A survey of recent advances in image synthesis

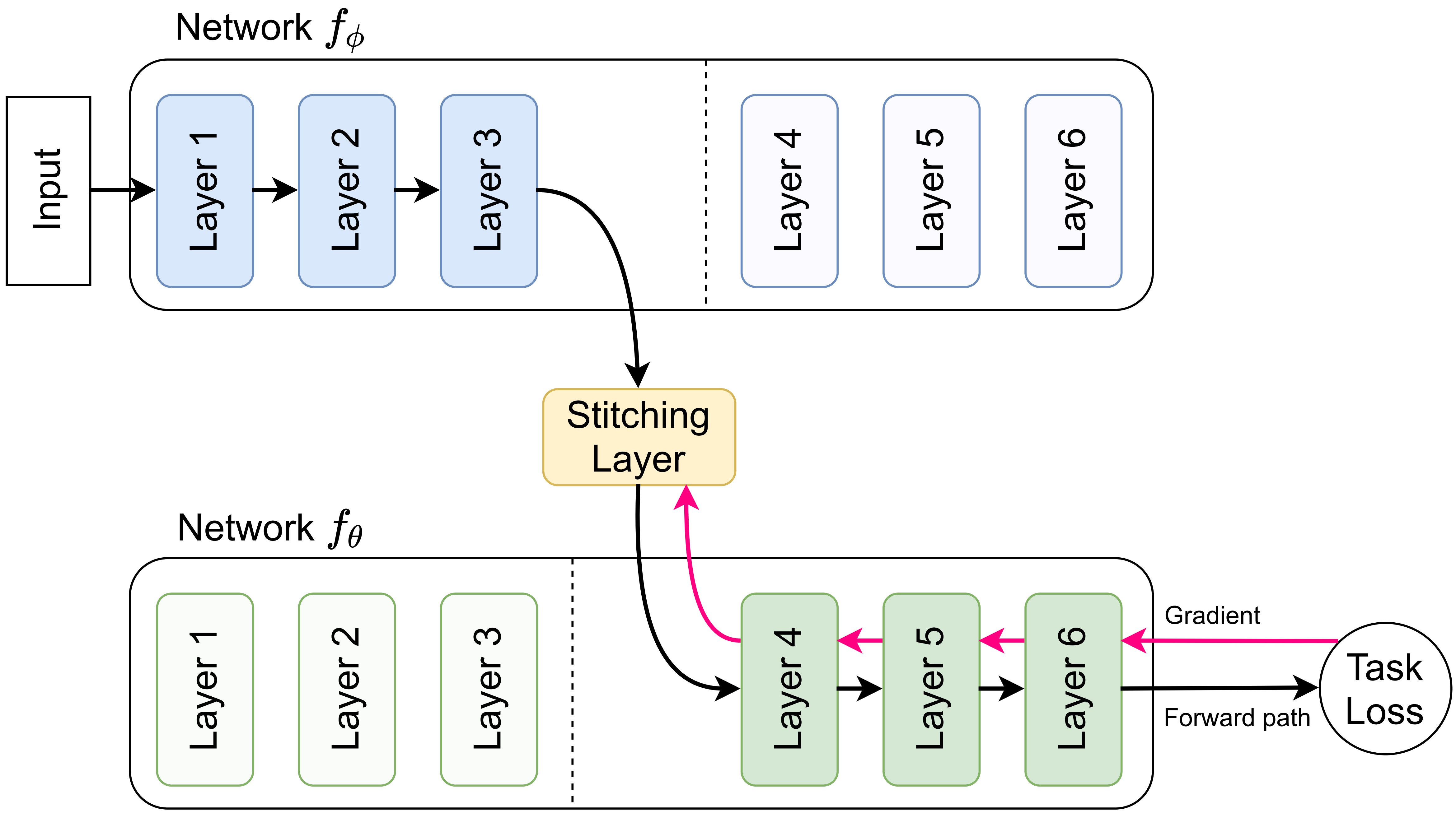
Dániel Varga,
Alfréd Rényi Institute of Mathematics

firstname@renyi.hu

Our current work

- Originally, I got an invitation to talk about our AI group's ongoing research at the Rényi Institute.
- Right now we are stitching together neural networks to investigate their internal representations.
- Similarity and Matching of Neural Network Representations. Adrián Csiszárik, Péter Kőrösi-Szabó, Ákos K. Matszangosz, Gergely Papp, Dániel Varga. NeurIPS 2021.

Model stitching



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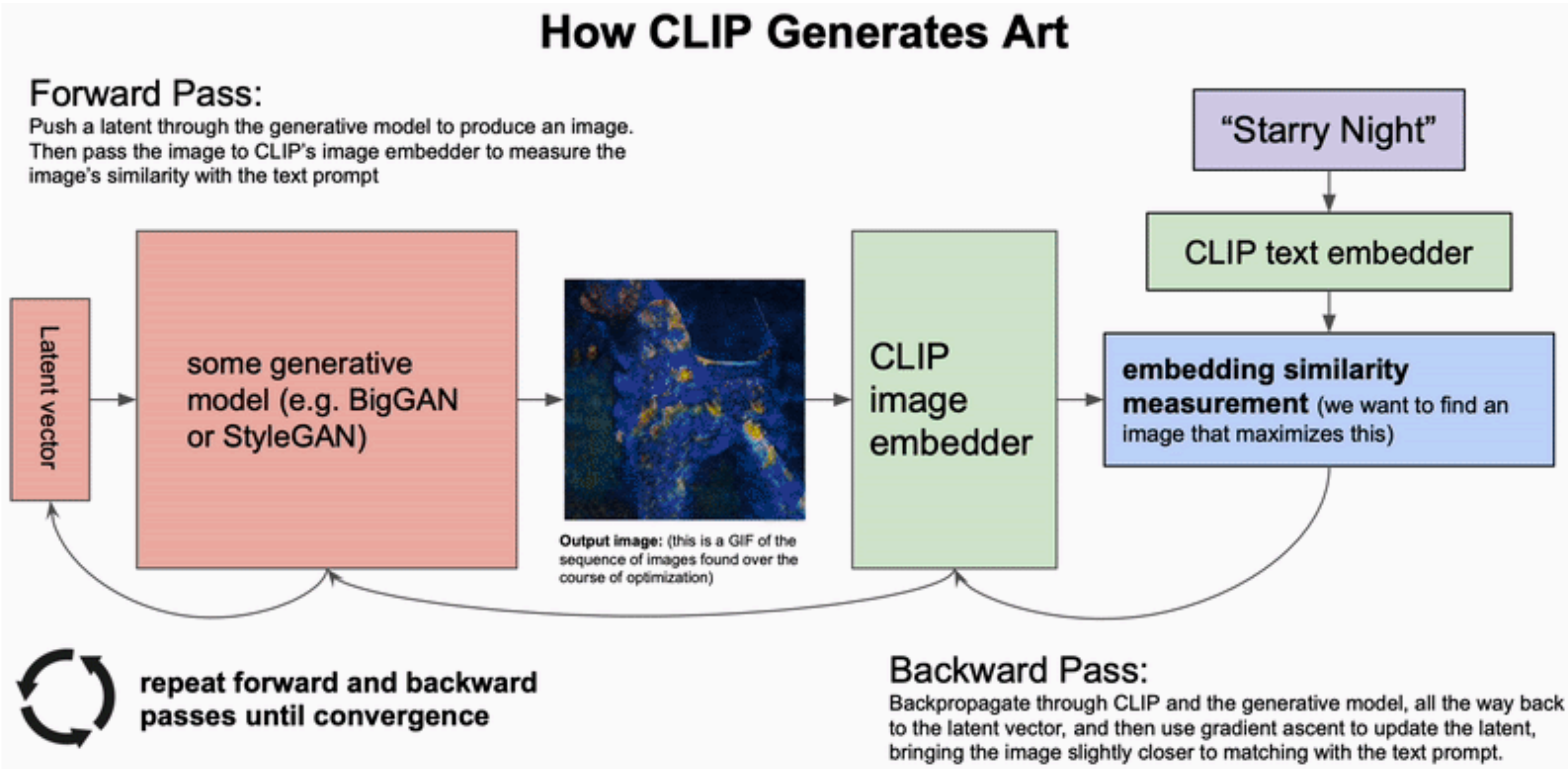
- I believe this is cool research, but frankly I deemed it a bit too technical for this venue.
- So I opted to talk about image synthesis instead.

Image synthesis

- Thanks to recent advances in multimodal (text+image) deep learning, we can now create compelling, original images by giving textual prompts to "AI artists".
- The main components of such systems are:
    - An artificial neural network capable of **generating images** by mapping real vectors to image output.
    - An artificial neural network **quantifying the relatedness** of a text and an image.
    - A gradient descent based optimization algorithm using the above two networks as "differentiable subroutines" to **gradually create an image** corresponding to the text prompt.



https://ml.berkeley.edu/blog/posts/clip-art/

“Girl looking annoyed”

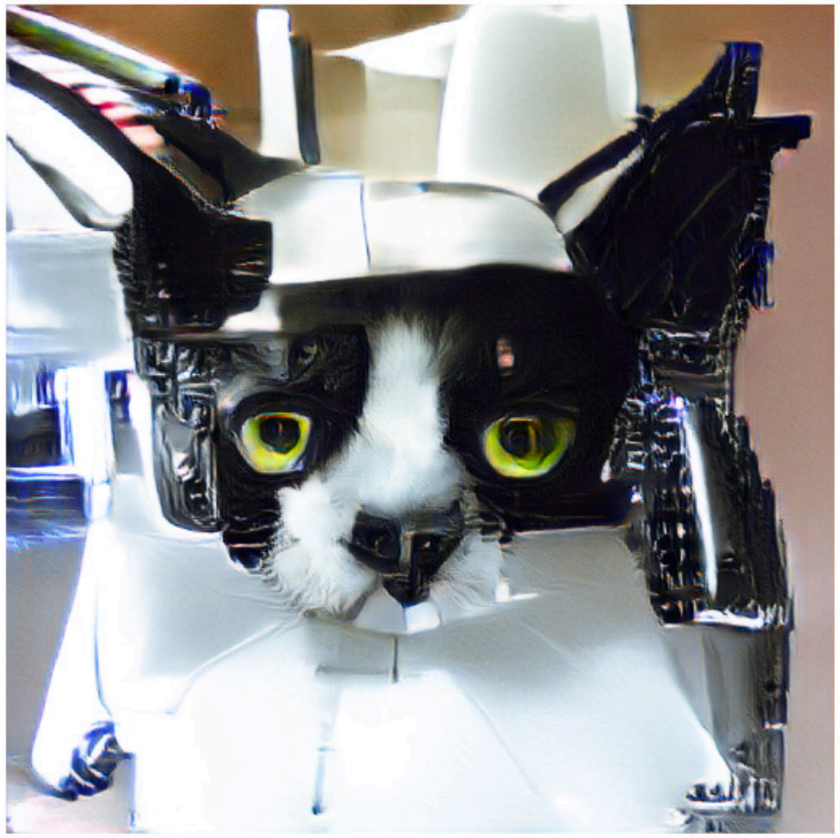
“Interdimensional portal in the middle of the street"

