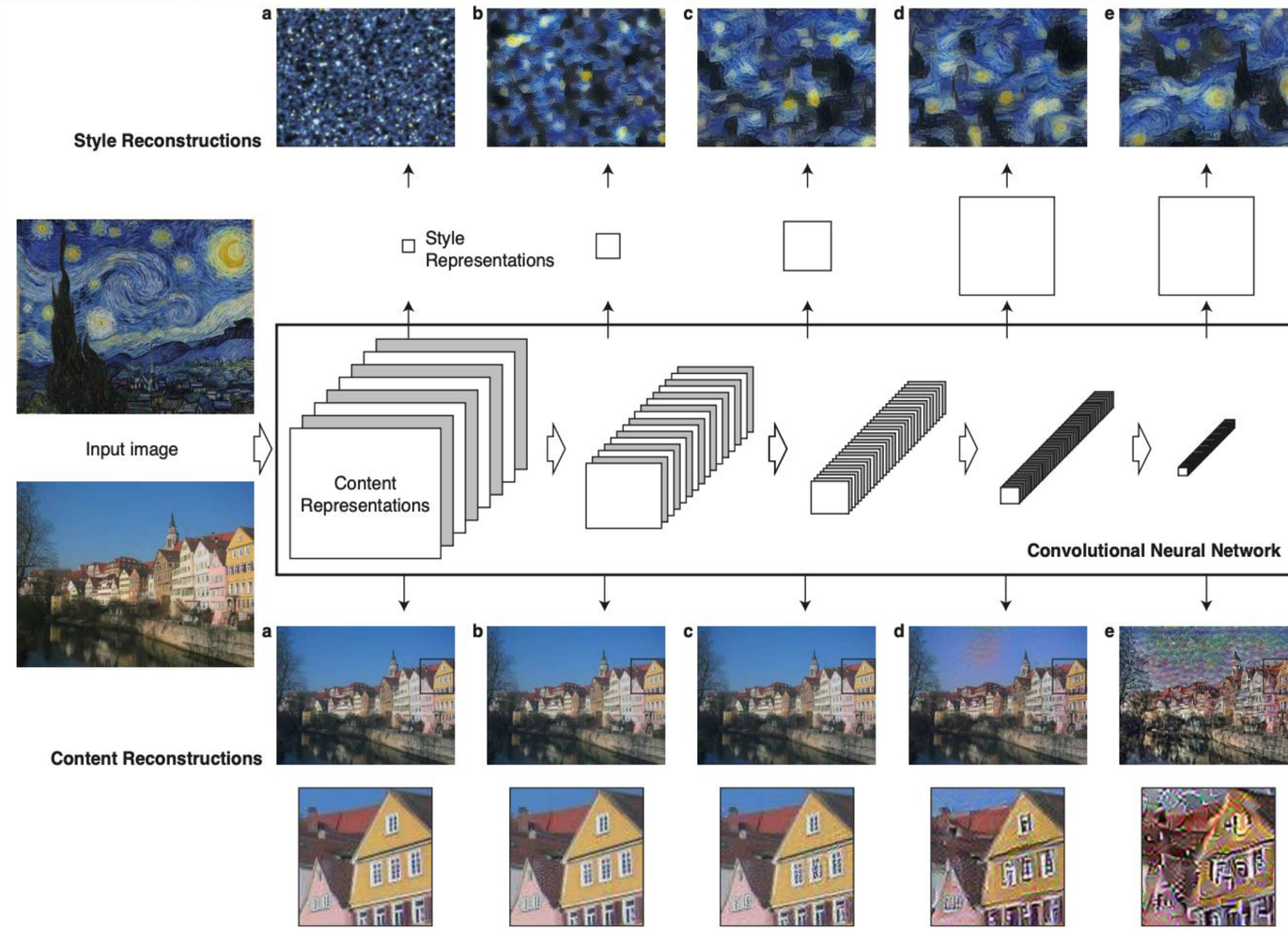
[Analyzing and Improving the Image Quality of StyleGAN]

Neural StyleTransfer

Match the correlation between the different filter response

Gram matrix: $$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}.$$

Loss: $$E_L = \sum \left(G^L - A^L\right)^2$$

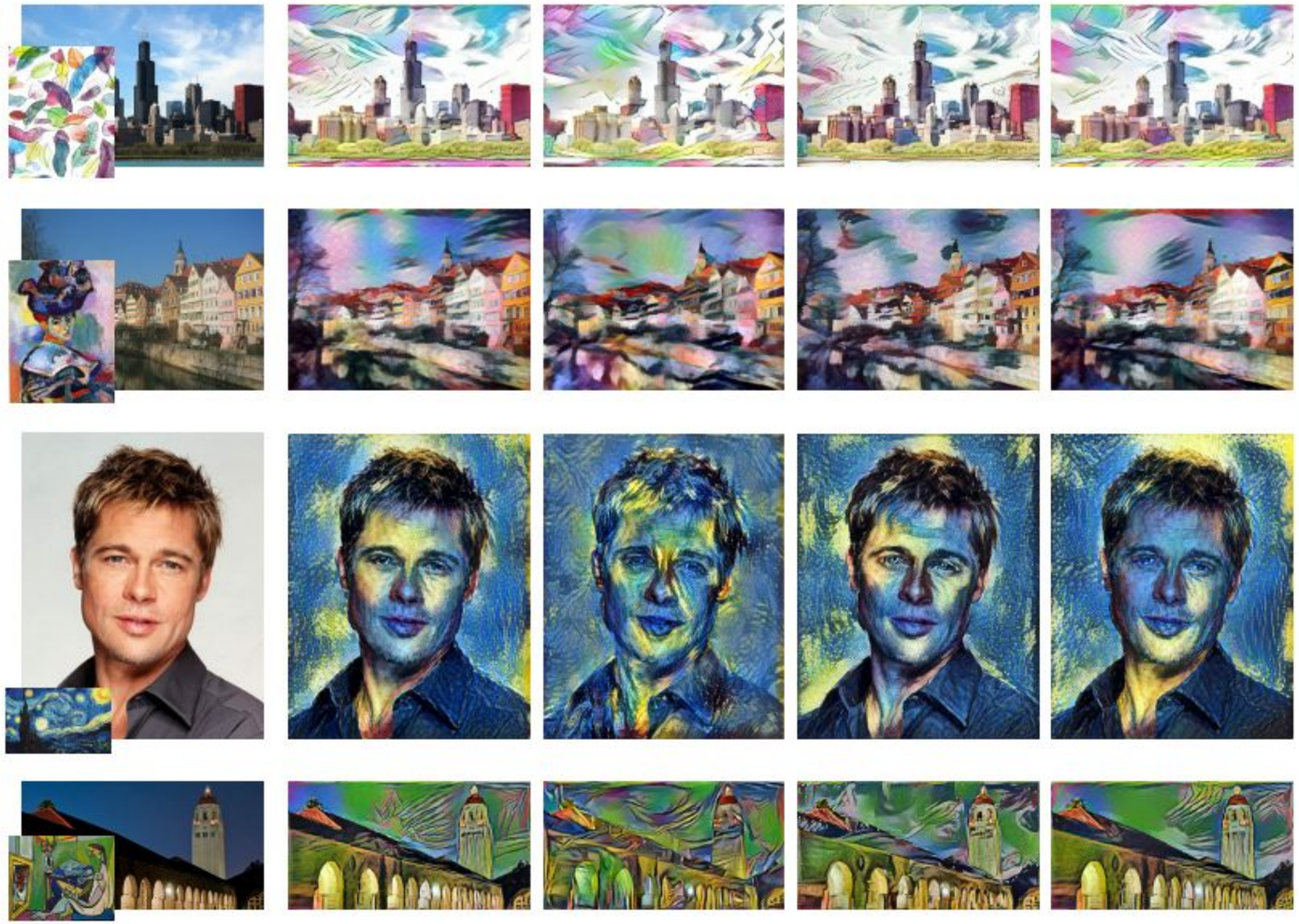


L. A Gatys et al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016

Matching other statistics

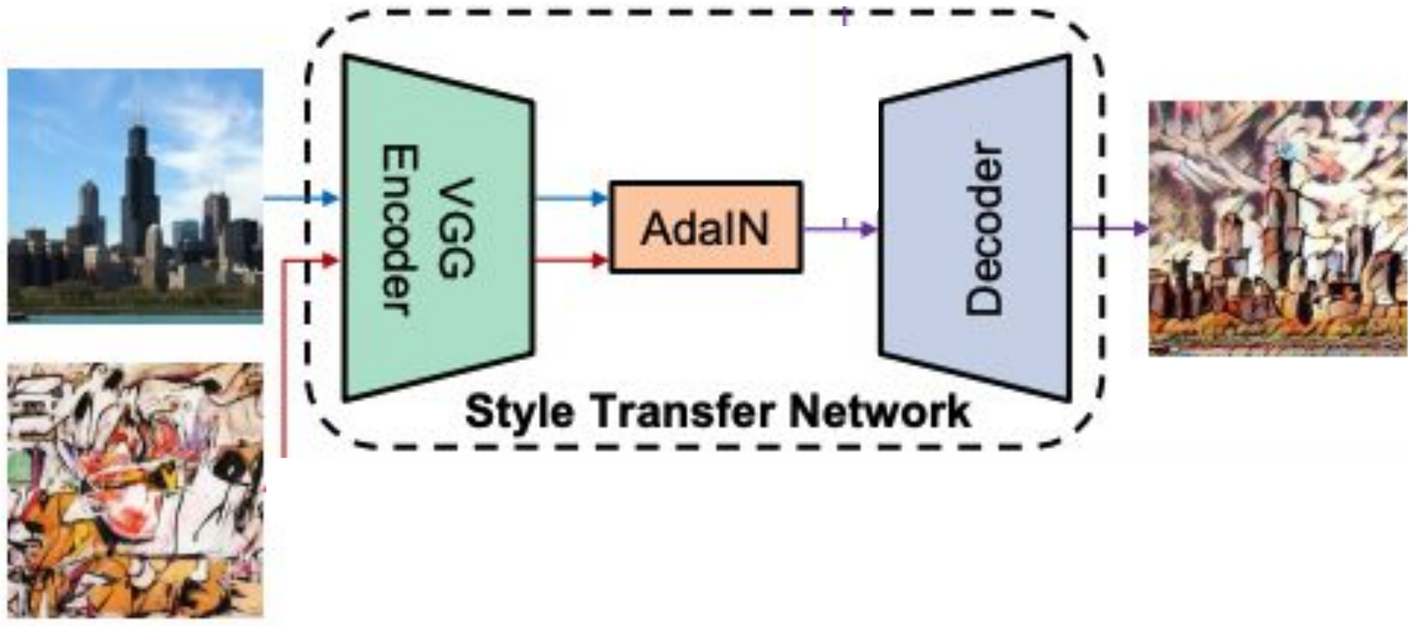
1. Style transfer as a distribution alignment

2. Matching other statistics, including channel-wise mean and variance



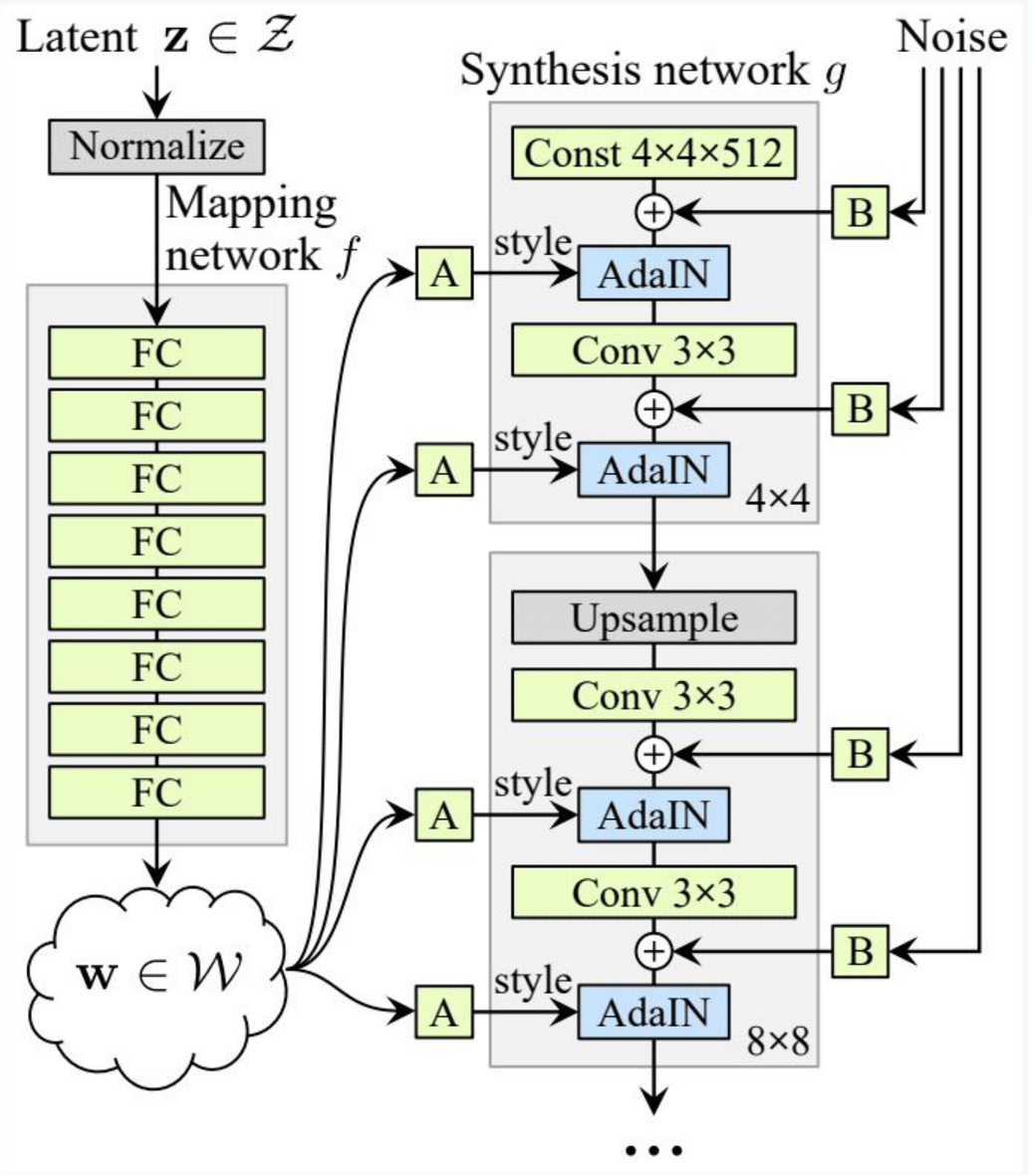
[Y. Li et al,. Demystifying neural style transfer. IJCAI 2017]

