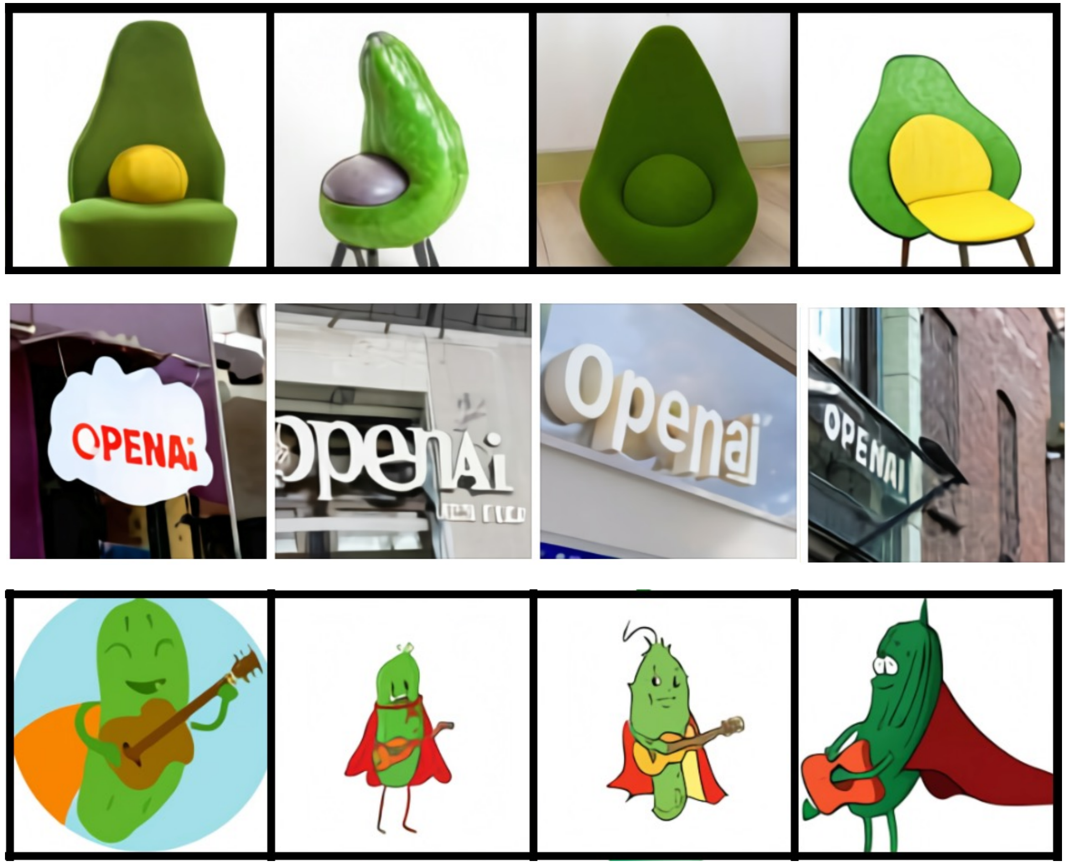
# OpenAI DALL-E

(Zero-shot Text to Image Generation[1])

30 Nov 2022

RIT

# DALL·E's Diverse Capabilities




an armchair in the shape of an avocado. — combining unrelated concepts in plausible ways

a store front that has the word 'openai' written on it — rendering text

an illustration of a baby cucumber in a cape playing a guitar. — creating anthropomorphized versions of animals and objects