“Photograph of David Bowie in Helsinki”

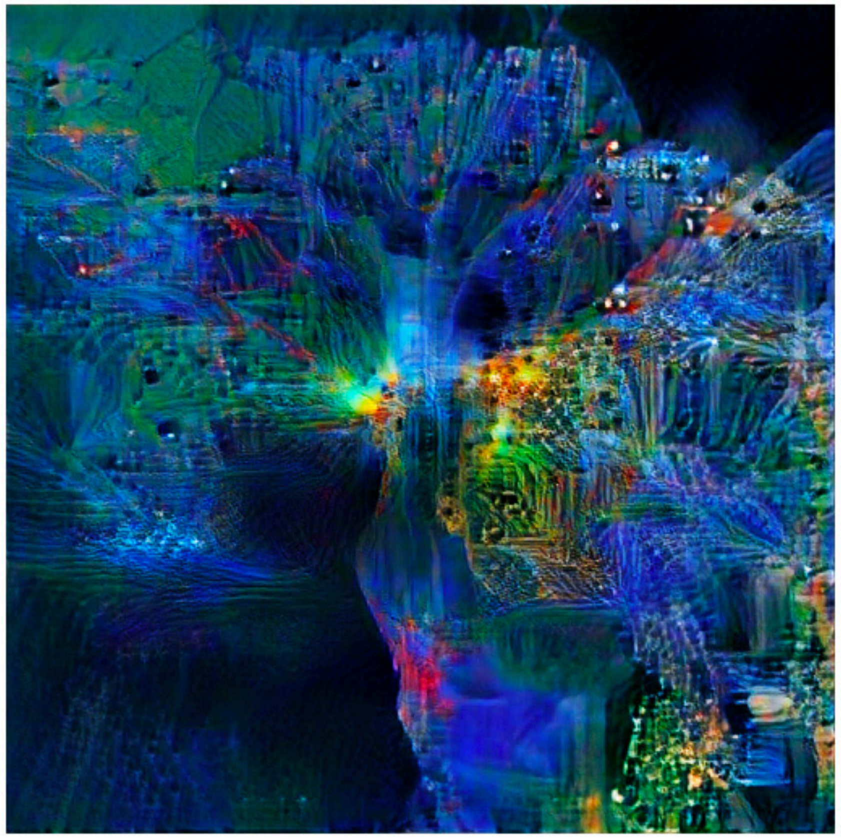
“Witches around a cauldron in the style of Synthwave”

“A lightsaber in the jungle”

“Robot cat”



“Inside an AI’s mind”



https://rossdawson.com/futurist/implications-of-ai/future-of-ai-image-synthesis/ https://colab.research.google.com/drive/1NCceX2mbiKOSlAd_o7IU7nA9UskK

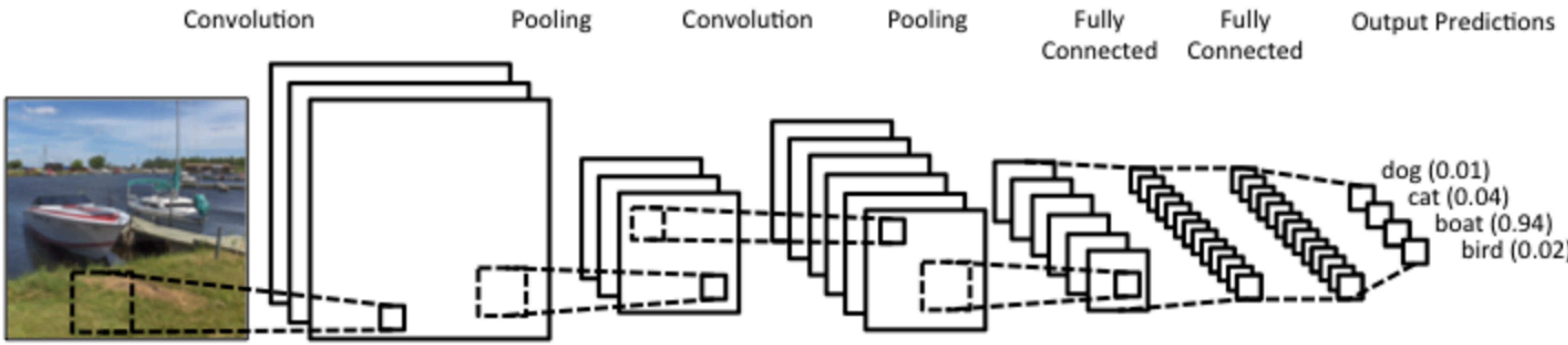
https://moultano.wordpress.com/2021/08/23/doorways/

Inversion	Photo → Monet Portrait	Photo → Anime Painting	Photo → Sketch	Human → Tolkien Elf	Goku → Super Saiyan Goku	Human → Zombie

https://github.com/rinongal/StyleGAN-nada

Preliminaries

How do we represent images and text?



input: RGB pixel-intensities (224x224x3 dim)

output: categorical (4 dim)

Character-based one-hot encoding

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
L →	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U →	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
K →	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A →	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S →	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

https://wandb.ai/site/tutorial/text-generation-with-lstms-and-grus

Token-based one-hot encoding

Vocabulary:
Man, woman, boy, girl, prince, princess, queen, king, monarch

	1	2	3	4	5	6	7	8	9
man	1	0	0	0	0	0	0	0	0
woman	0	1	0	0	0	0	0	0	0
boy	0	0	1	0	0	0	0	0	0
girl	0	0	0	1	0	0	0	0	0
prince	0	0	0	0	1	0	0	0	0
princess	0	0	0	0	0	1	0	0	0
queen	0	0	0	0	0	0	1	0	0
king	0	0	0	0	0	0	0	1	0
monarch	0	0	0	0	0	0	0	0	1

Each word gets a 1x9 vector representation

https://www.shanelynn.ie/get-busy-with-word-embeddings-introduction/

Preliminaries

How do we represent functions?

Neural networks

For our purposes, artificial neural networks are parametrized function classes

$$f_\Theta : \mathbb{R}^n \to \mathbb{R}^m$$

$\Theta \in \mathbb{R}^N$ is a real parameter vector. Before fixing a specific Θ, we call such an $f : \mathbb{R}^N \times \mathbb{R}^n \to \mathbb{R}^m$ a neural network architecture, and after fixing Θ, we call $f_\Theta : \mathbb{R}^n \to \mathbb{R}^m$ a trained neural network.

We assume that f is continuous for all Θ, and that $\frac{\partial f_\Theta(x)}{\partial \Theta}$ exists almost everywhere.

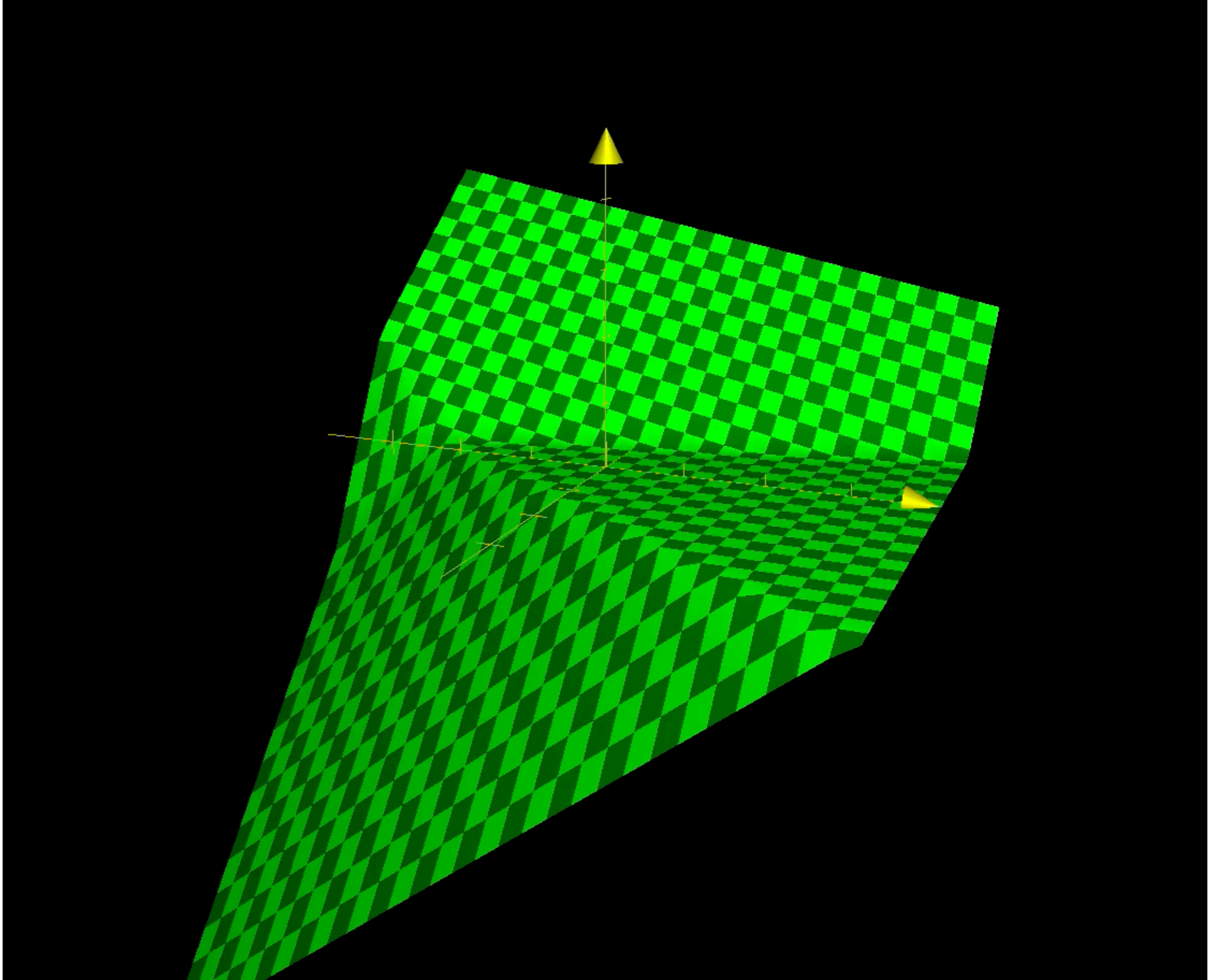
Neural networks: toy example

$$\Theta = [p, q, r, s, t, u, v, w]$$

$$f_\Theta \colon \mathbb{R}^2 \to \mathbb{R}$$

$$f_\Theta(x, y) = v \max(px + qy + r, 0) + w \max(sx + ty + u, 0)$$

(An 8-parameter network mapping from $\mathbb{R}^2$ to $\mathbb{R}$.)