Introducing AdaIN Block



X. Huang, S. Belongie, Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization. ICCV 2017

StyleGAN



[Analyzing and Improving the Image Quality of StyleGAN]

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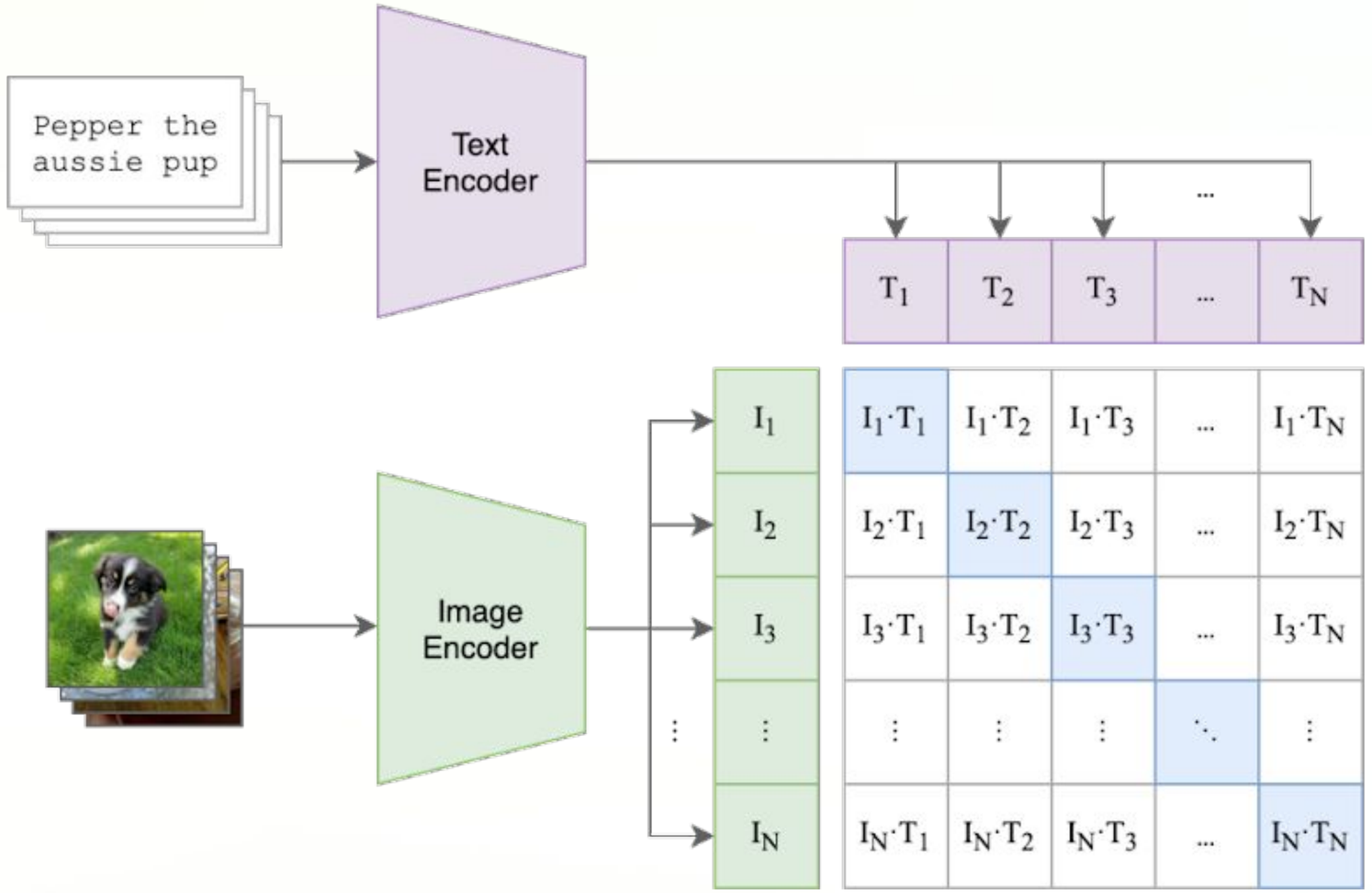
CLIP- Text and Image encoder

OpenAI, Jan 2021

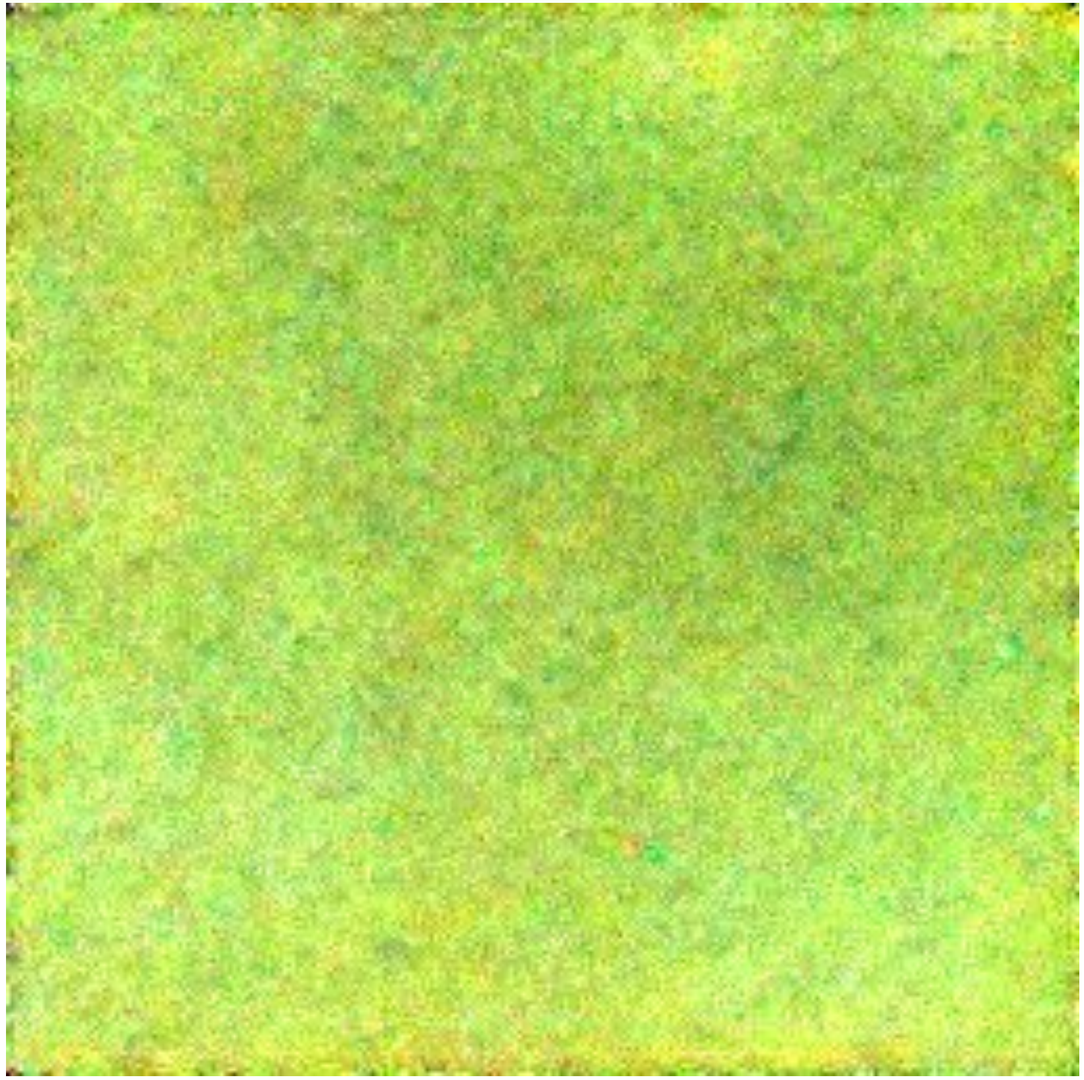


Diffusion models

Guided image generation

UC Berkeley, June 2020
OpenAI, June 2021
Google Brain, July 2021

- Model that learns to Iteratively de-noise until image is formed.
- A new form of image synthesis architectures.
- Can be conditioned on a class of images, text embedding, low-res image, etc.
- Slow to run and train, but inference becoming faster and faster these days.



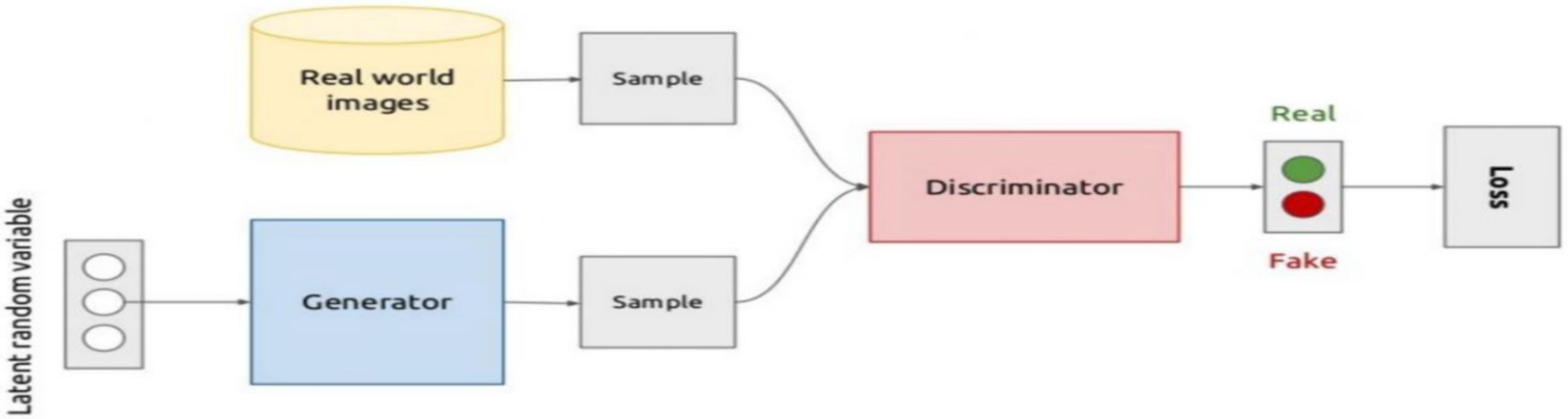
DiscoDiffusion v5, “Cheese and grapes next to a glass of wine”

Diffusion model

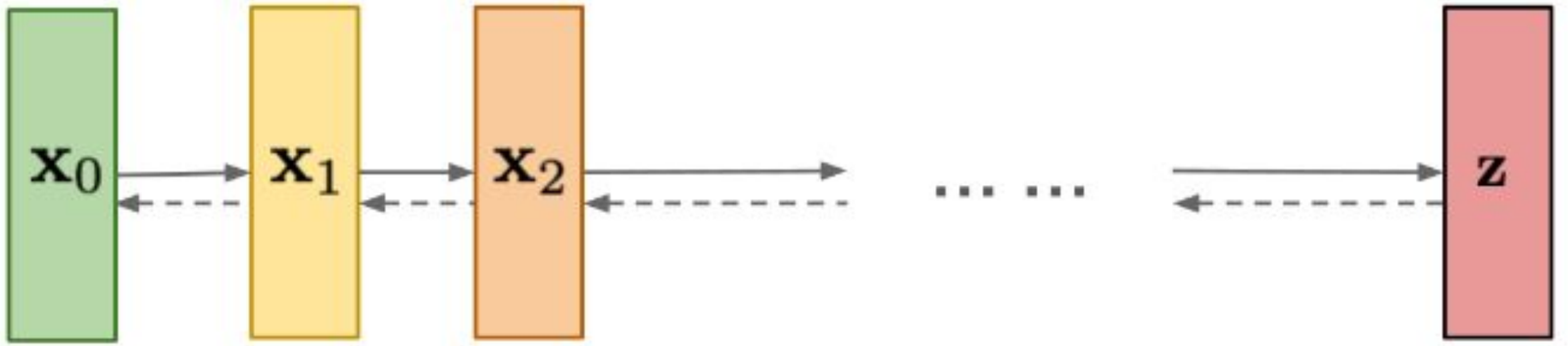
Input: random noise tensor (dimensions - 64x64x6)

Output: Image (dimensions 64x64x3)