**Input Text Prompt**

**Generated Images**

# Text to Image Generation

Input Text Prompt

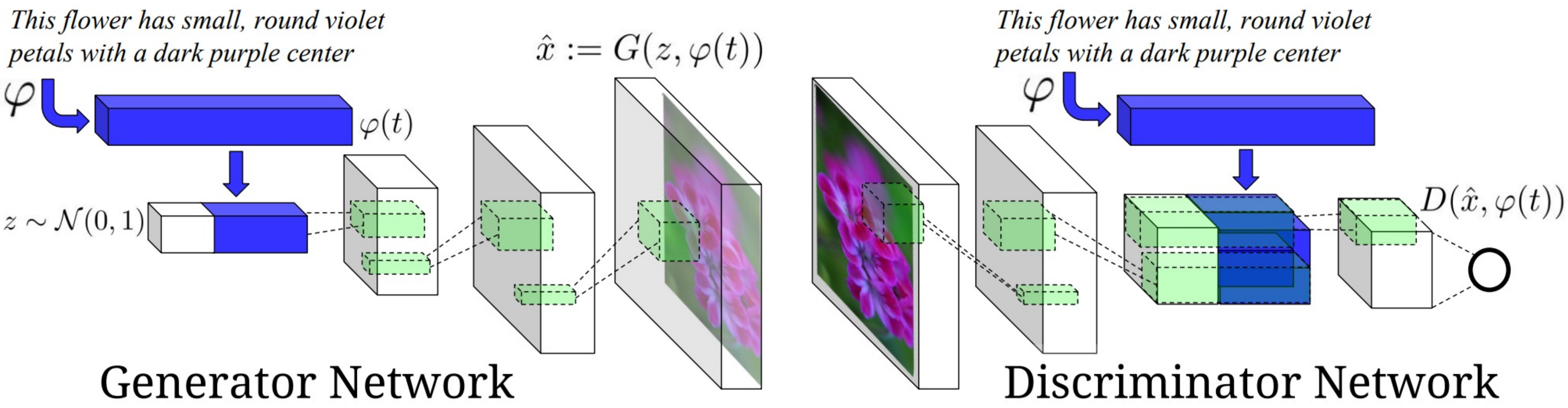
| a group of urinals is near the trees | a crowd of people standing on top of a beach. | a woman and a man standing next to a bush bench. | a bathroom with two sinks, a cabinet and a bathtub. | a man riding a bike down a street past a young man. |
|---|---|---|---|---|

Generated Images

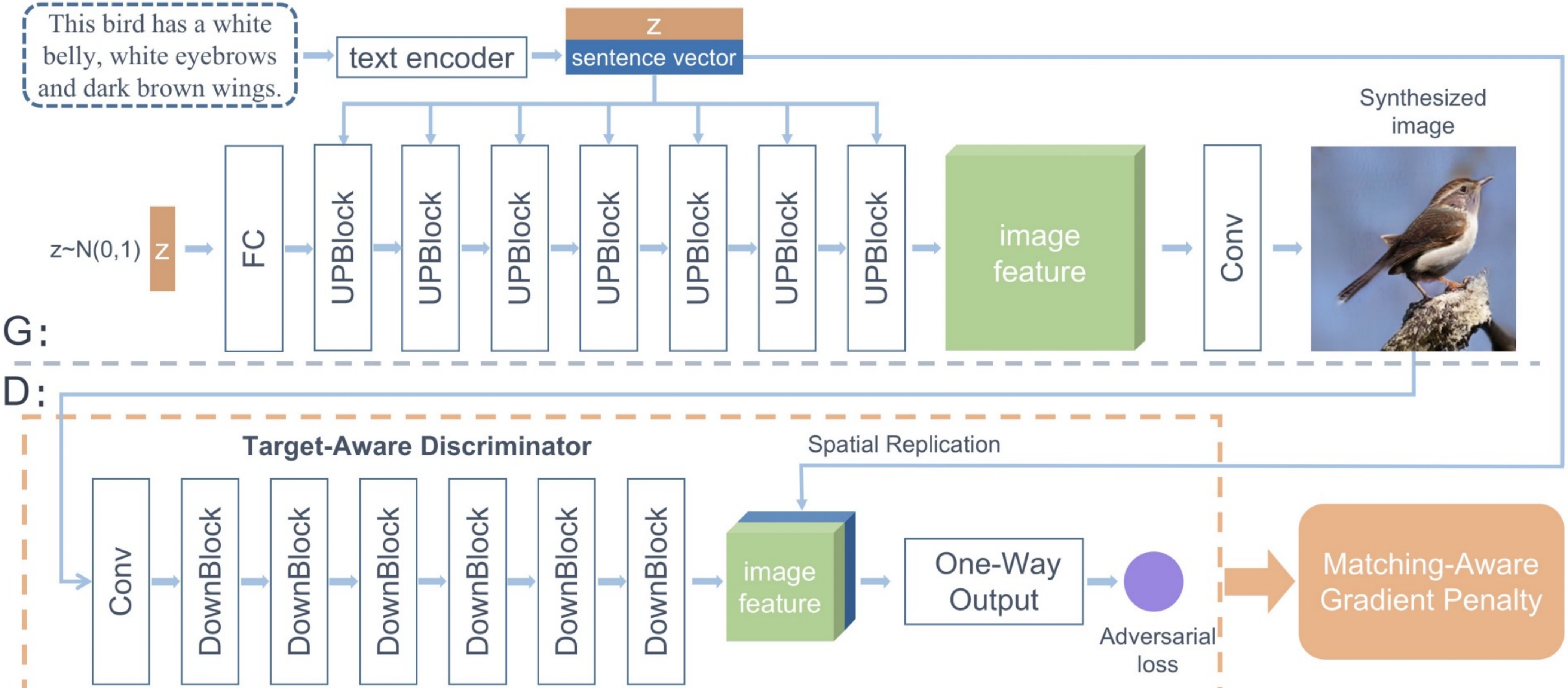
# Related Works: Text to Image Generation