Neural networks: non-toy examples

- Using mainly the same simple building blocks (namely, affine transformations and the maximum function), deep learning researchers have built network architectures that (with the right choice of Θ) can represent and **learn** extremely complex functions.

- These network architectures are HUGE, nowadays often with 10^8 parameters, sometimes even reaching 10^{11}.

- Examples are: Residual networks, Transformers, Vision Transformers, MLP-Mixer.

- They can reach close to human performance on tasks like “what is on this image?”.

How do artificial neural networks learn?

- We define a real-valued L(y) loss function that takes the output of the f neural network, and evaluates it: L(f(x)).
- By definition, smaller losses are better.
- We start from a random Θ, and iteratively move it in the direction that decreases the loss, calculating $\frac{\partial L(f_\Theta(x))}{\partial \Theta}$ for a random x (or random subset of X).

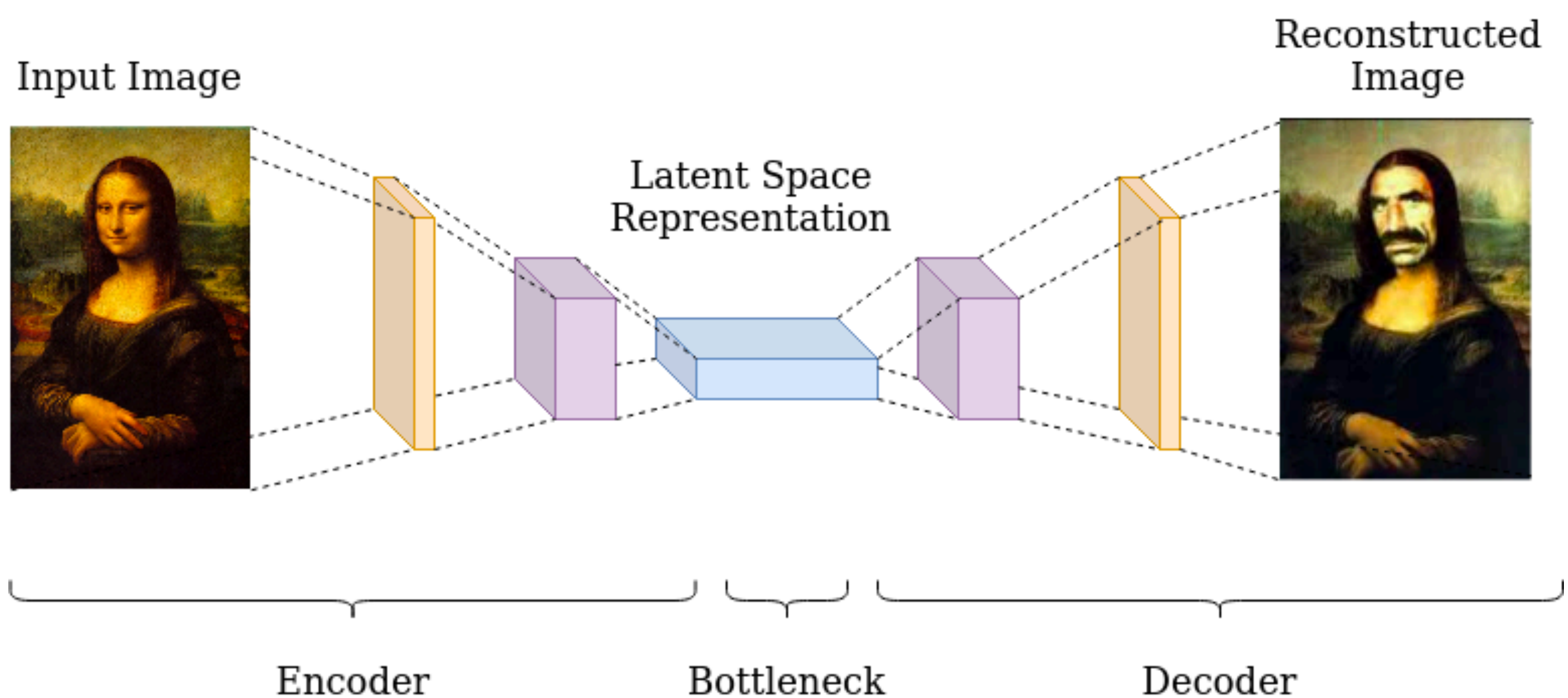
Encoders, decoders

- We will call an *encoder* any neural network that takes some real-world data as input (image, text, sound, video), and maps it onto an abstract d-dimensional vector space.

- We will call a *decoder* any neural network that maps elements of an abstract d-dimensional vector space to real-world data (image, text, sound, video).

Autoencoders

- When we have an encoder architecture and a decoder architecture, we can plug them into each other. Their function composition maps from images to images. We can define a trivial loss function: the mean square error of the reconstruction:

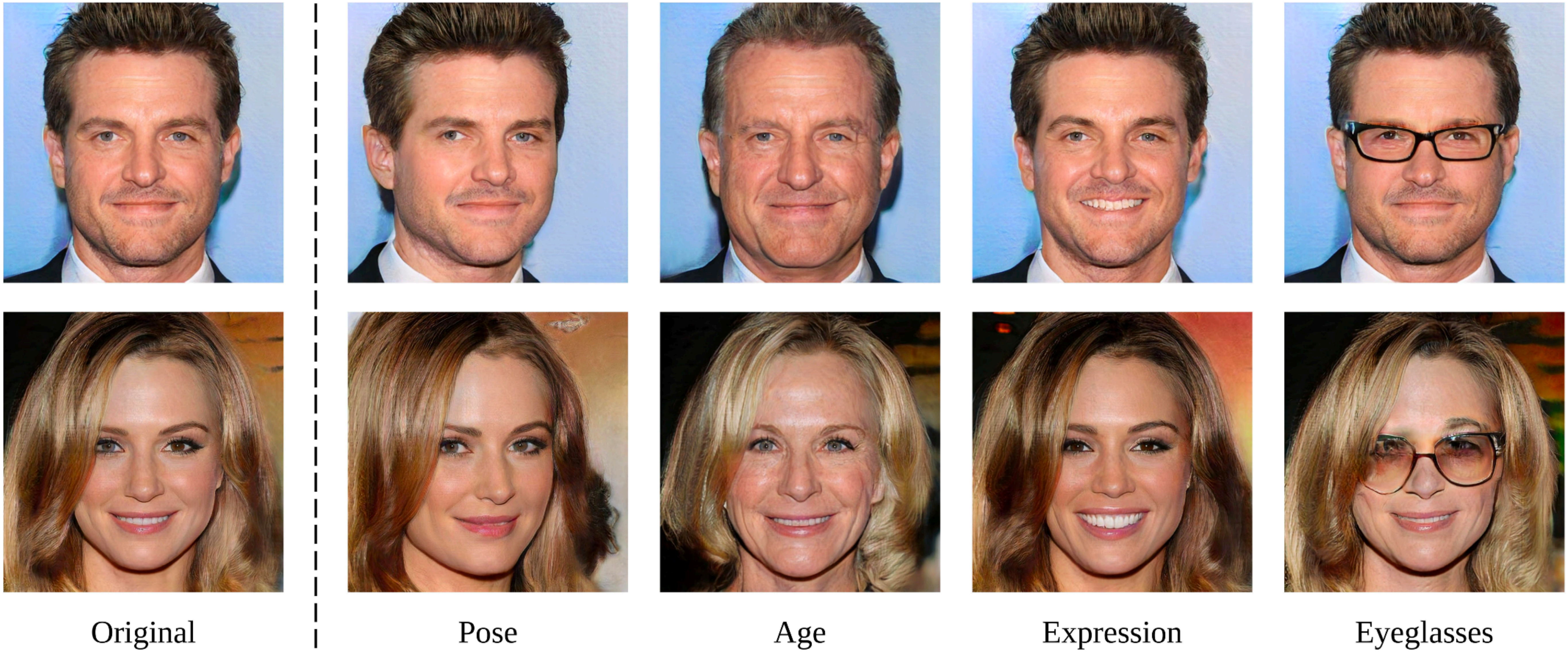


https://emkademy.medium.com/1-first-step-to-generative-deep-learning-with-autoencoders-22bd41e56d18

Generators

- A *generator* is a kind of decoder, mapping latent vectors to data vectors.
- You train the generator on some data distribution X.
- You then give it a random vector as input (standard normal distribution, say).
- It is supposed to give you a random element of the data distribution X.
- Most famously GANs, but also Variational Autoencoders, Energy-based models, Autoregressive models etc.

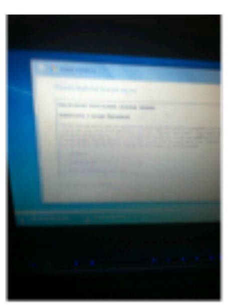
Latent arithmetic



https://github.com/genforce/interfacegan

Text to Image

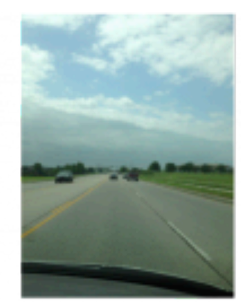
- Let’s plug an image decoder into a text encoder, and train the combination on image-caption pairs.
- Easier said than done.
- It was finally done in January 2021 by OpenAI.



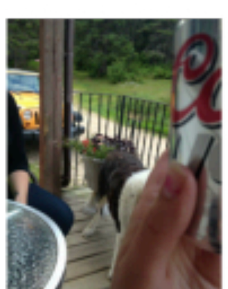
A computer screen with a Windows message about Microsoft license terms.

A can of green beans is sitting on a counter in a kitchen.

A photo taken from a residential street in front of some homes with a stormy sky above.

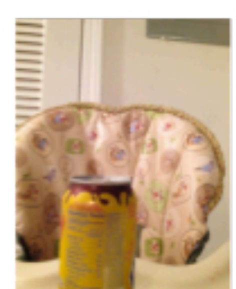


A blue sky with fluffy clouds, taken from a car while driving on the highway.

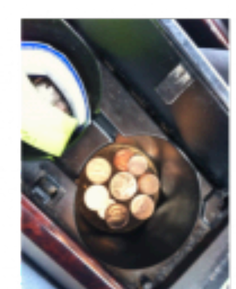


A hand holds up a can of Coors Light in front of an outdoor scene with a dog on a porch.

A digital thermometer resting on a wooden table, showing 38.5 degrees Celsius.