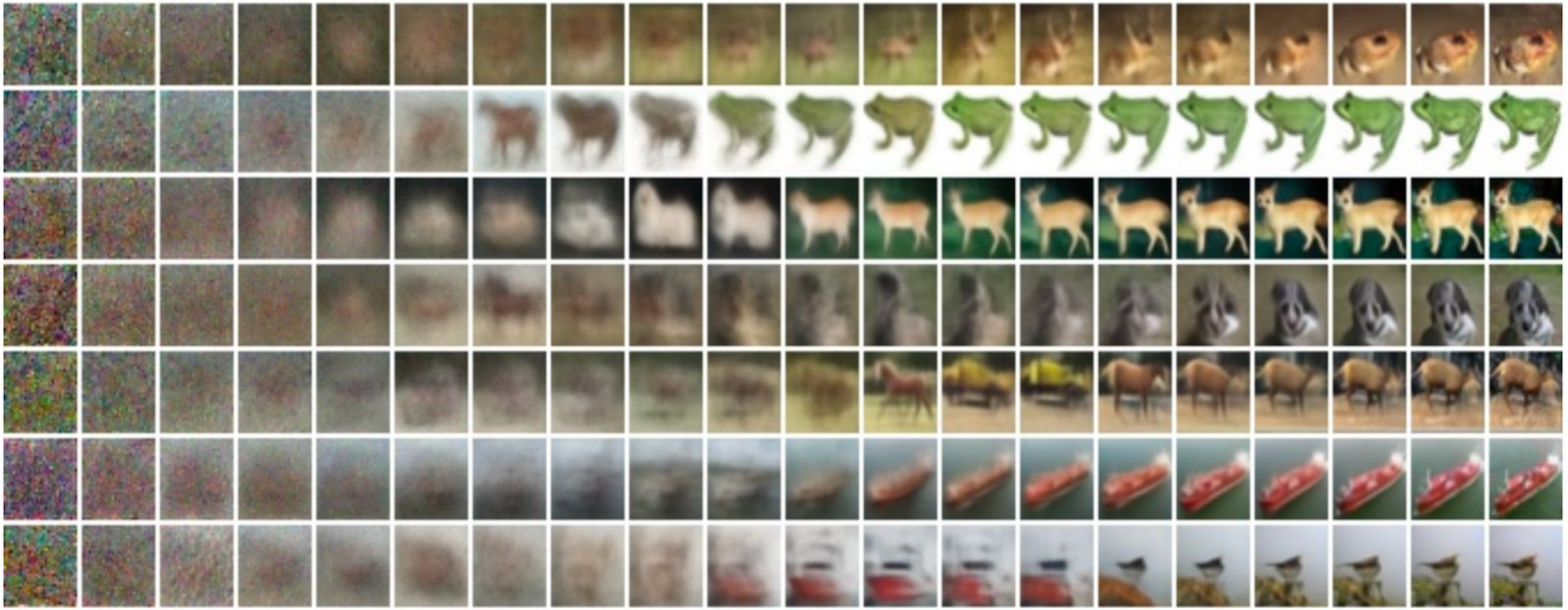
GAN: Adversarial training



Diffusion models: Gradually add Gaussian noise and then reverse



Diffusion models: from gaussian noise to images in small steps



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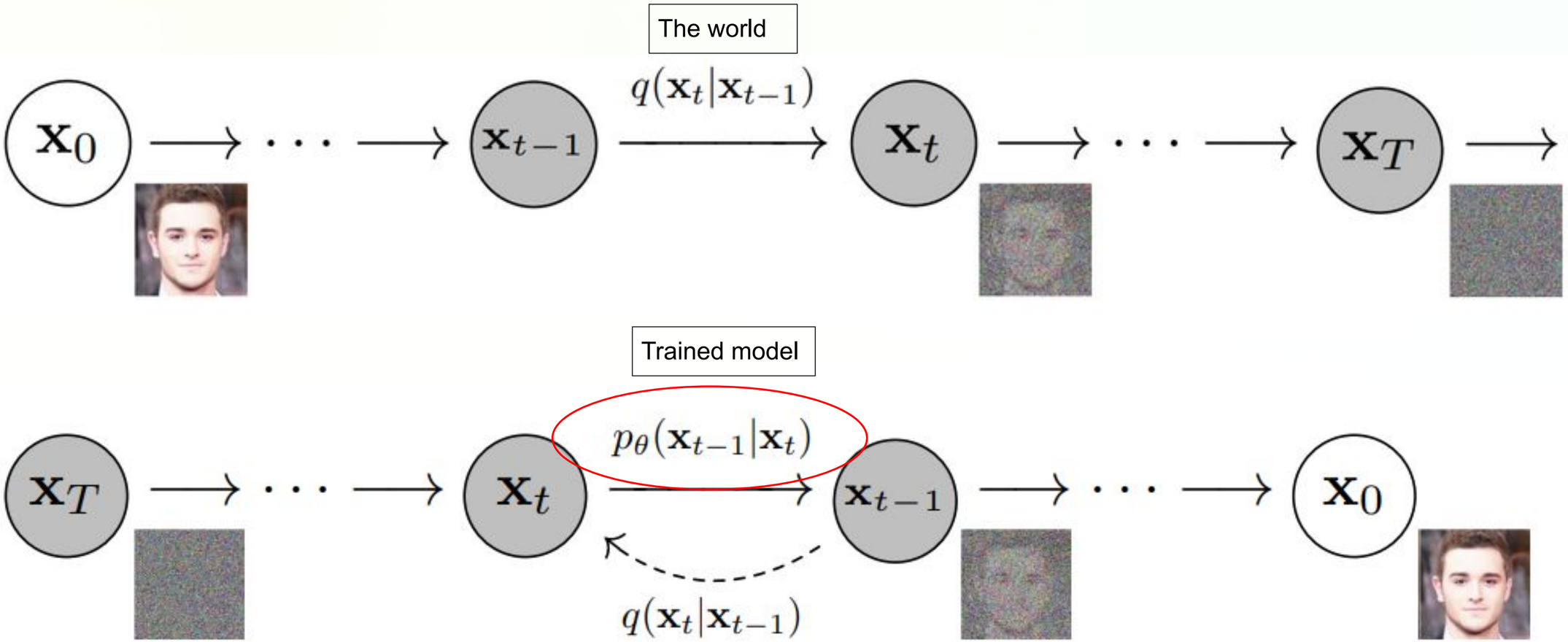
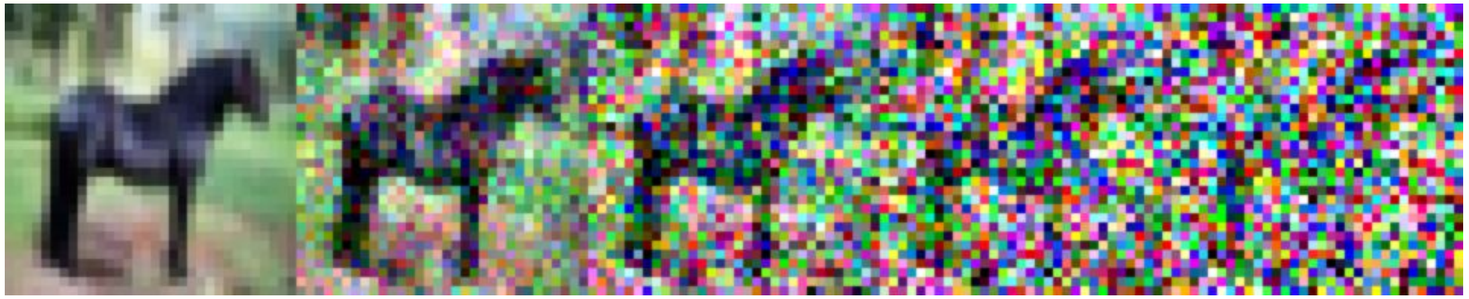

The world
$\mathbf{x}_0$
$\mathbf{x}_{t-1}$
$q(\mathbf{x}_t|\mathbf{x}_{t-1})$
$\mathbf{x}_t$
$\mathbf{x}_T$
Trained model
$\mathbf{x}_T$
$\mathbf{x}_t$
$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$
$\mathbf{x}_{t-1}$
$\mathbf{x}_0$
$q(\mathbf{x}_t|\mathbf{x}_{t-1})$

Creating noised images

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



sample an arbitrary step of the noised latents directly conditioned on the input x0

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I}) \text{ where } \bar{\alpha}_t = \prod_{i=1}^{T} \alpha_i \qquad \alpha_t := 1-\beta_t$$

$$x_t = \sqrt{\bar{\alpha}_t}x_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$$

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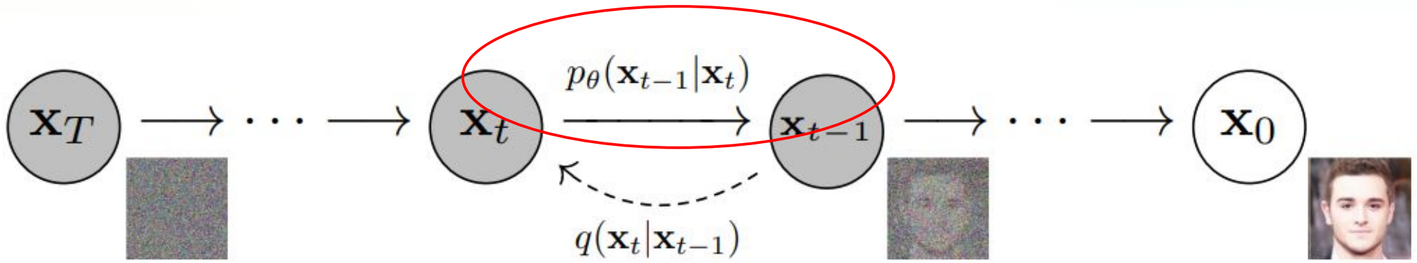
Training a diffusion model - The reverse step

Diffusion model can be trained to predict $\mathbf{x}_{t-1}$ given $\mathbf{x}_t$, t

But, In practice those models are trained to predict the added noise



$$x_t = \sqrt{\bar{\alpha}_t}x_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$$

Loss: L2($noise_\theta(\mathbf{x}_t), \epsilon$)

Iteration step: $\mathbf{x}_{t-1} = \sqrt{\bar{\alpha}_t}(\mathbf{x}_t - noise_\theta(\mathbf{x}_t)) + \sqrt{(1-\bar{\alpha}_t)}noise_\theta(\mathbf{x}_t)$

Dimensions:

$\bar{\alpha}_t$ - scalar

$\mathbf{x}_t$ Tensor 64x64x3

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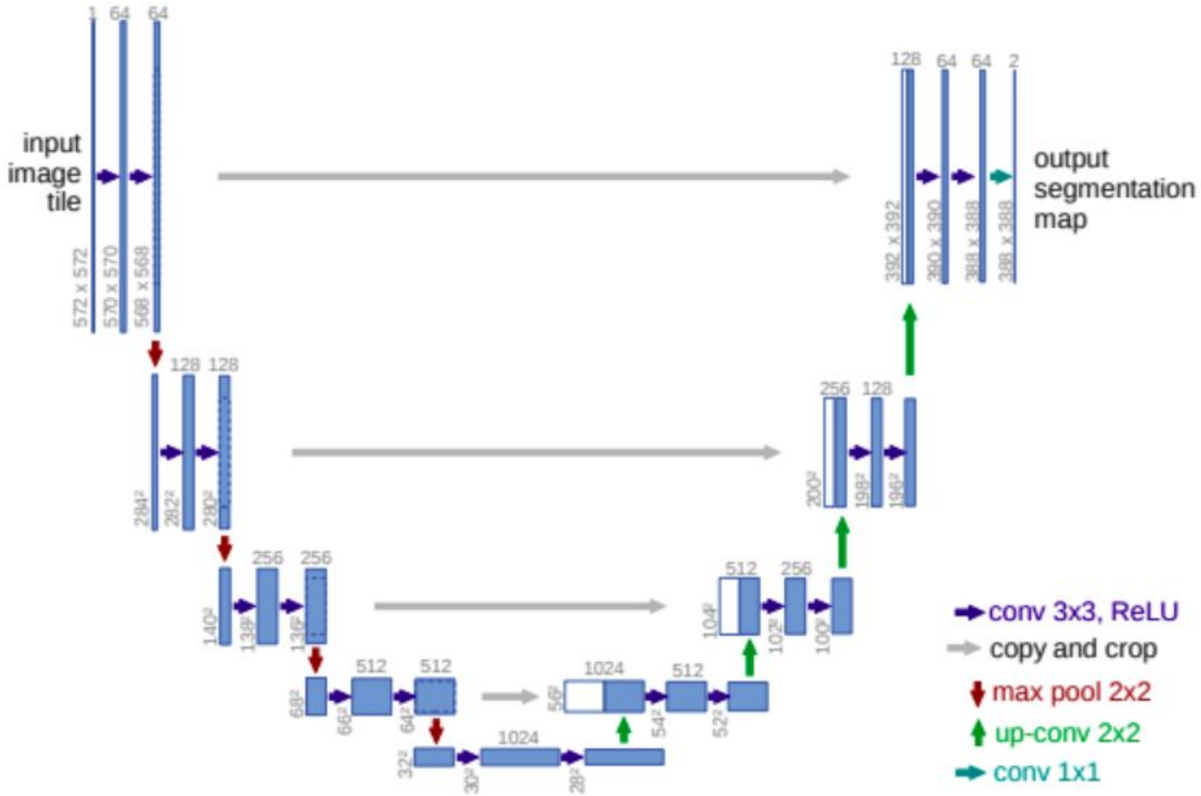
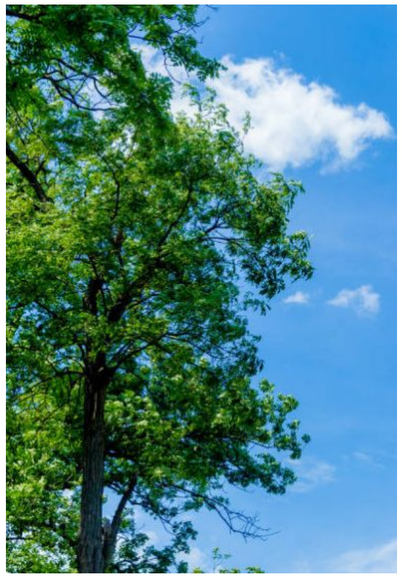
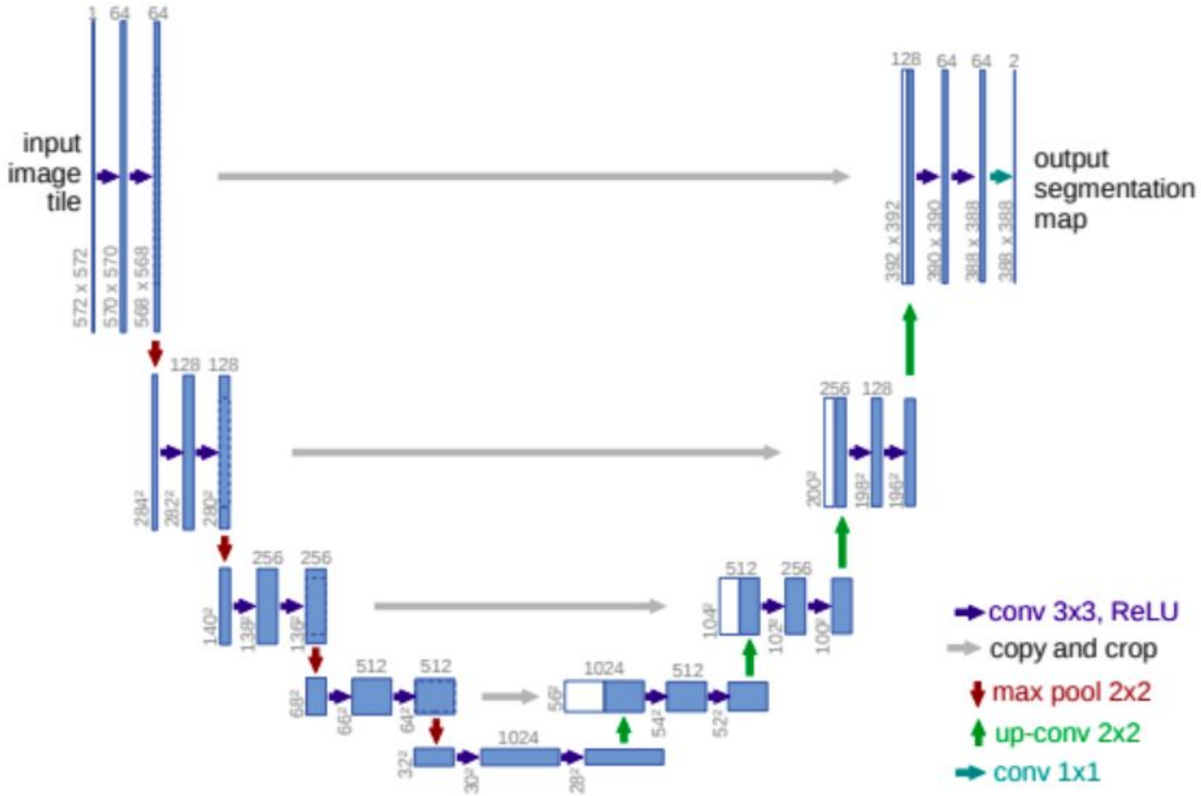
Unet Architecture