- AlignDRAW (DRAW generative model + condition on image caption)
- GAN based conditional image generation – Reed et. Al.
- StackGAN 2017
- StackGAN++ 2018
- AttentionGAN
- DMGAN
- DFGAN
- TReCS – uses mouse traces

# GAN based Conditional Image Generation[1]



# Deep Fusion GAN (DF-GAN[2])




G: generator network D: discriminator network FC: fully connected layer UPBlock: upsample + residual block + DFBlock DownBlock: downsample + residual block

# DALL·E

Could scaled dataset size and model enhance performance?

with Transformer??

# Technical Details

# DALL·E

- 12B parameter transformer decoder + discrete VAE
- 250M image-text pairs

# Data Collection

- Statistics: 250M image-text pairs

- Sources
  - Google's Conceptual Captions
  - text – image pairs from Wikipedia
  - filtered subset of YFCC100M (obtained from Flicker)

- Data Overlap Test
  - Train a contrastive model
  - Sort and manual inspection for threshold to remove images

# DALL·E Modeling

Joint distribution of text $x$, image $y$ and image tokens $z$,

$$p_{\theta,\psi}(x, y, z) = p_\theta(y|x, z)\ p_\psi(x, z)$$

where,

$p_\theta(y|x, z)$ - likelihood of image $y$ given caption $x$ and image tokens $z$

$p_\psi(x, z)$ - joint distribution over caption $x$ and image tokens $z$.

# DALL·E Modeling

$$
\begin{aligned}
\log p_{\theta,\psi}(y|x) &= \log \int p_{\theta,\psi}(y,z|x)dz. \\
&= \log \int \frac{p_{\theta,\psi}(y,z|x)}{q_\phi(z|y)} q_\phi(z|y)dz \\
&= \log \mathbb{E}_{q_\phi(z|y)}\left[\frac{p_{\theta,\psi}(y,z|x)}{q_\phi(z|y)}\right] \\
&\geq \mathbb{E}_{q_\phi(z|y)}\left[\log \frac{p_\theta(y,z|x)}{q_\phi(z|y)}\right] \\
&= \mathbb{E}_{q_\phi(z|y)}\left[\log \frac{p_\theta(y|z,x)\, p_\psi(z|x)}{q_\phi(z|y)}\right] \\
&= \mathbb{E}_{q_\phi(z|y)}\left[\log p_\theta(y|z,x)\right] + \mathbb{E}_{q_\phi(z|y)}\left[\log \frac{p_\psi(z|x)}{q_\phi(z|y)}\right] \\
&= \mathbb{E}_{q_\phi(z|y)}\left[\log p_\theta(y|z,x)\right] - \mathbb{KL}\Big[q_\phi(z|y) \mid p_\psi(z|x)\Big] \quad \text{Lower Bound}
\end{aligned}
$$