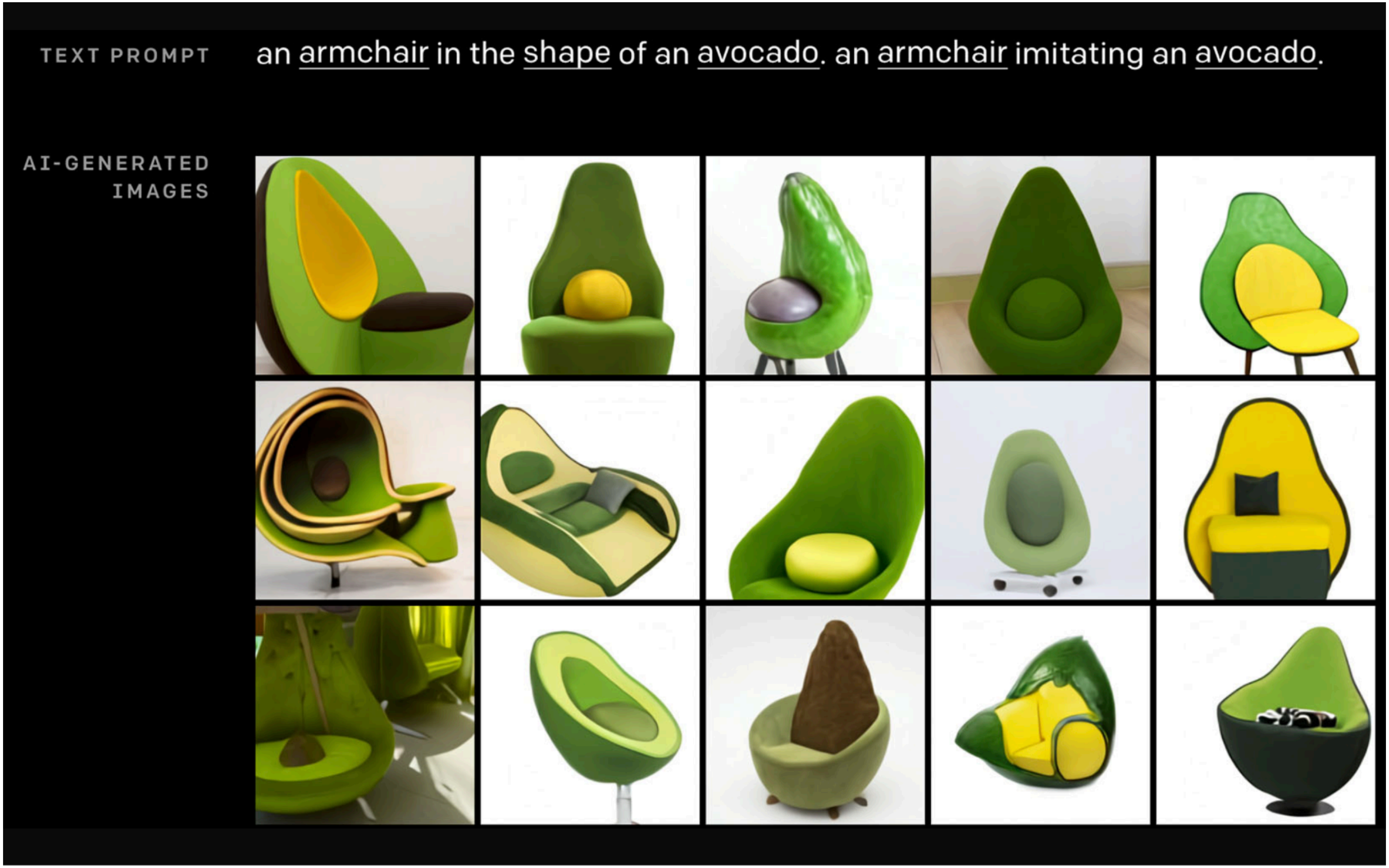


A Winnie The Pooh character high chair with a can of Yoohoo sitting on it in front of a white wall.

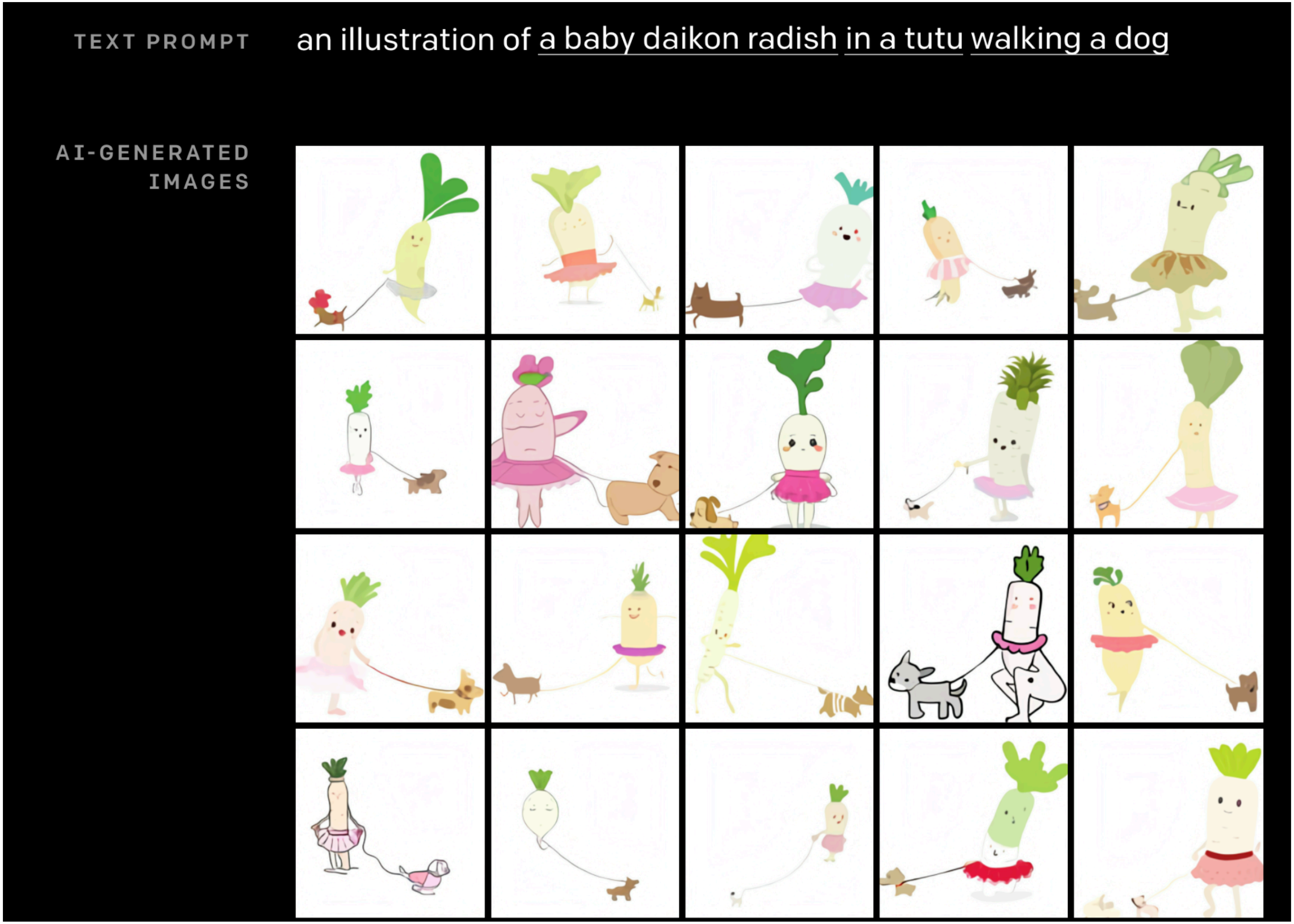


A cup holder in a car holding loose change from Canada.

DALL-E - text to image



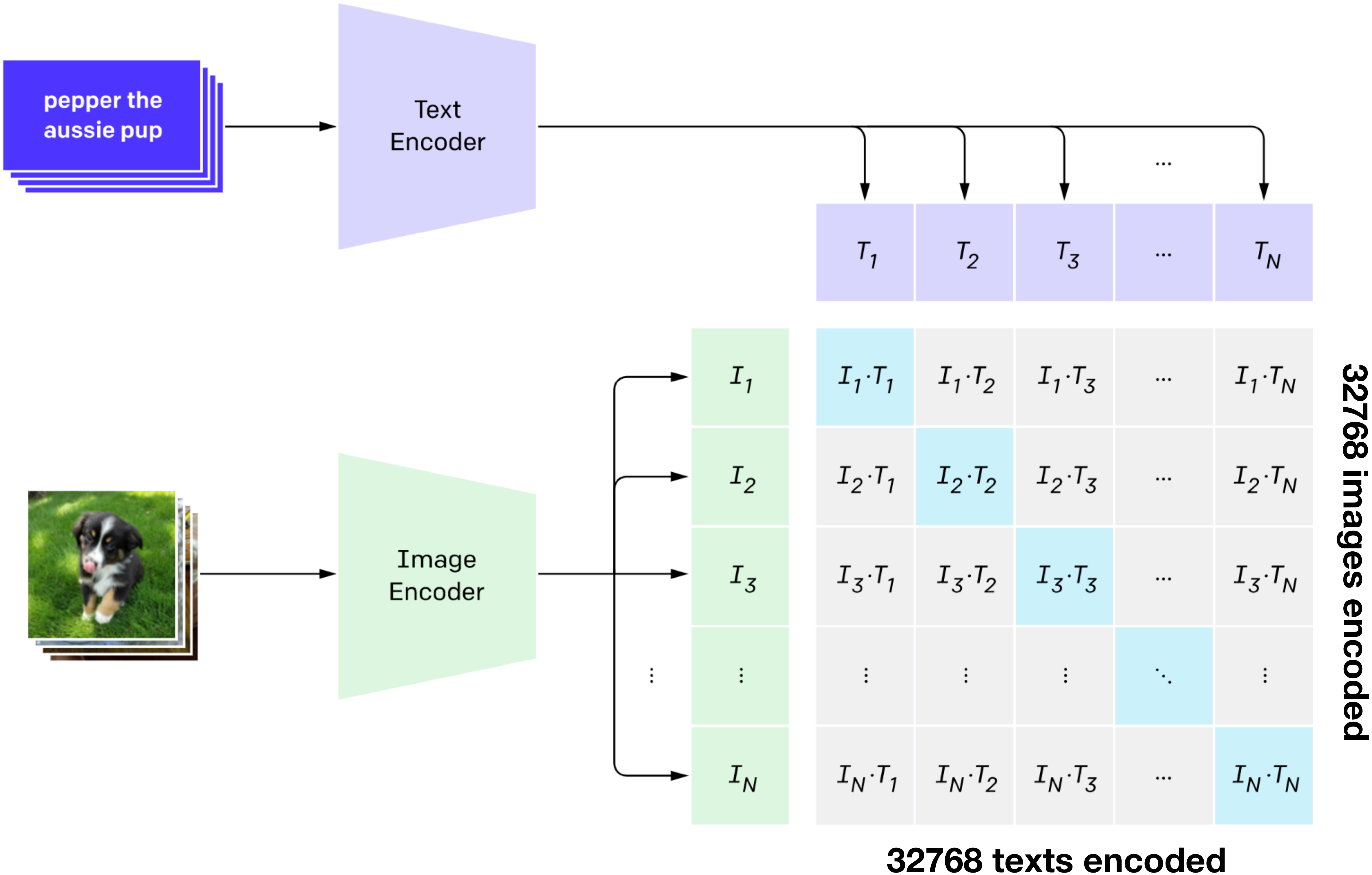
DALL-E - text to image



CLIP

- OpenAI have never published the text encoder + image decoder DALL-E model.
- But they have published another model based on a text encoder + image encoder architecture.
- That is CLIP.