Unet 2015

Unet Architecture





Unet 2015

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Questions?

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Hands on session

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Hands on session (30 minutes)

Training a denoising model

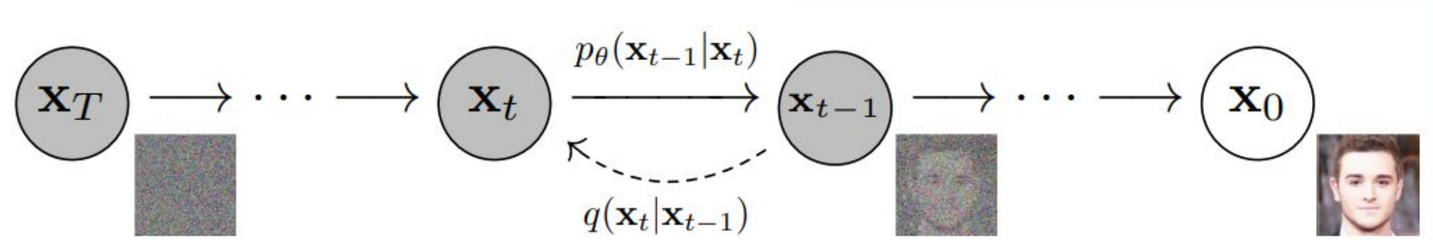
1. Go to
-https://github.com/Naomi-Ken-Korem/text-to-image-datatalks

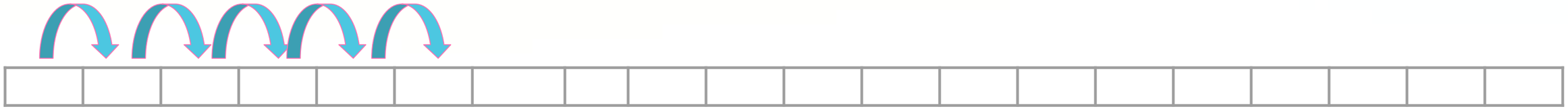
2. Open Diffusion models part 1.ipynb
(solution:
Diffusion models part 1_solution.ipynb)

3.Solve notebook till the training cell, and we will continue from there.

Inference

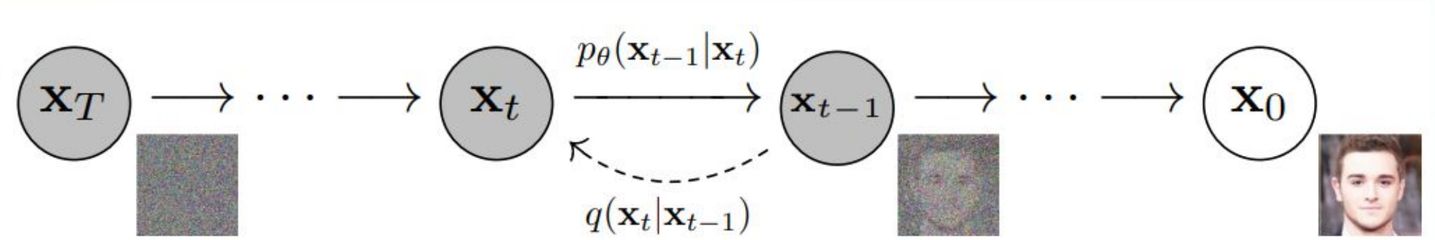
1000 steps??

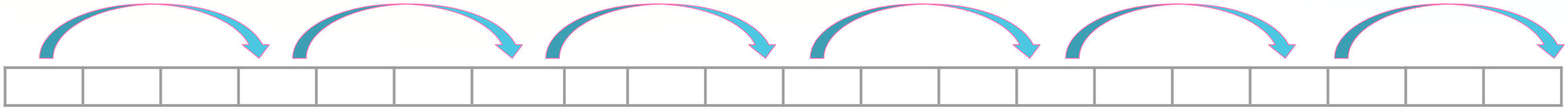




Inference

1000 steps??

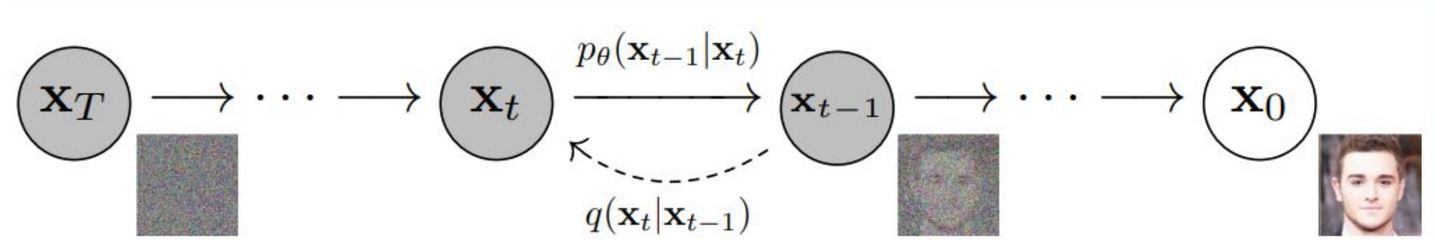


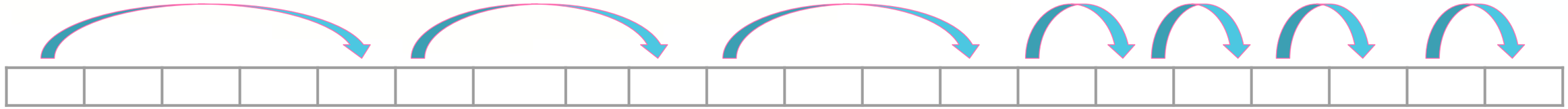


$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

Inference

1000 steps??





$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

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Part 2 - Text condition Diffusion models

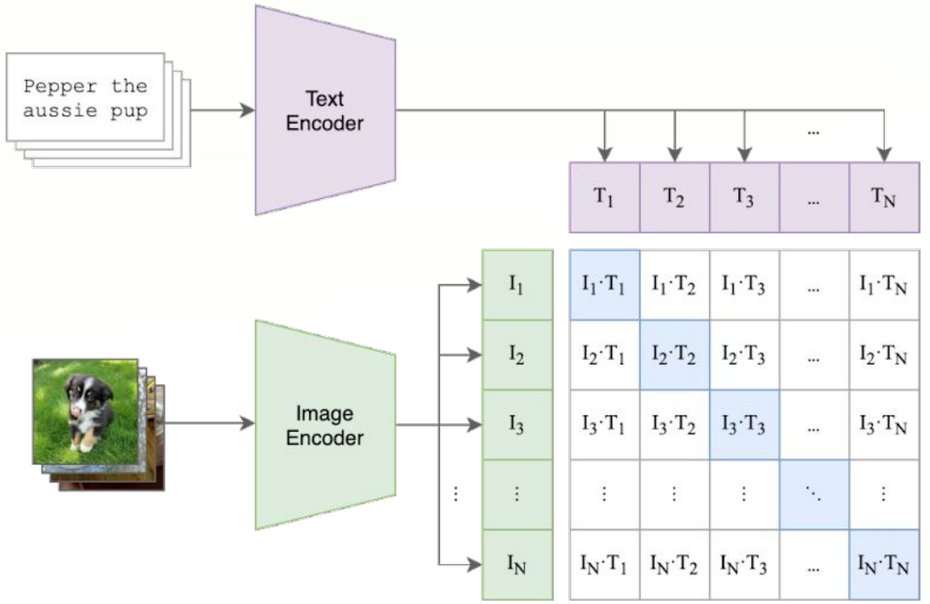
A dragon fruit wearing karate belt in the snow.

An art gallery displaying Monet paintings. The art gallery is flooded. Robots are going around the art gallery using paddle boards.

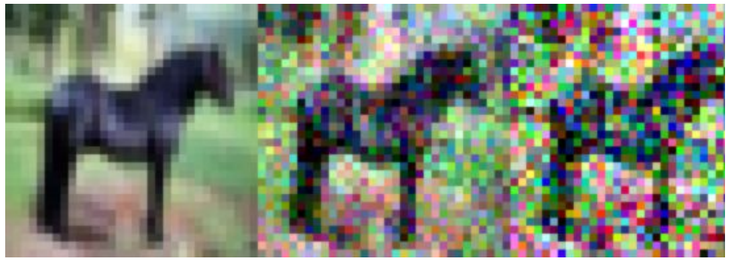
A marble statue of a Koala DJ in front of a marble statue of a turntable. The Koala is wearing large marble headphones.

Recap

StyleGAN



CLIP



Diffusion models

GLIDE

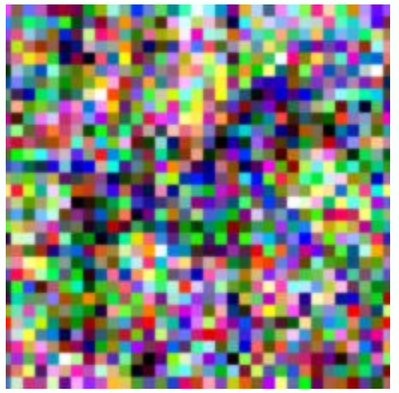
OpenAI, Dec 2021

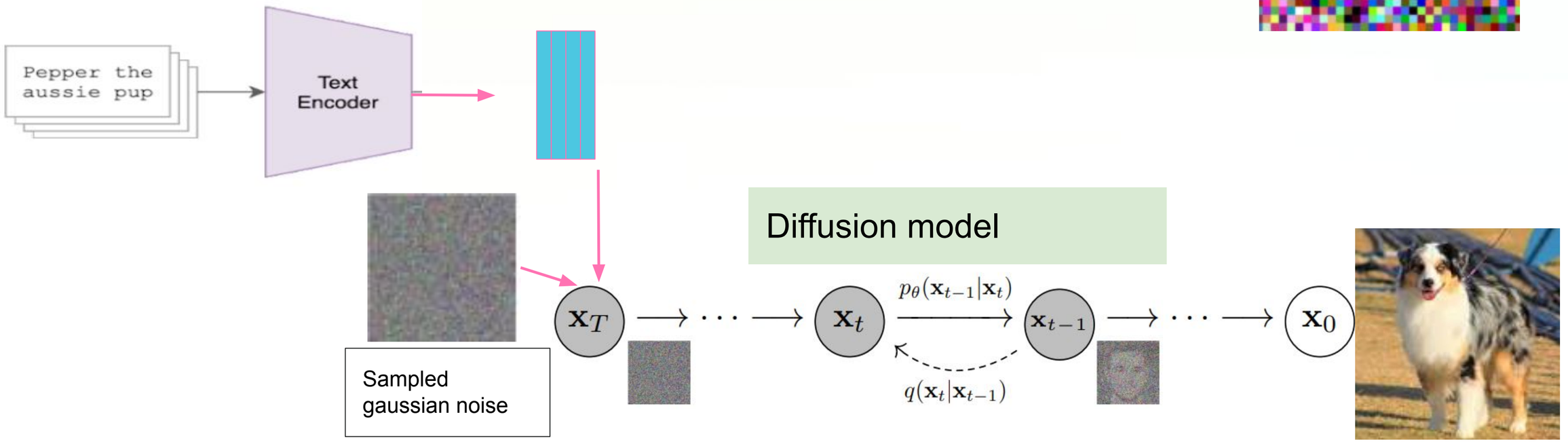
Given a text prompt + random noise image, generates a related image using a text transformer model based on the model of “Attention is all you need” (Bert) and a conditioned diffusion model.