Contrastive training



CLIP pseudocode

```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

https://arxiv.org/pdf/2103.00020.pdf

Categorical cross-entropy loss

This is how we turn network outputs into predictions:

$$p_i(x) = \frac{e^{y_i}}{\sum_i e^{y_i}}$$

(By construction, $\forall i : 0 < p_i < 1$ and $\sum_i p_i = 1$.)

And this is how we turn predictions and a known correct label into a loss function:

$$L_{XENT}(p, i) = -\ln p_i$$

where i is the correct label, and p_j is the probability assigned to class j by the model.

By the way, this is just a special case of

$$L_{XENT}(p_{model}, p_{known}) = -\sum_i p_{known,i} \ln p_{model,i}$$

Lots of data, lots of compute

- CLIP was trained on 400 million (image, text) pairs.
- Contrastive batch size is 32768.
- 32 epochs. (Each of the 400M pairs was shown this many times to the network during training.)
- Training took 18 days on 592 NVIDIA V100 GPUs.
- That amount of computation would cost a few 100 thousand dollars on the market. (OpenAI can thank Microsoft, though.)

Zero-shot learning

FOOD101

guacamole (90.1%) Ranked 1 out of 101 labels

✓ a photo of **guacamole**, a type of food.

× a photo of **ceviche**, a type of food.

× a photo of **edamame**, a type of food.

× a photo of **tuna tartare**, a type of food.

× a photo of **hummus**, a type of food.

SUN397

television studio (90.2%) Ranked 1 out of 397

✓ a photo of a **television studio**.

× a photo of a **podium indoor**.

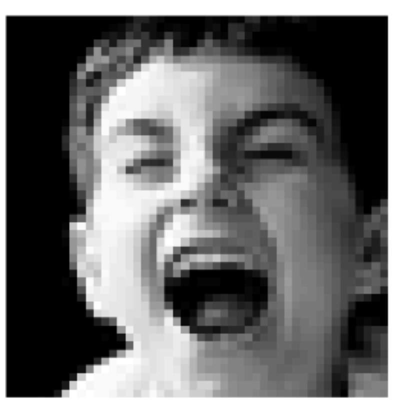
× a photo of a **conference room**.

× a photo of a **lecture room**.

× a photo of a **control room**.