“a boat in the canals of venice”

“a painting of a fox in the style of starry night”

Glide text 2 image architecture





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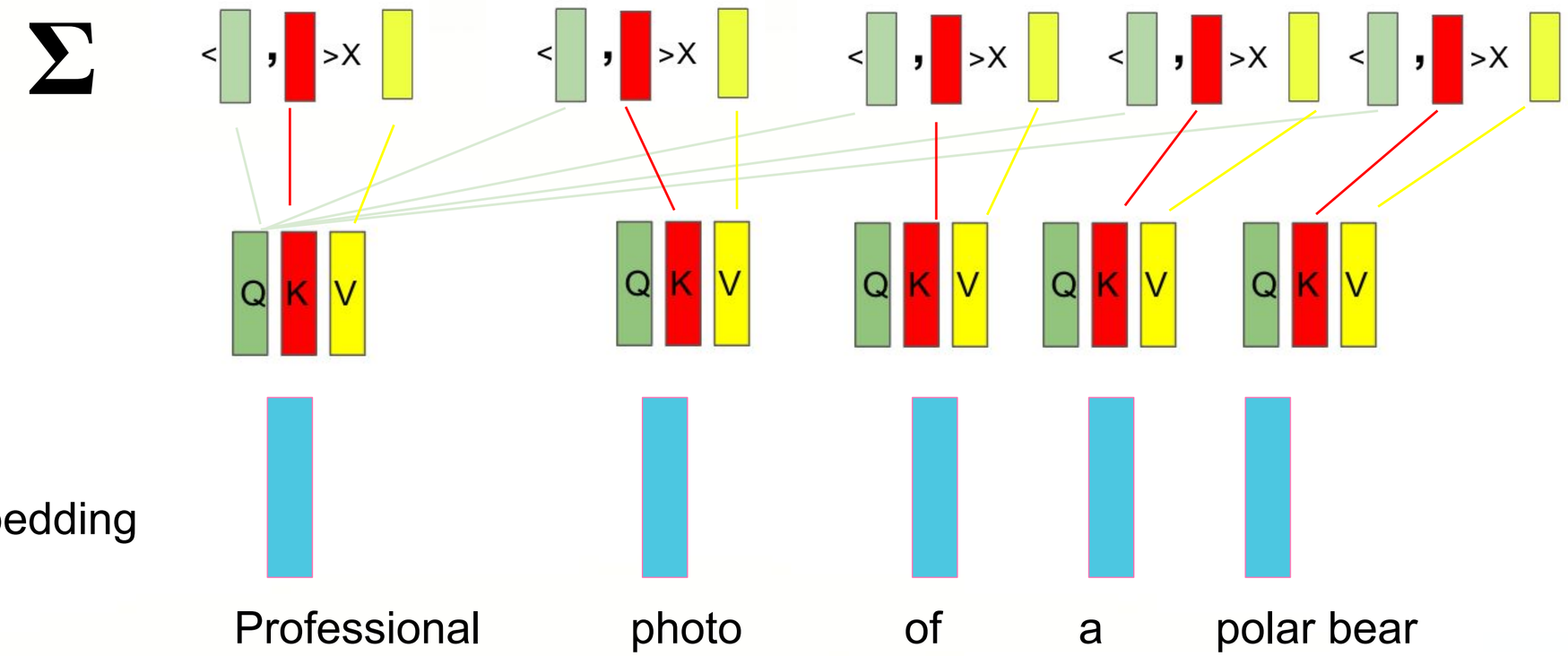
Transformers

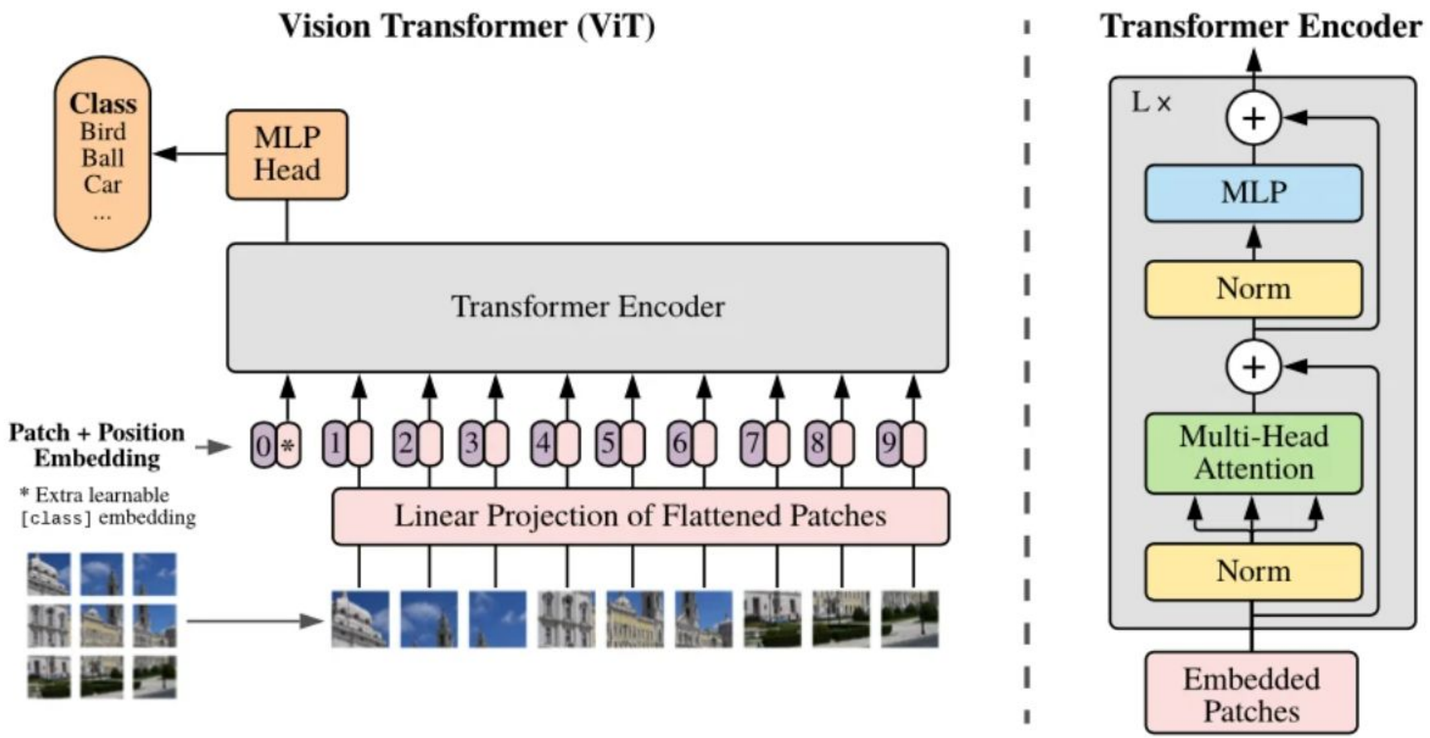
Google, Dec 2017

Attention Layer



[Attention is all you need]

Visual Transformers



[An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale]

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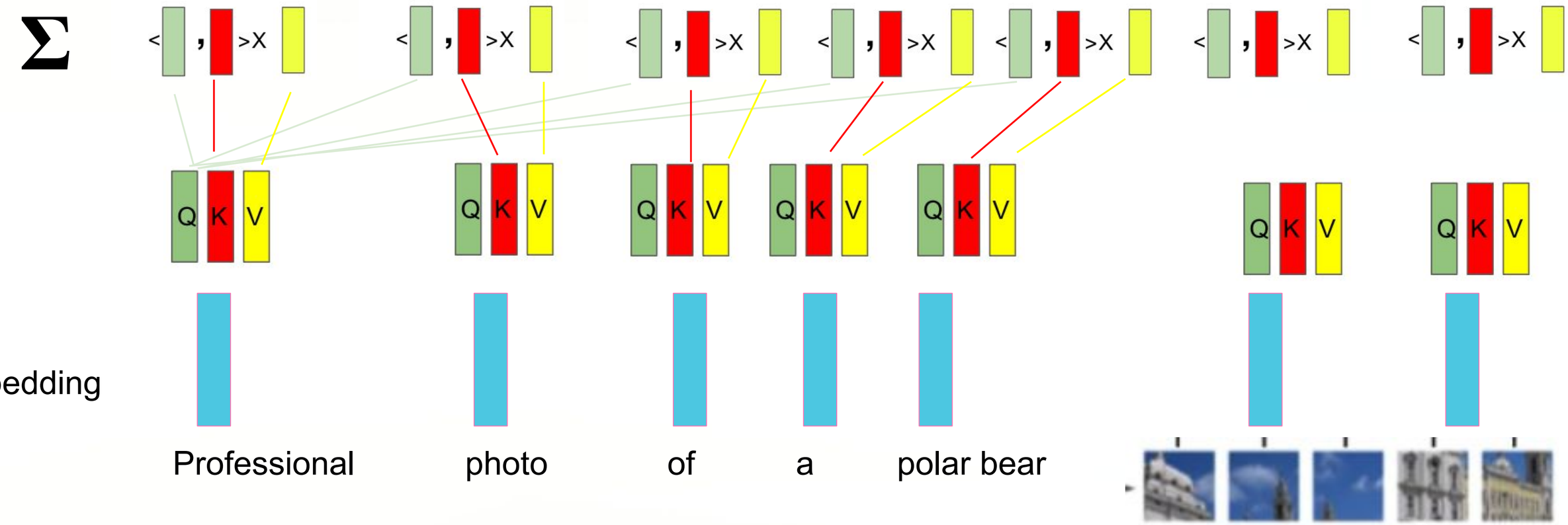
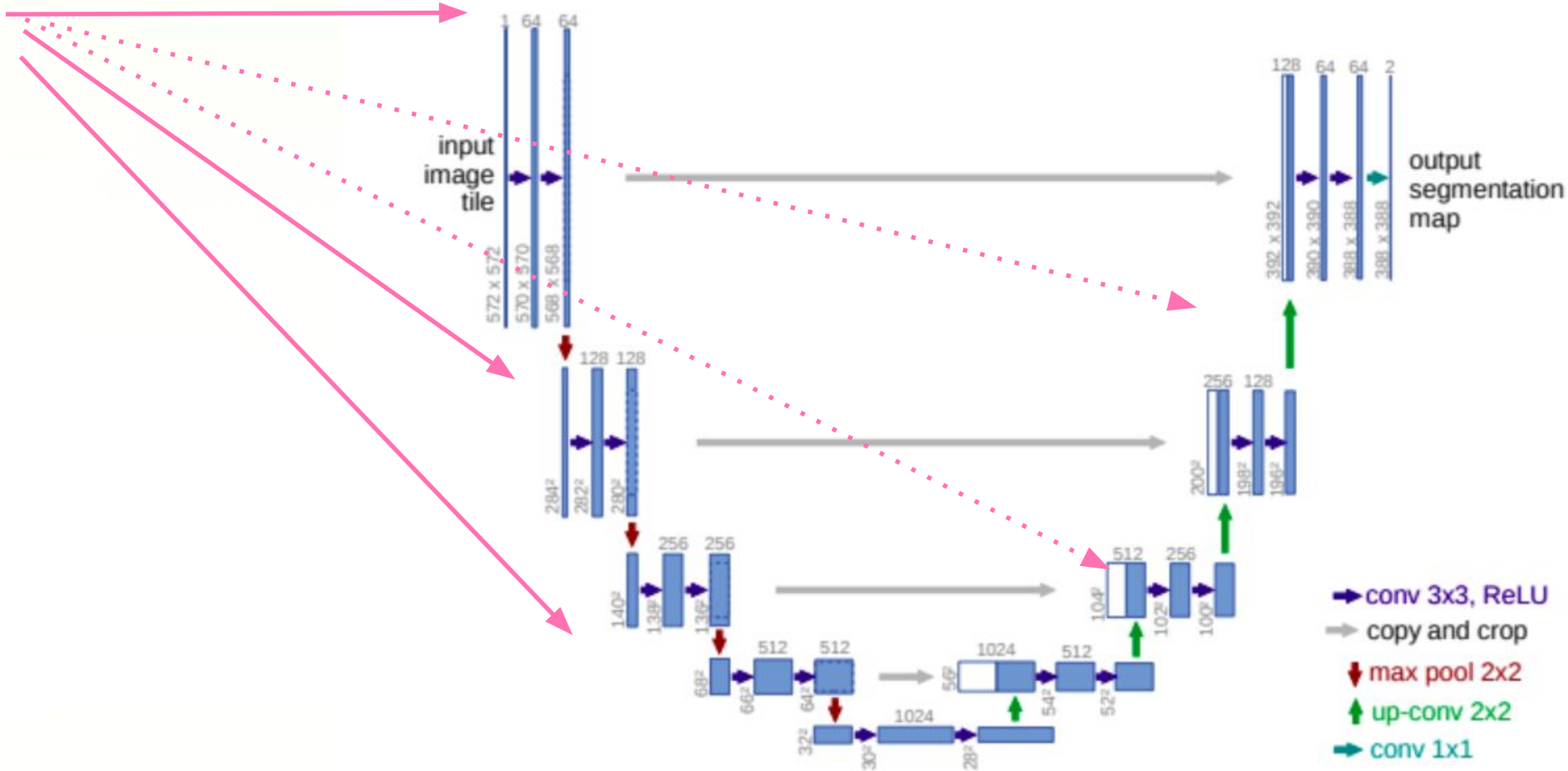
Cross Attention Layer