FACIAL EMOTION RECOGNITION 2013 (FER2013)

angry (8.2%) Ranked 5 out of 7



× a photo of a **happy** looking face.

× a photo of a **neutral** looking face.

× a photo of a **surprised** looking face.

× a photo of a **fearful** looking face.

✓ a photo of a **angry** looking face.

UCF101

Volleyball Spiking (99.3%) Ranked 1 out of 101

✓ a photo of a person **volleyball spiking**.

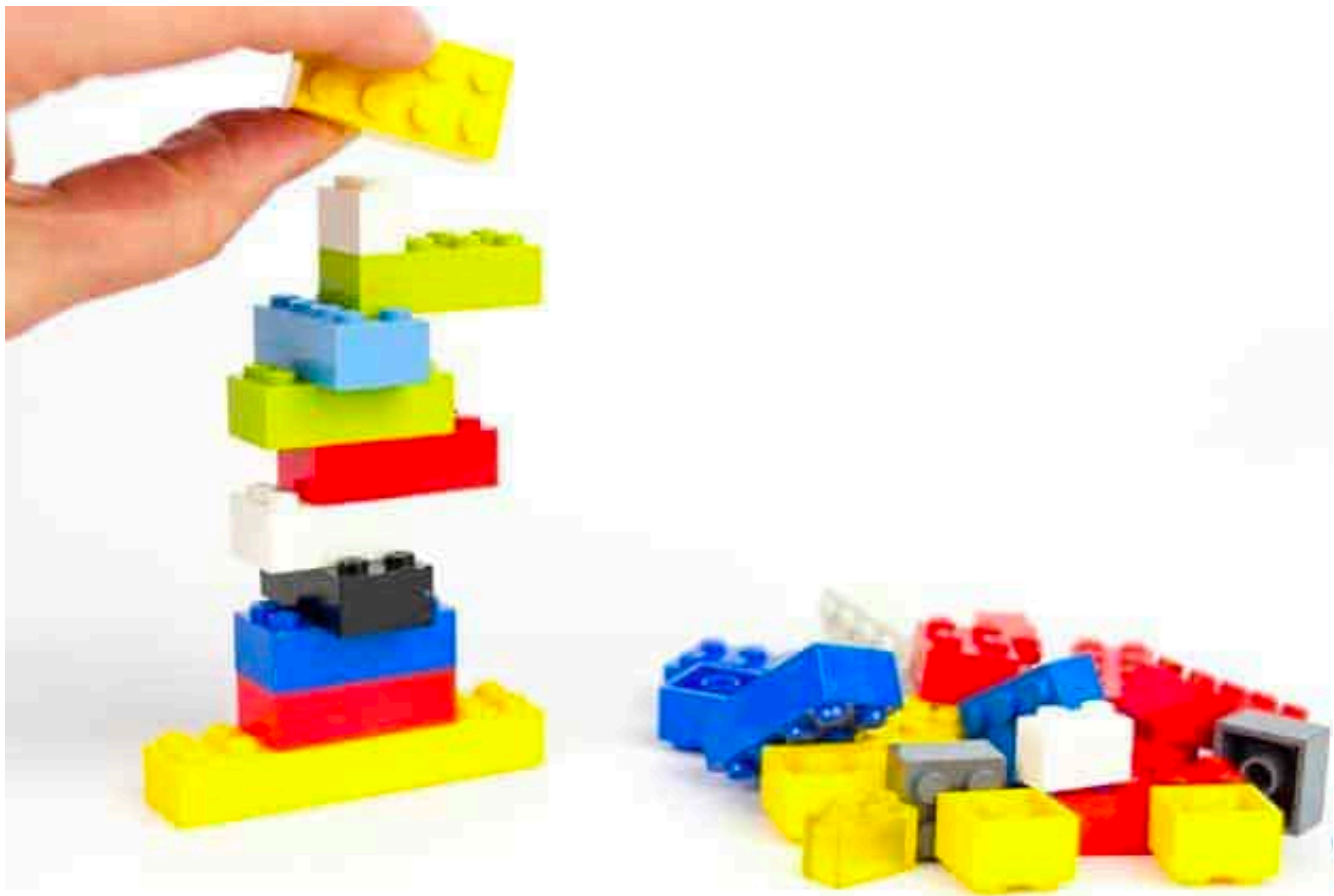
× a photo of a person **jump rope**.

× a photo of a person **long jump**.

× a photo of a person **soccer penalty**.

× a photo of a person **table tennis shot**.

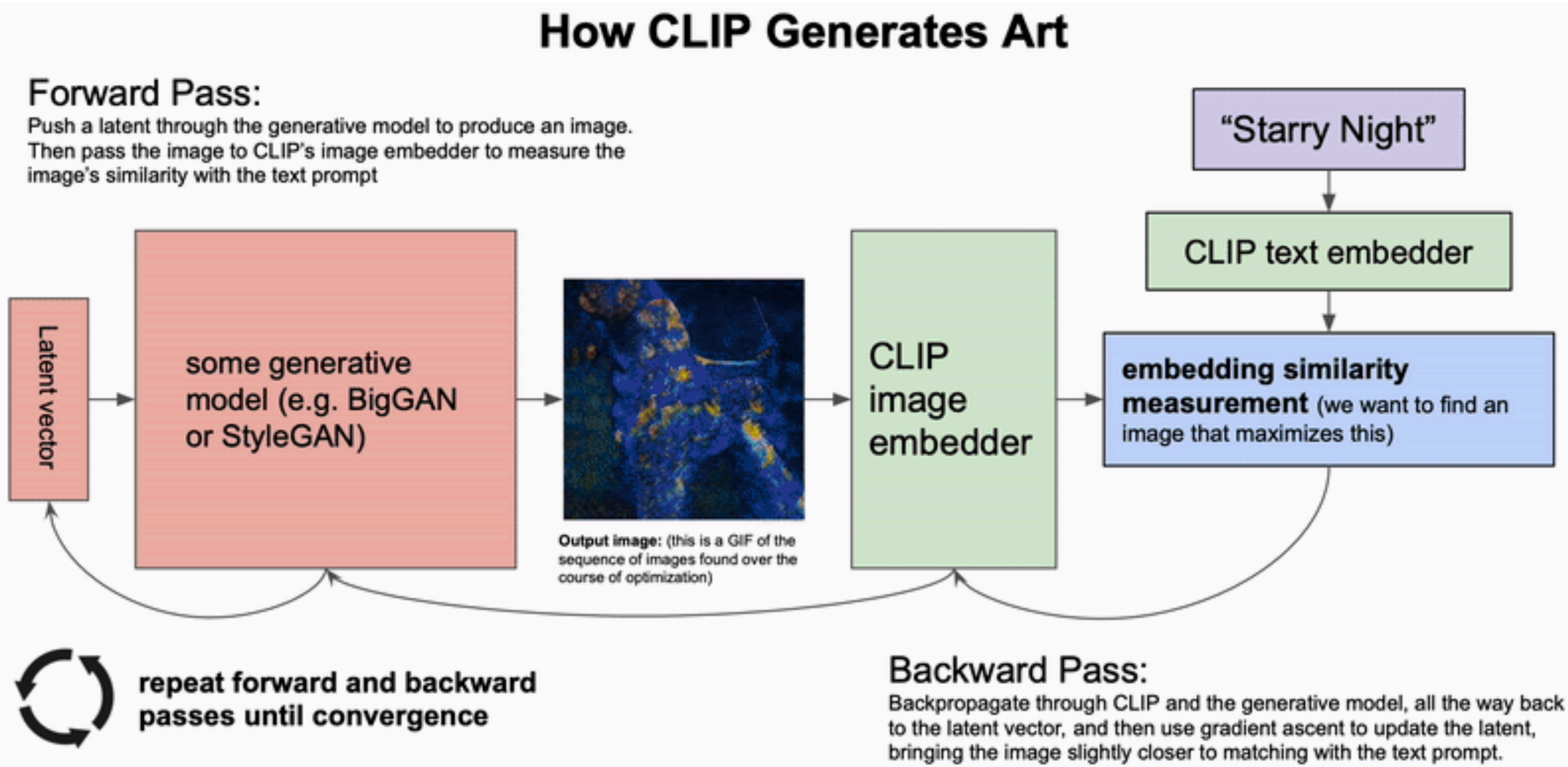
Let's try to build something from this



CLIP as a poor man's DALL-E

- People soon figured out that they can combine CLIP with an image generator to do something like what DALL-E does.

- (Remember: a generator takes a random embedding vector, and outputs an image.)

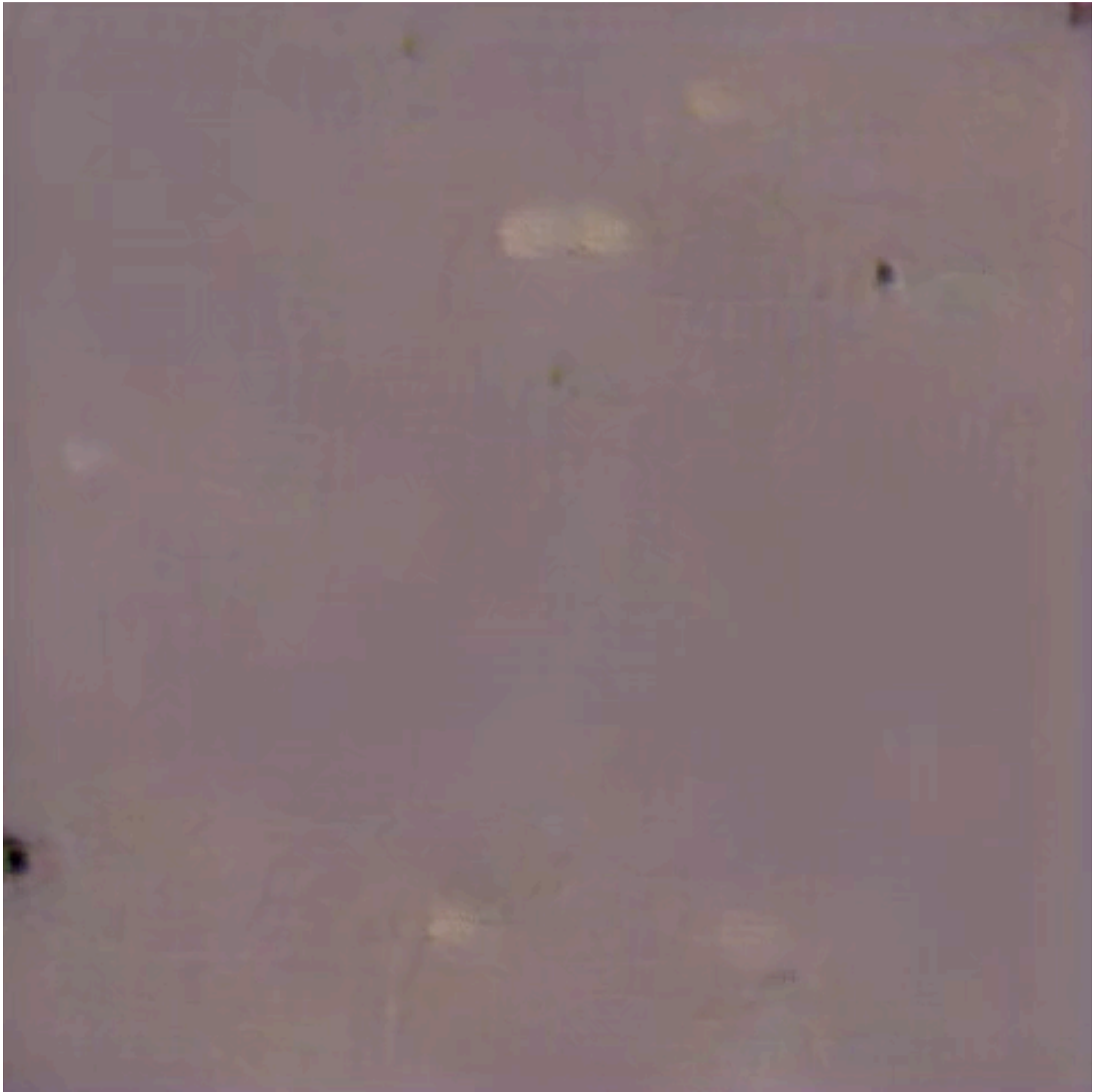


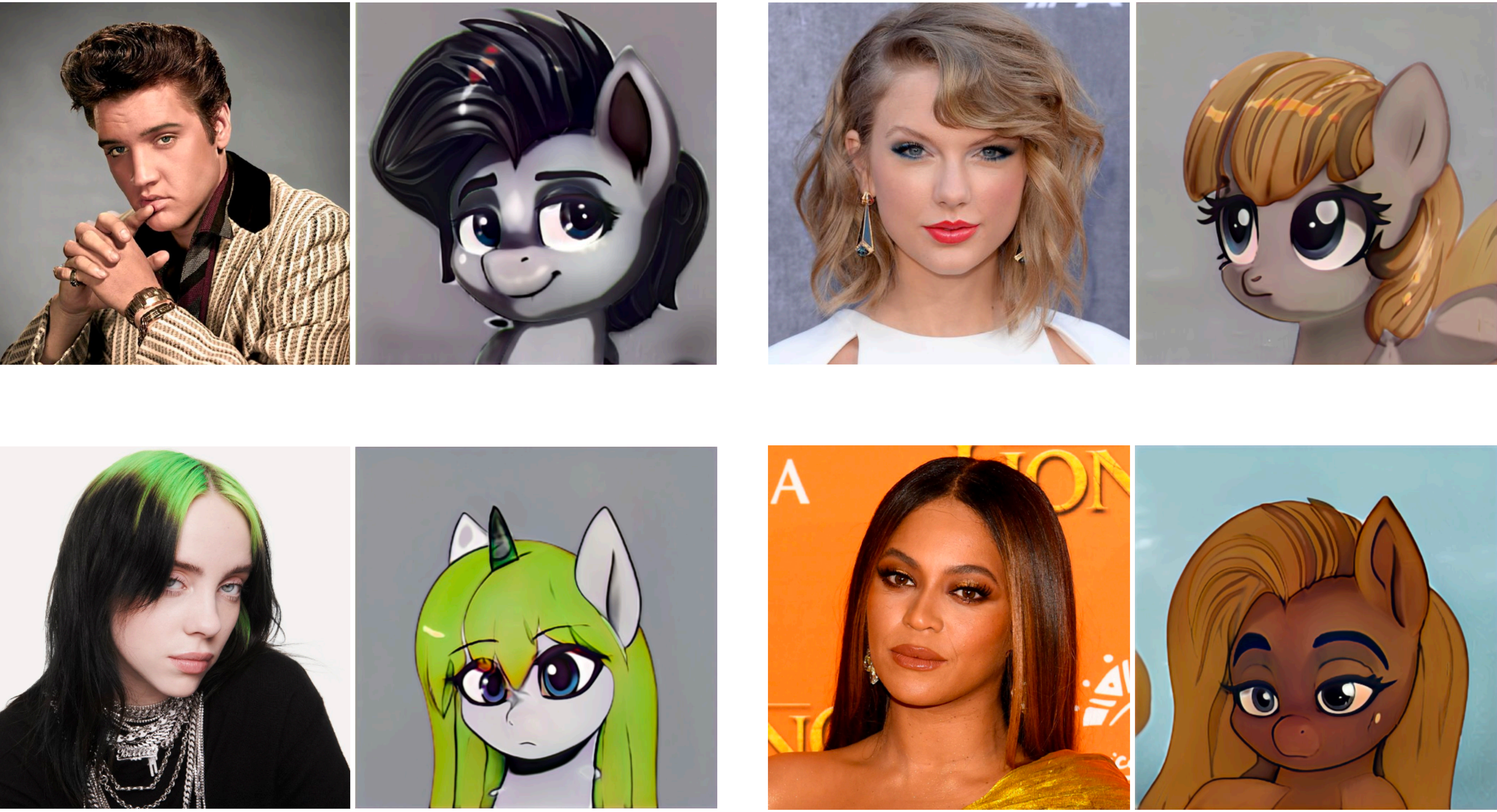
https://ml.berkeley.edu/blog/posts/clip-art/

“Man looking like Frankenstein’s monster”

“Geisha"

“The cactus man” (VQ-GAN generator)





These are fully text directed. Left image is just illustration.
CLIP knows how these people look, just from their names.

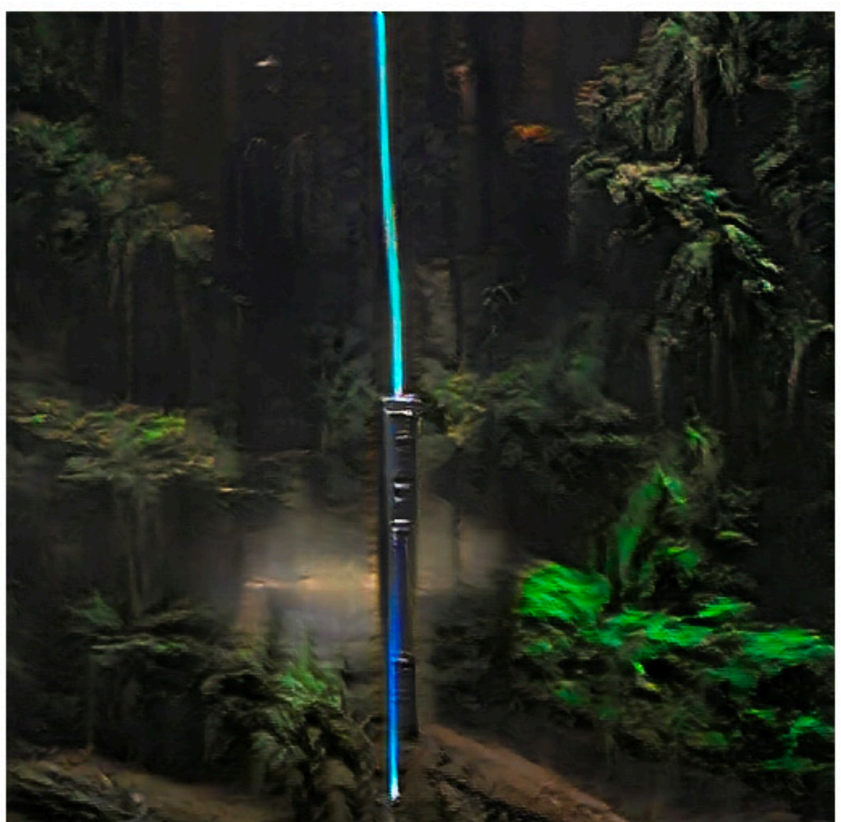
https://twitter.com/metasemantic/status/1368713208429764616

"Interdimensional portal in the middle of the street"

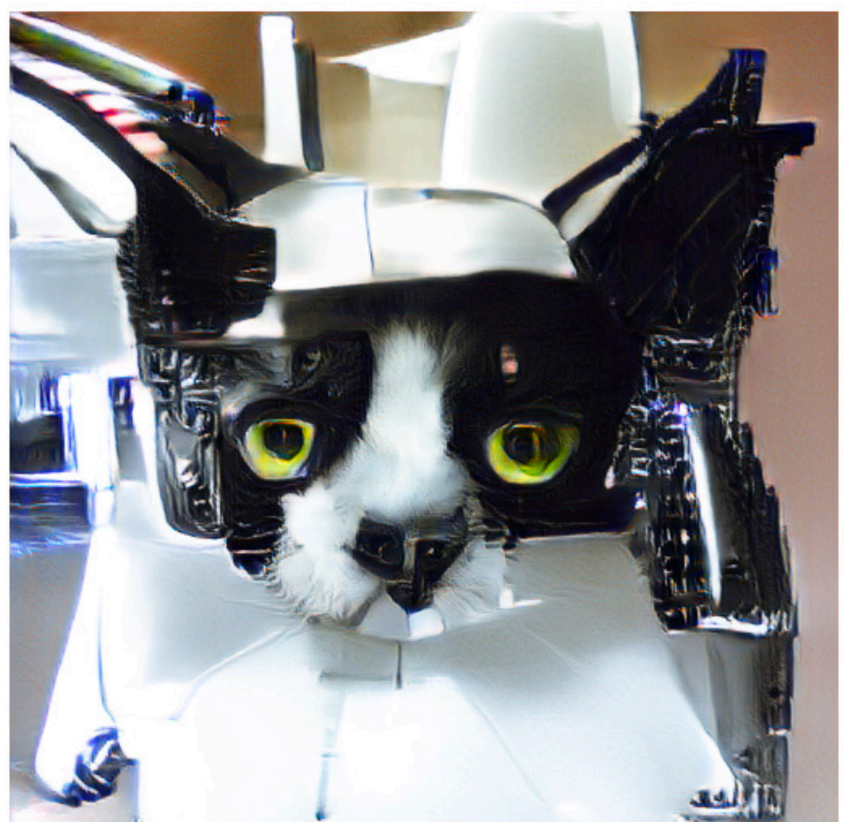
"Photograph of David Bowie in Helsinki"

"Witches around a cauldron in the style of Synthwave"

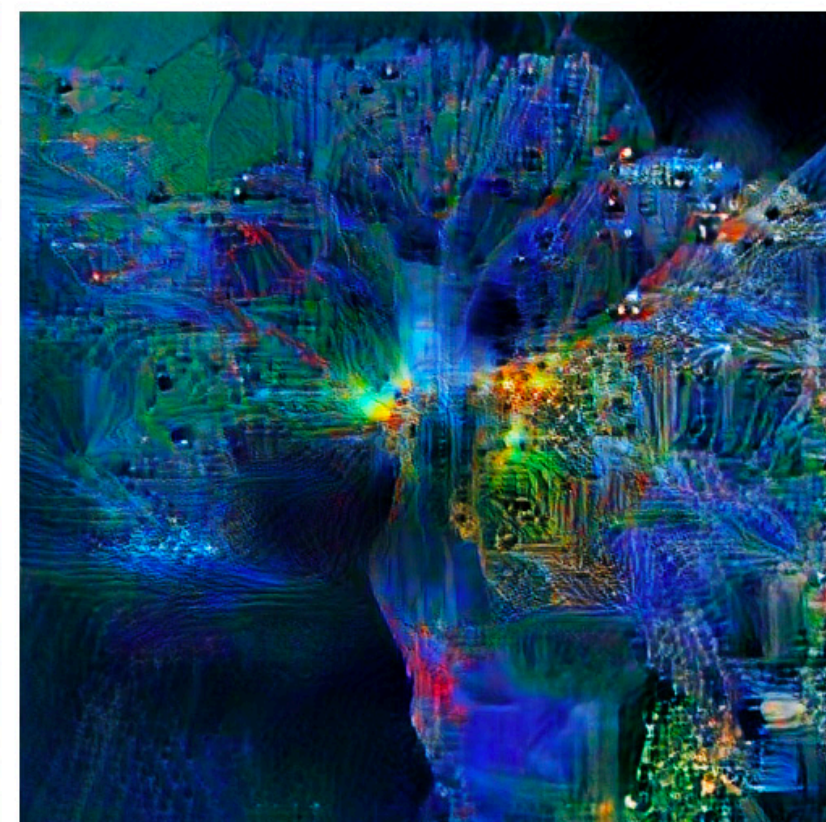
"A lightsaber in the jungle"



"Robot cat"



"Inside an AI's mind"



https://rossdawson.com/futurist/implications-of-ai/future-of-ai-image-synthesis/ https://colab.research.google.com/drive/1NCceX2mbiKOSlAd_o7IU7nA9UskK

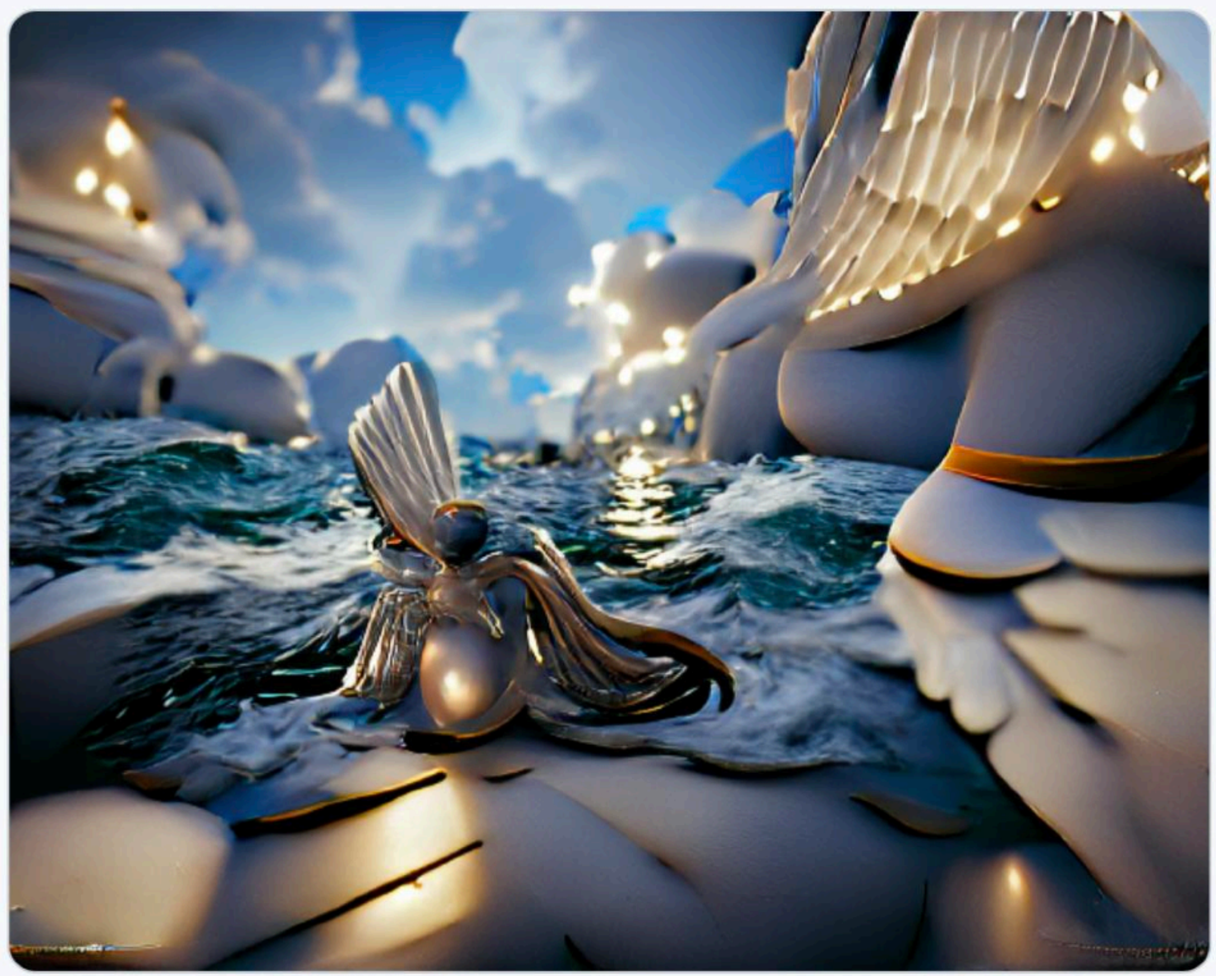
The Unreal Engine trick

Aran Komatsuzaki
@arankomatsuzaki

When you generate images with VQGAN + CLIP, the image quality dramatically improves if you add "unreal engine" to your prompt.

People are now calling this "unreal engine trick" lol

e.g. "the angel of air. unreal engine"



4:02 PM · May 31, 2021

2.4K   40   Share this Tweet

The Unreal Engine trick

- “trending on artstation”
- “painting by James Gurney”
- “in the style of Studio Ghibli”
- “charcoal”
- “hyperrealistic”
- “dramatic desktop wallpaper high definition”

"matte painting of a house on a hilltop at midnight with small fireflies flying around in the style of studio ghibli | artstation | unreal engine" (VQ-GAN+CLIP)

https://twitter.com/ak92501/status/1407477121174364160

“The Yellow Smoke That Rubs Its Muzzle On The Window-Panes” by @RiversHaveWings, (VQ-GAN+CLIP)

“Dancing in the moonlight” by @RiversHaveWings, (VQ-GAN+CLIP)

https://moultano.wordpress.com/2021/08/23/doorways/

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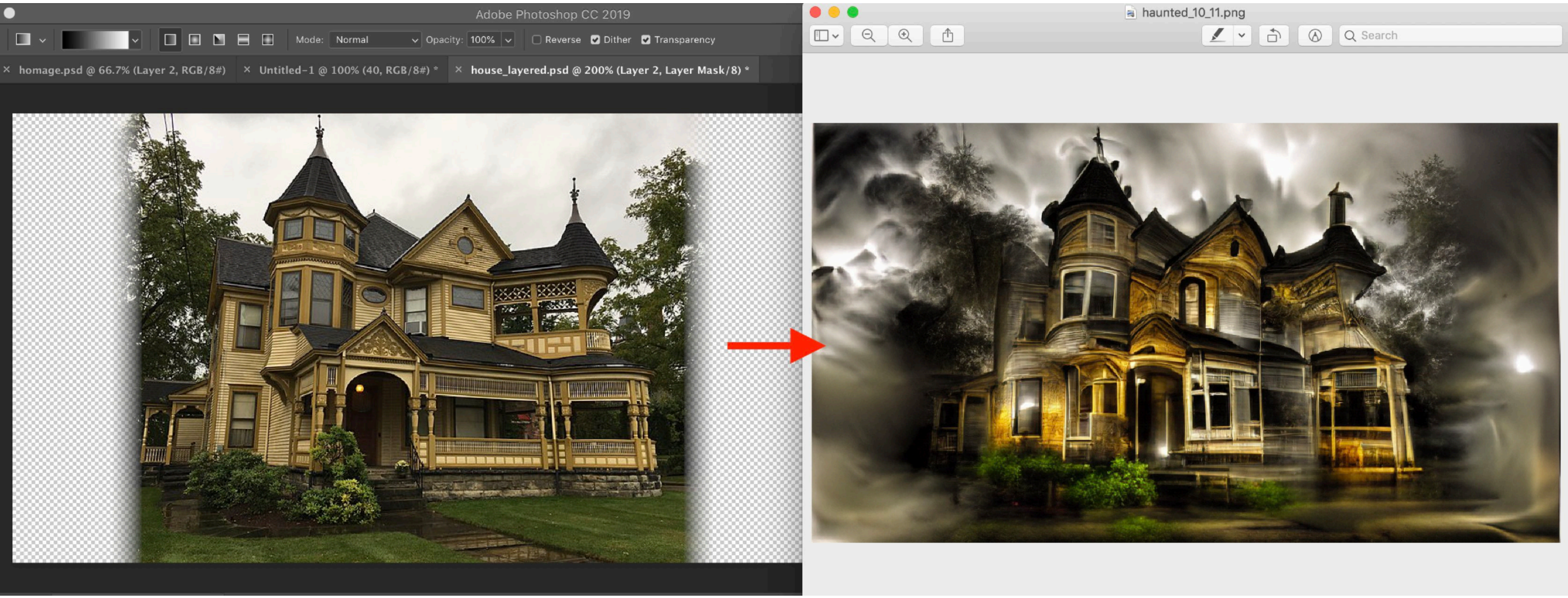
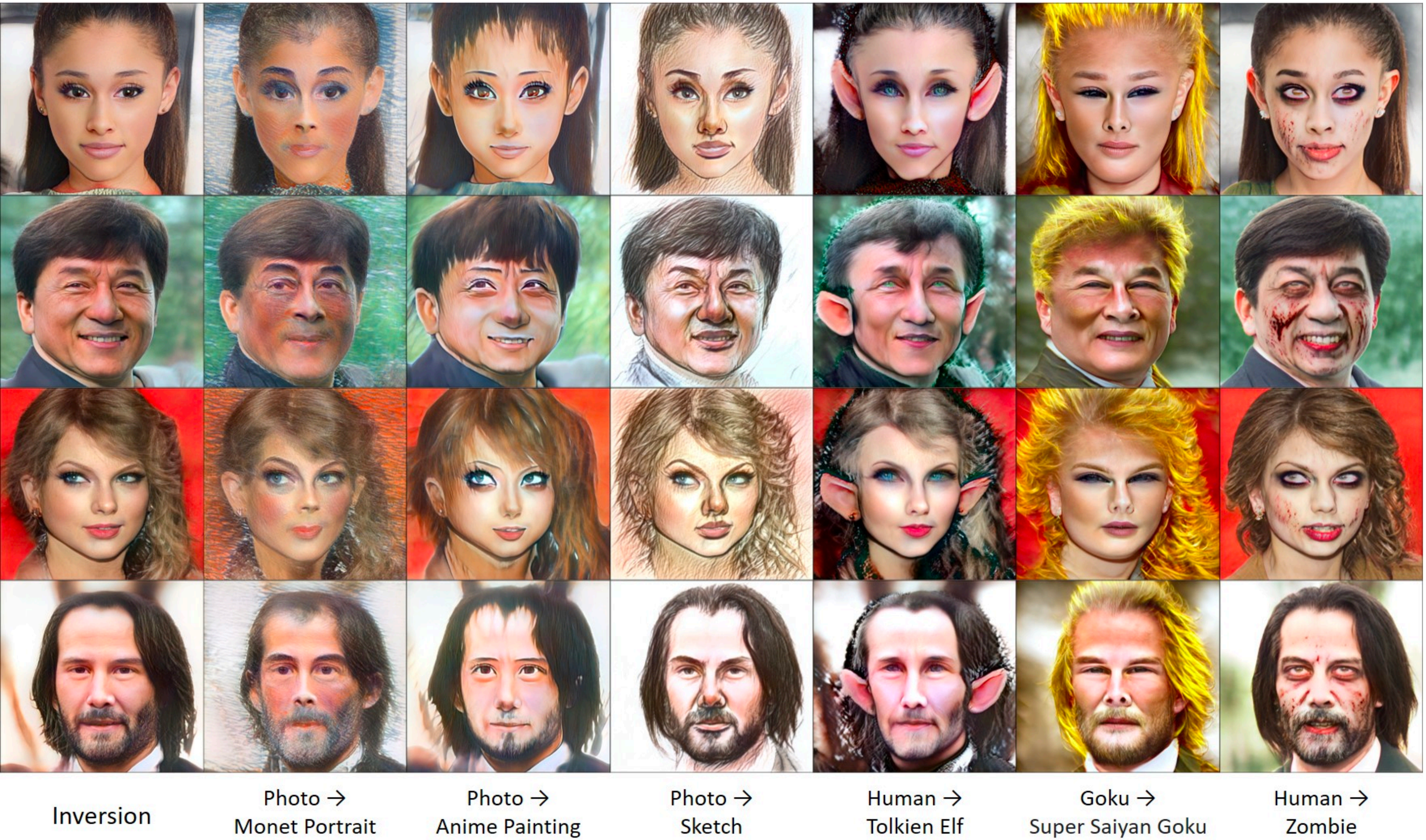
Image inversion

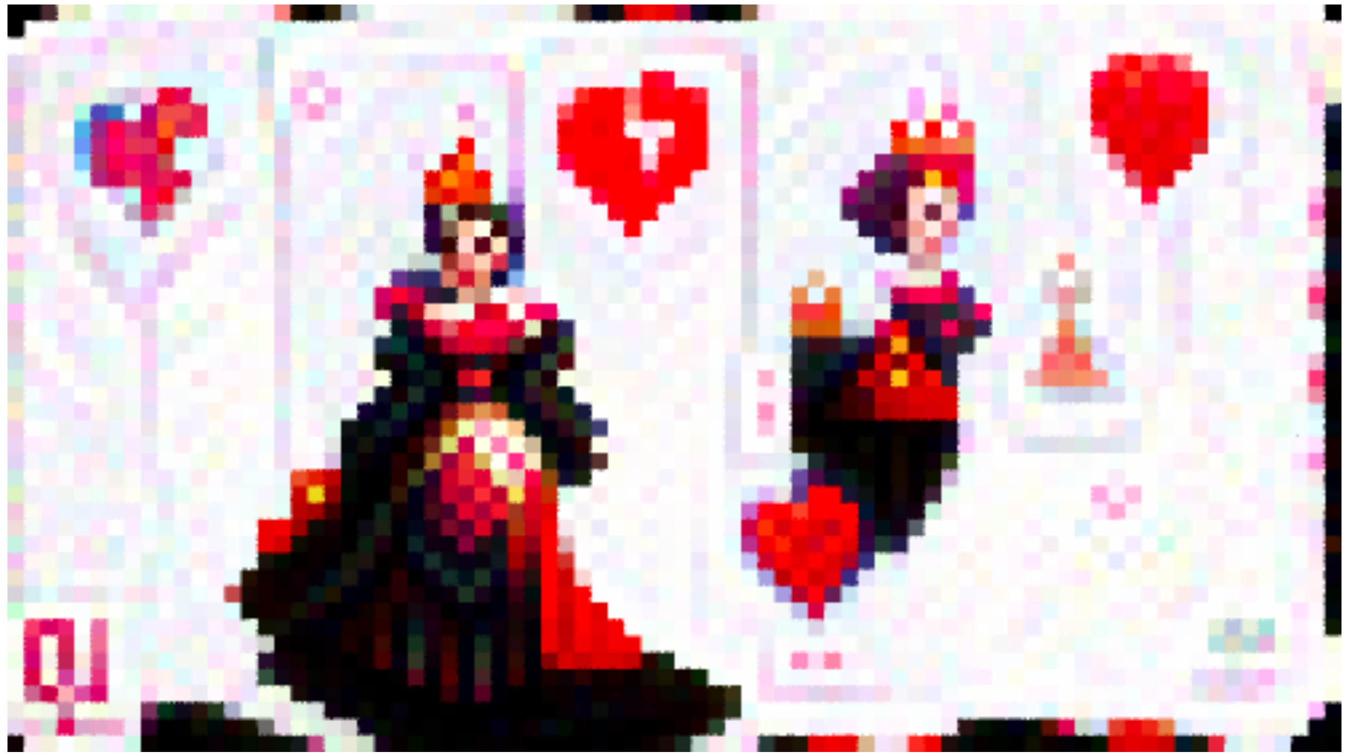


https://twitter.com/dribnet/status/1447496500024545287



https://github.com/rinongal/StyleGAN-nada

PixelDraw generator



https://twitter.com/altsoph/status/1429516389895843841

Distraction, social commentary