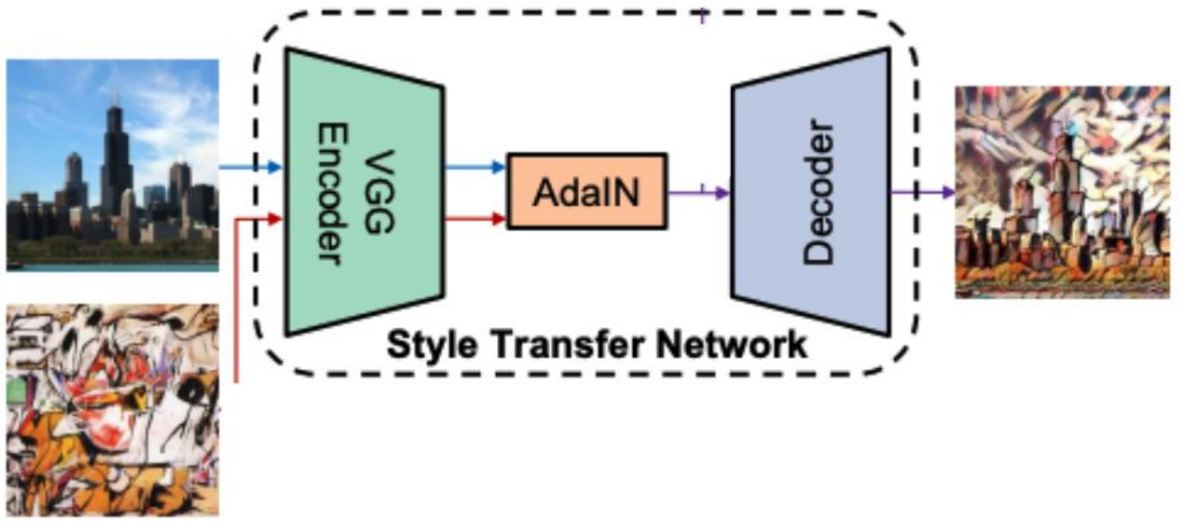
Adding textual input into the diffusion model

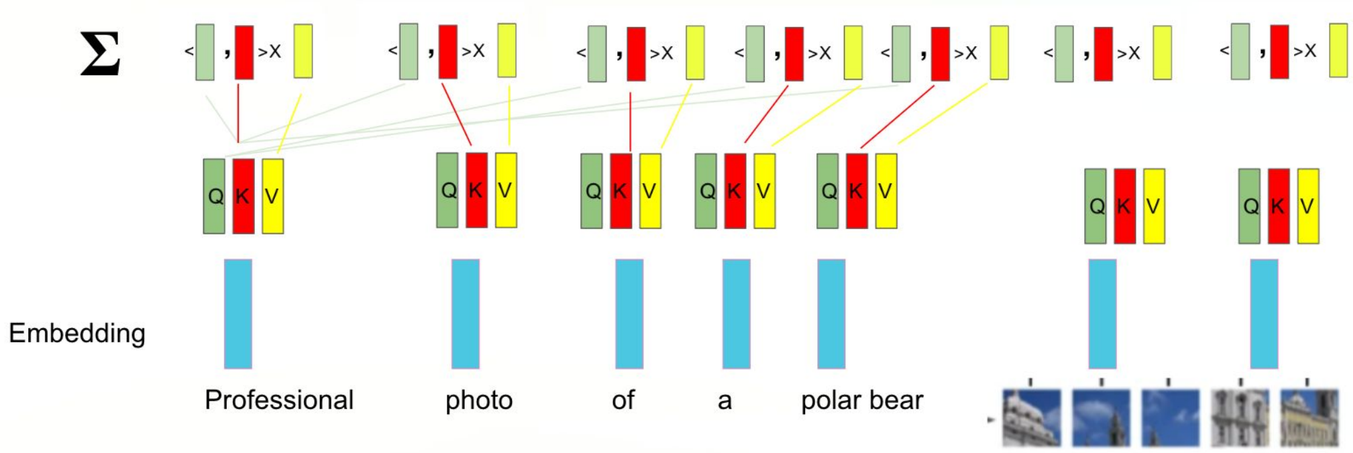


Lightricks

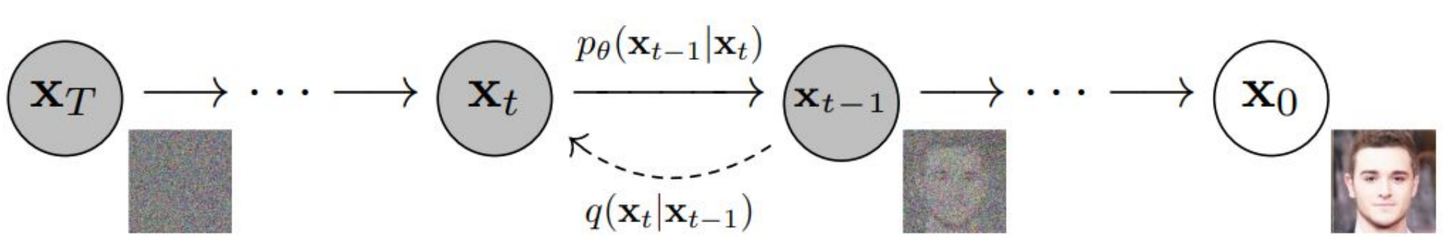
Multimodal layers

1. Style/Text injection via channel statistics
2. Style/Text injection via Cross attention





Class free guidance - extrapolation toward the textual concept



$$x = \mathbf{x}_{empty} + guidancescale * (\mathbf{x}_{prompt} - \mathbf{x}_{empty})$$

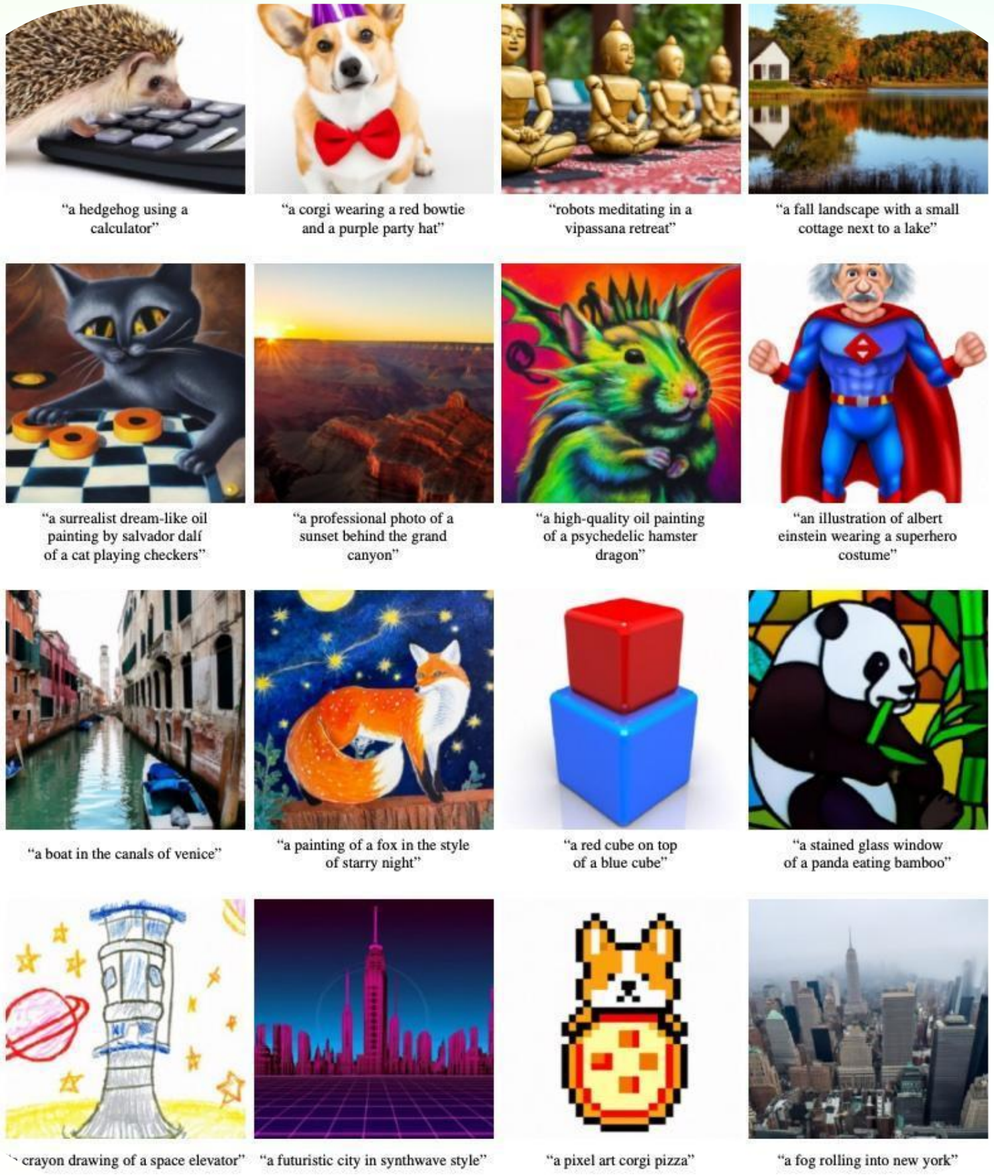
$$\mathbf{x}_{empty:t-1} = P(x_t, \text{""})$$

$$\mathbf{x}_{prompt:t-1} = P(x_t, \text{" prompt "})$$

Lightricks

Seminal publications

Now we can understand Imagen and Dalle-2



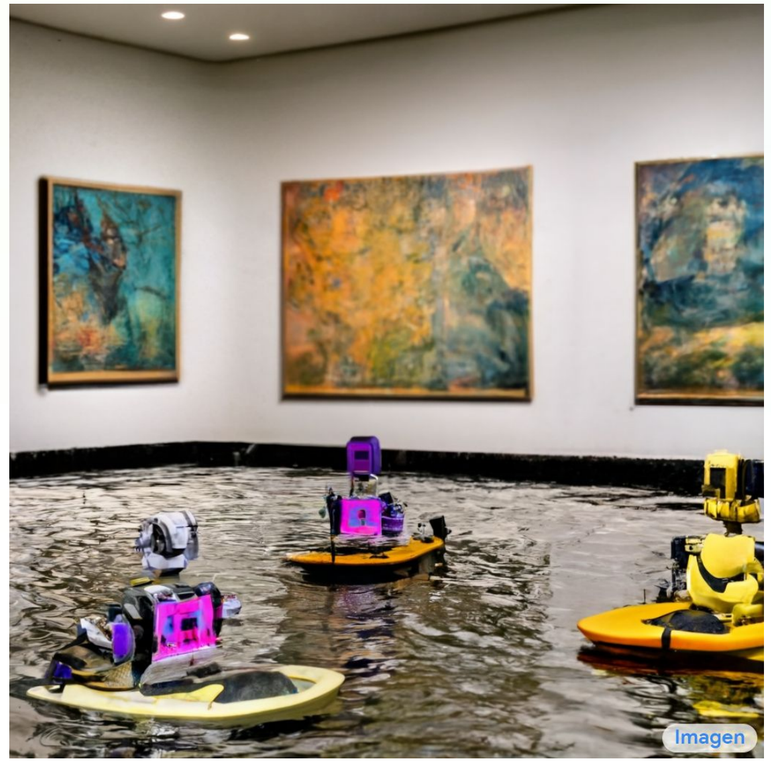
Imagen

Google Brain, May 2022

Huge text model (T5-XXL)

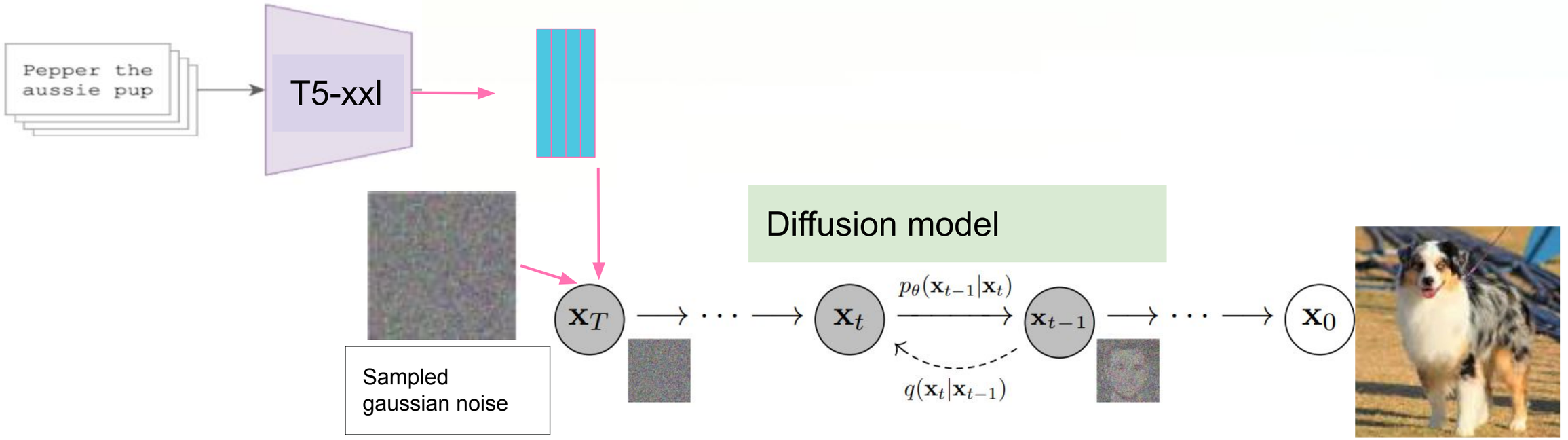
Given text embedding generates an image using a guided diffusion model.

Learn two 4x super-resolution steps (16x in total).