- Right-clicked on the above three images and saved them.
- At the time of this writing, their NFTs trade for a few thousand USDs each.
- “To right-click is one thing, but to have a right-clicker mentality implies an ontological break between crypto-fans and critics. Indeed, it implies the person saving the JPEG to their hard drive isn’t just wrong, they’re broken in some way.” (Matthew Gault)

https://twitter.com/quasimondo/status/1439889876468576259

Summary

- I believe the most important takeaway is: **colab**.
- There are very few people in the world who can train something like CLIP, or architect something like StyleGAN3.
- But there are millions of people who can assemble cool stuff from them. They put their creations on https://colab.research.google.com/ and share them on blogs and Twitter.
- And anyone with an internet connection can try these creations, and inspect them, and learn from them.

Colab notebooks

- https://colab.research.google.com/drive/1NCceX2mbiKOSlAd_o7IU7nA9UskKN5WR Big Sleep (BigGAN + CLIP)

- https://colab.research.google.com/github/rinongal/stylegan-nada/blob/main/stylegan_nada.ipynb StyleGAN-Nada (Photo transformation, StyleGAN2-ADA + CLIP)

- https://colab.research.google.com/drive/1fWka_U56NhCegbbrQPt4PWpHPtNRdU49?usp=sharing#scrollTo=RWjzl82Nv7IG CLIP-GLaSS (Various generators + CLIP)

- https://colab.research.google.com/drive/1L8oL-vLJXVcRzCFbPwOoMkPKJ8-aYdPN or https://huggingface.co/spaces/akhaliq/VQGAN_CLIP VQGAN+CLIP

- https://colab.research.google.com/github/dribnet/clipit/blob/master/demos/PixelDrawer.ipynb Pixray PixelArt (CLIPDraw / Pixel generator + CLIP)