An art gallery displaying Monet paintings. The art gallery is flooded. Robots are going around the art gallery using paddle boards.

Imagen architecture



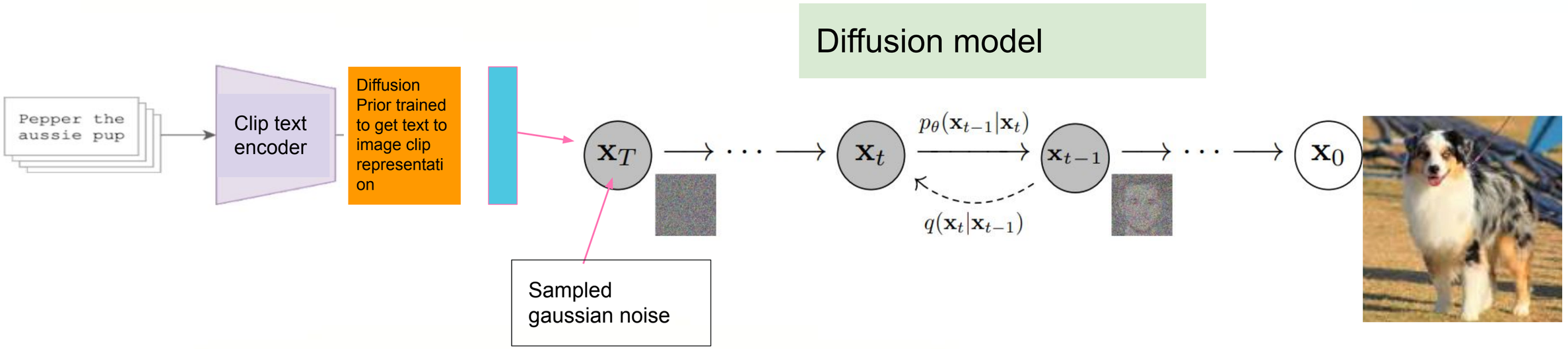
Lightricks

Imagen: Super Resolution models

Lightricks

Dalle-2
openAI april 2022

Unclip - from clip image vector back into image



...

Emad
@EMostaque

Delighted to announce the public open source release of #StableDiffusion!

Please see our release post and retweet!
stability.ai/blog/stable-di...

Proud of everyone involved in releasing this tech that is the first of a series of models to activate the creative potential of humanity

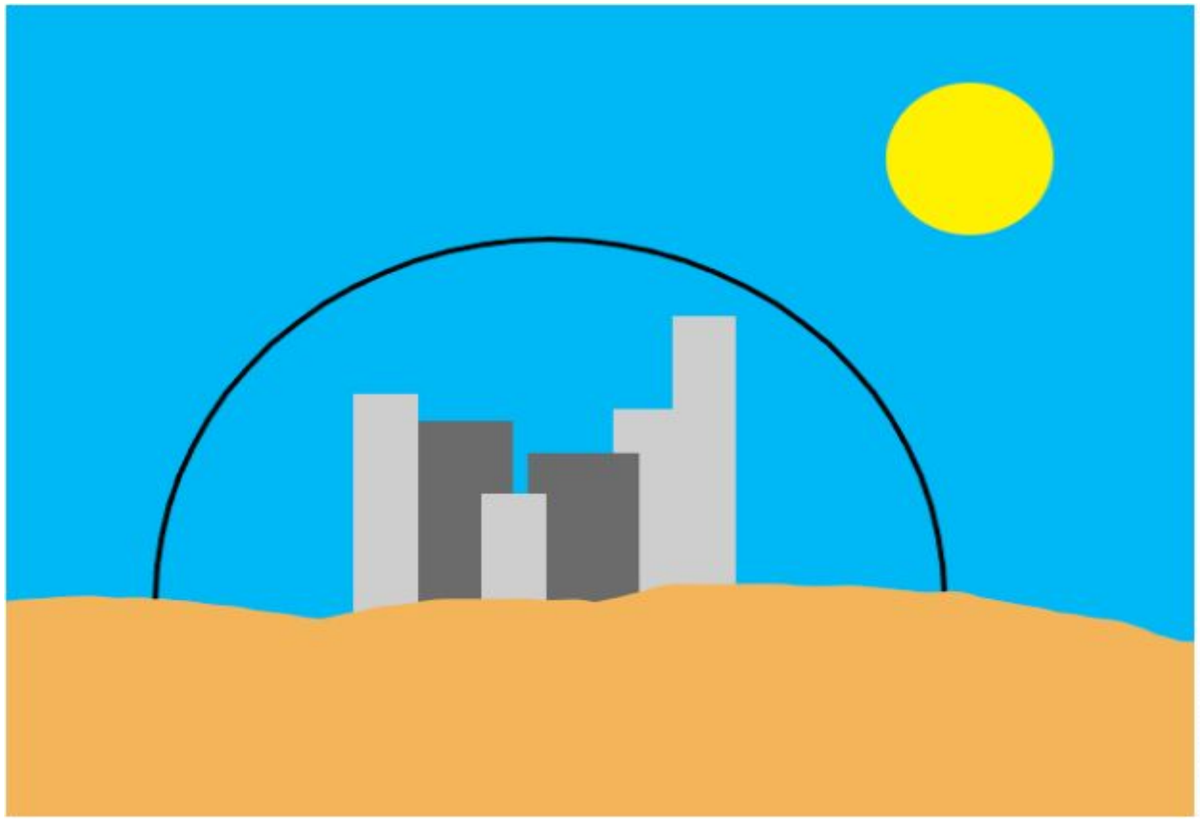
תרגם את הציוץ

stability.ai
Stable Diffusion Public Release — Stability.Ai
We are delighted to announce the public release of Stable Diffusion and the launch of DreamStudio Lite.

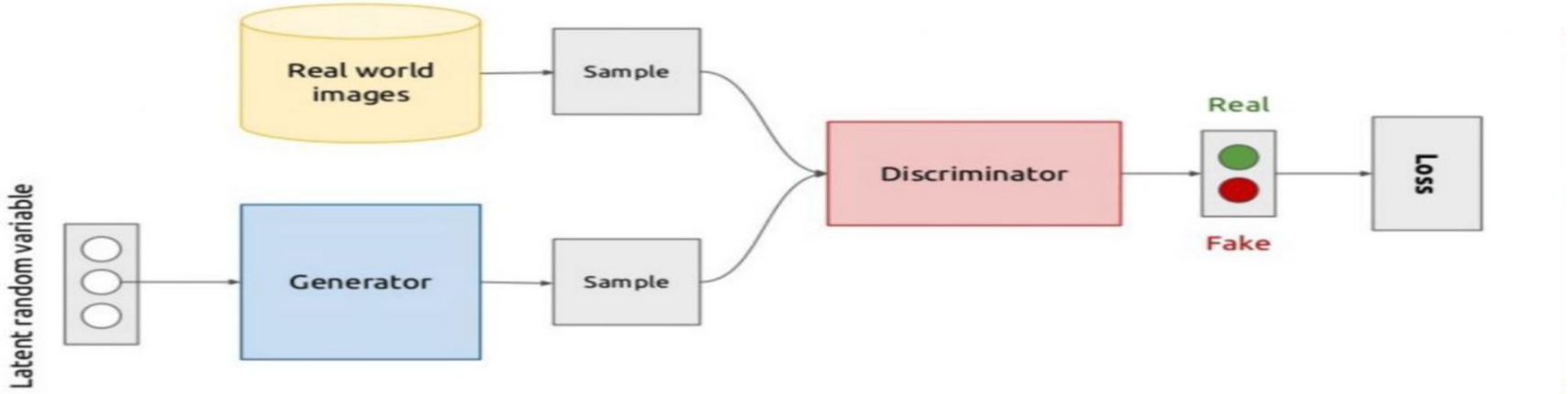
9:07 אחה"צ · 22 באוג' 2022 · Twitter Web App

Lightricks

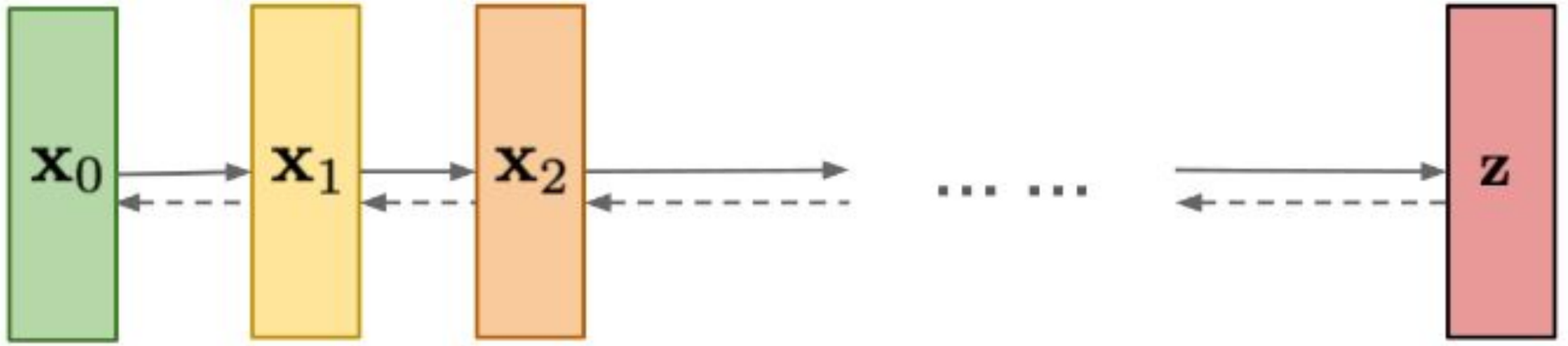
Stable Diffusion (Image to Image pipe)



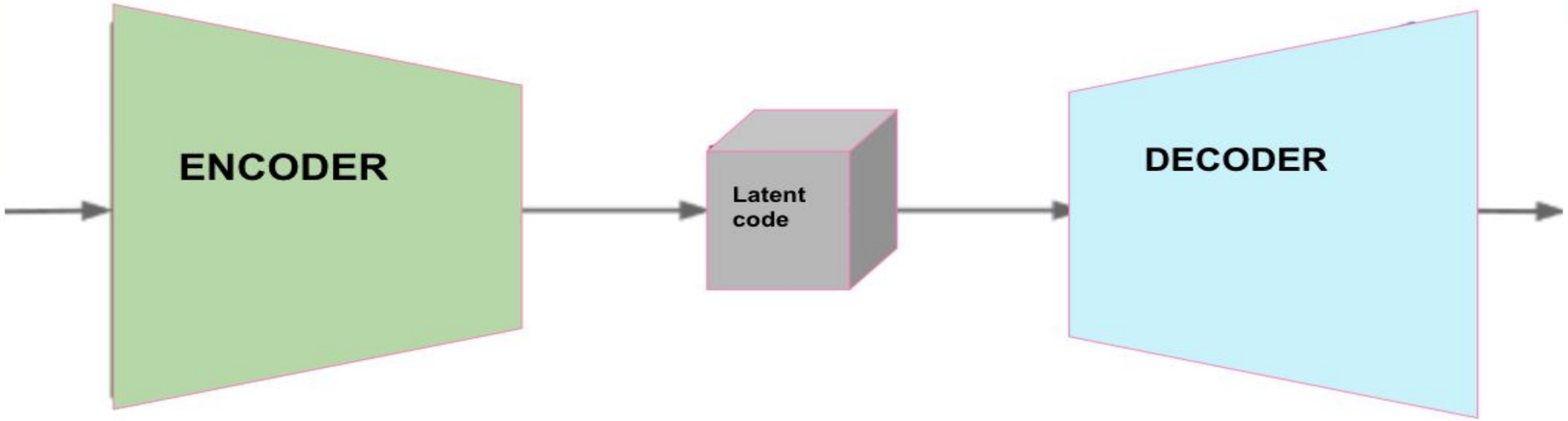
GAN: Adversarial training



Diffusion models: Gradually add Gaussian noise and then reverse

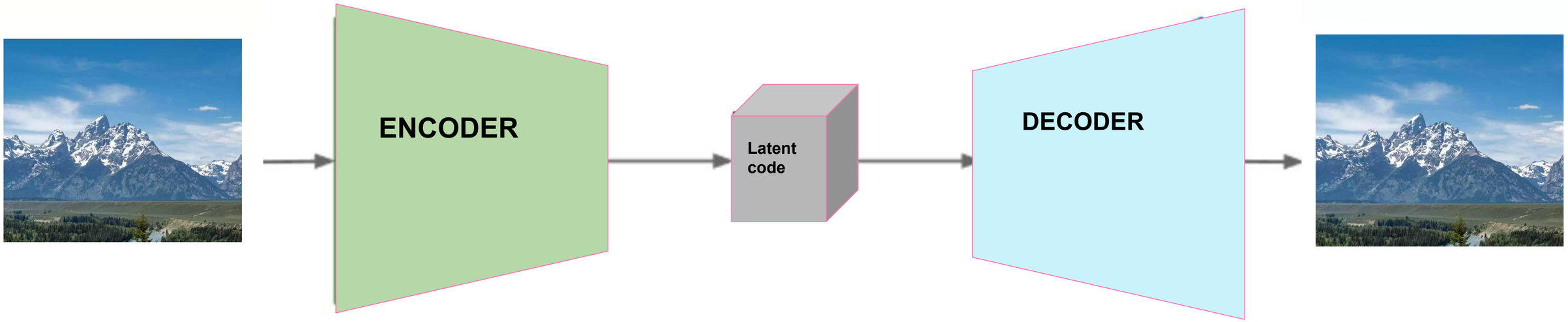


Variational Autoencoder:



Lightricks

AutoEncoder



Lightricks

Variational AutoEncoder

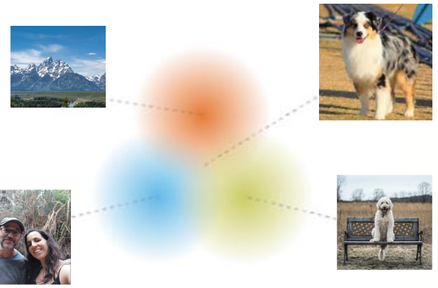
ENCODER

Latent code

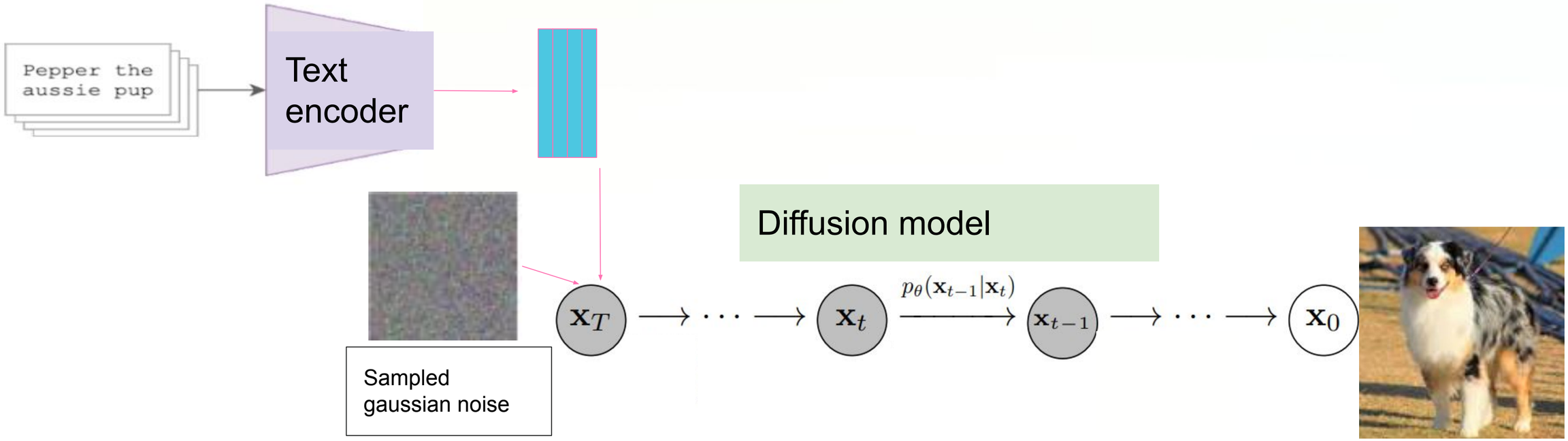
DECODER

VAR

MEAN

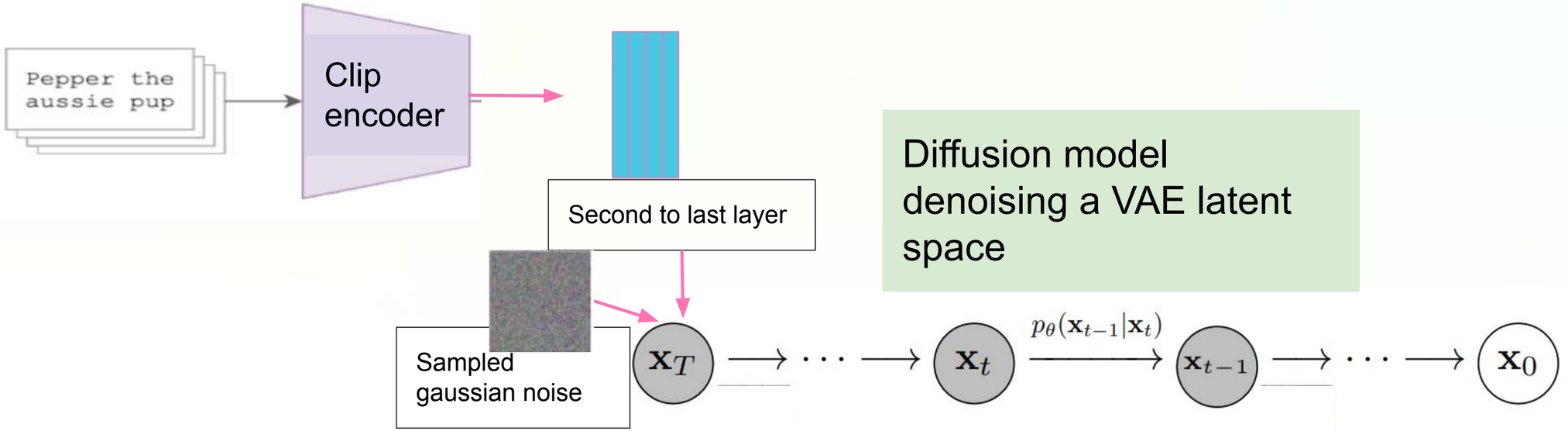


Original Text to Image pipe



Lightricks

Stable Diffusion Text to Image pipe



Diffusion model denoising a VAE latent space

VAE Decoder

[High-Resolution Image Synthesis with Latent Diffusion Models]

Lightricks

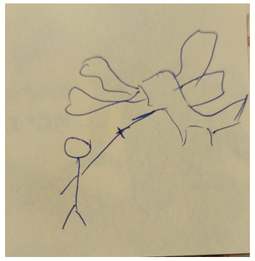
Editing pipelines

Lightricks

Stable Diffusion Image to Image pipe

A hero fighting a fire-breathing dragon

Clip encoder

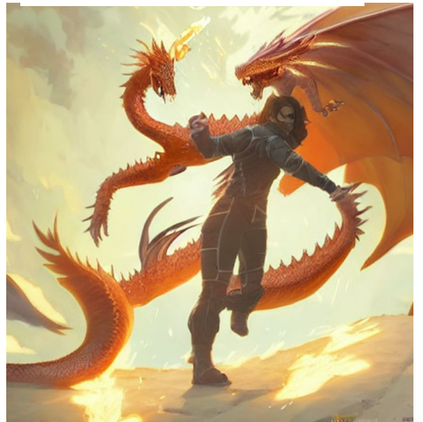


Encoder $q_\phi(\mathbf{z}|\mathbf{x})$

Diffusion model denoising a VAE latent space

$\mathbf{x}_T \longrightarrow \cdots \longrightarrow \mathbf{x}_t \xrightarrow{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} \mathbf{x}_{t-1} \longrightarrow \cdots \longrightarrow \mathbf{x}_0$

VAE Decoder



[High-Resolution Image Synthesis with Latent Diffusion Models]

Lightricks

Stable Diffusion Inpainting pipe (legacy)

A magic castle on the mountains

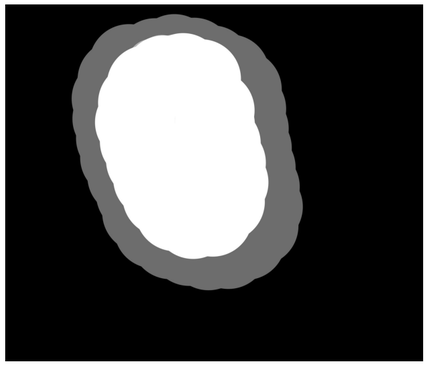
Clip encoder

Encoder $q_\phi(\mathbf{z}|\mathbf{x})$

Diffusion model denoising a VAE latent space

$\mathbf{x}_T \longrightarrow \cdots \longrightarrow \mathbf{x}_t \xrightarrow{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} \mathbf{x}_{t-1} \longrightarrow \cdots \longrightarrow \mathbf{x}_0$

VAE Decoder



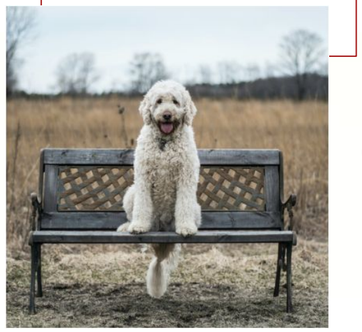
[High-Resolution Image Synthesis with Latent Diffusion Models]

Lightricks

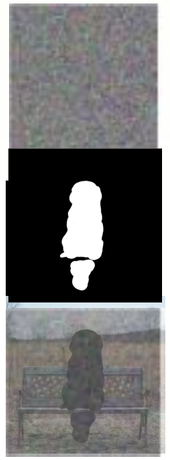
Stable Diffusion Inpainting pipe

Face of a yellow cat, high resolution, sitting on a park bench

Clip encoder



Encoder $q_\phi(\mathbf{z}|\mathbf{x})$



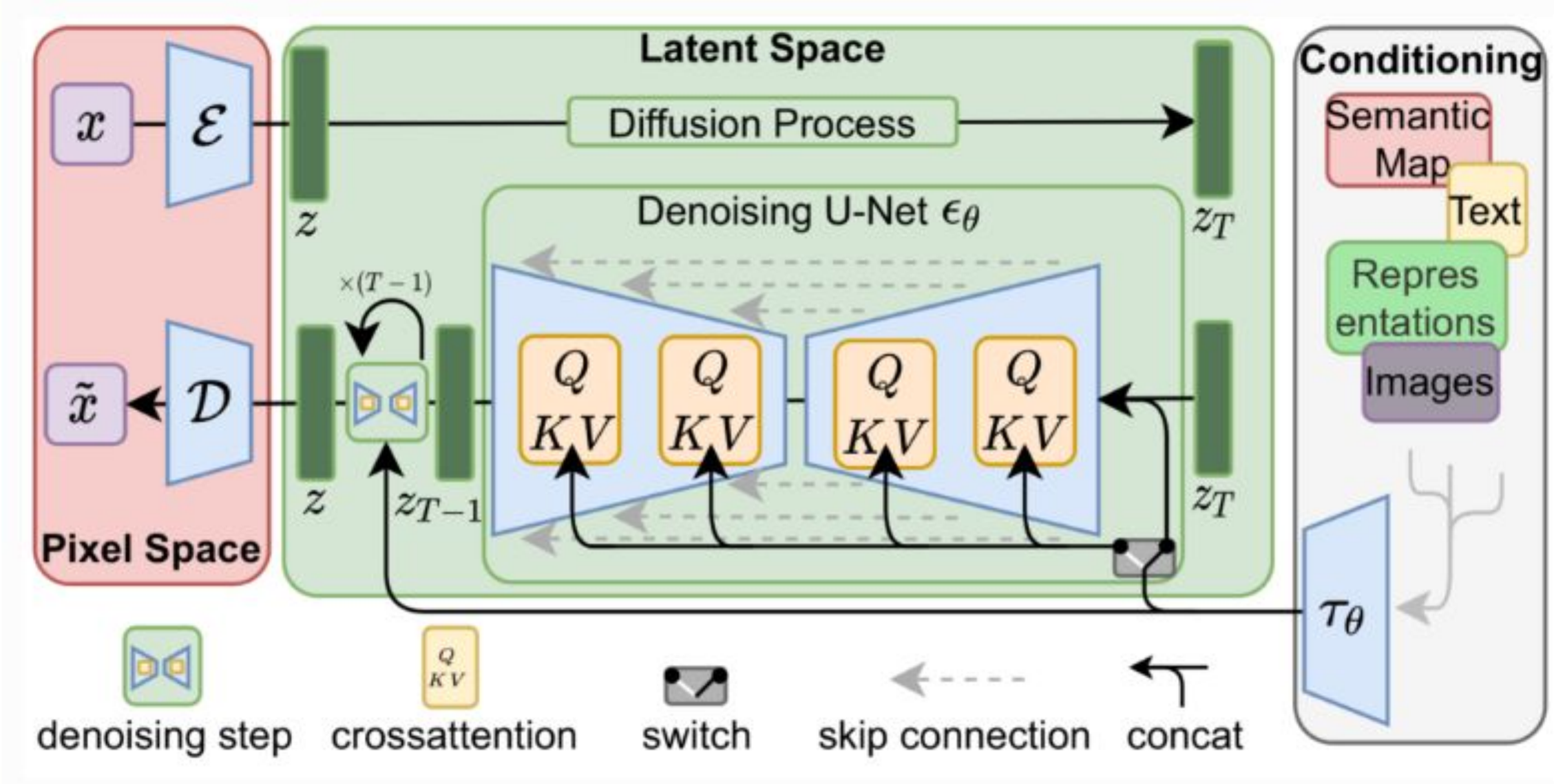
Inpainting finetuned diffusion model denoising a VAE latent space

$$\mathbf{x}_T \longrightarrow \cdots \longrightarrow \mathbf{x}_t \xrightarrow{p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)} \mathbf{x}_{t-1} \longrightarrow \cdots \longrightarrow \mathbf{x}_0$$

VAE Decoder

Lightricks

Inpainting


Latent Space
Diffusion Process
Denoising U-Net ϵ_θ
$\times(T-1)$
x
$\mathcal{E}$
z
z_T
$\tilde{x}$
$\mathcal{D}$
z_{T-1}
Q
K V
Pixel Space
Conditioning
Semantic Map
Text
Repres entations
Images
τ_θ
denoising step
crossattention
switch
skip connection
concat

Useful gits to follow

https://github.com/huggingface/diffusers

https://github.com/AUTOMATIC1111/stable-diffusion-webui

Good image 2 image example:

https://colab.research.google.com/github/patil-suraj/Notebooks/blob/master/image_2_image_using_diffusers.ipynb

Lightricks

Questions?

Hands on workshop

1. Go to : https://github.com/Naomi-Ken-Korem/text-to-image-datatalks

2. Optional: Class free guidance trick- Glide_text2image.ipynb

3. Stable diffusion editing pipelines
   Stable_diffusion_editing_pipes.ipynb
   OR stable_diffusion_pipes_full_version.ipynb

Takeaway

1. Multimodel domain inherits ideas from computer vision, and nlp.

2. We covered a lot of architectures, and technical ideas. Combining those existing ideas leads to great progress

3. When you read papers and tweets on the topic try to look for the building blocks that we mentioned today

Lightricks

Thank you!