# DALL·E Modeling

$\beta$-VAE

Lower Bound

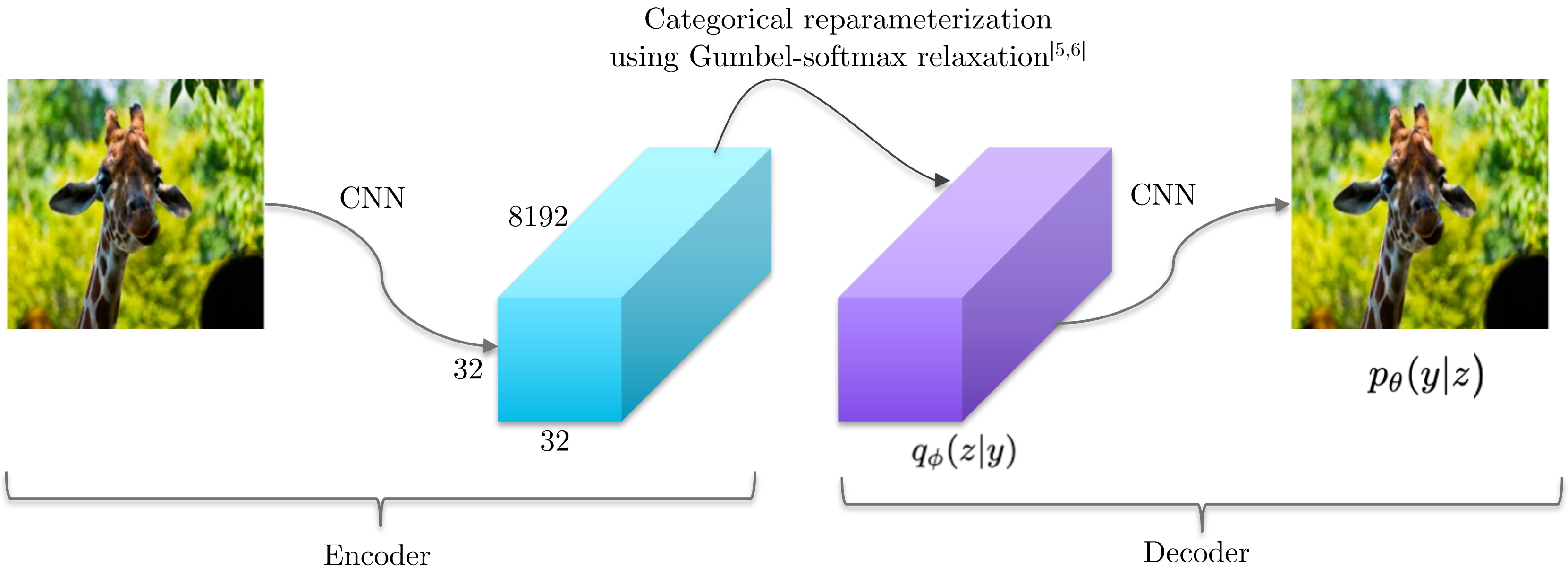
$$\mathcal{L}(\theta, \phi, \psi) = \mathbb{E}_{q_\phi(z|y)} \Big[ \log p_\theta(y|z, x) \Big] - \beta \ \mathbb{KL}\Big[ q_\phi(z|y) \mid p_\psi(z|x) \Big]$$

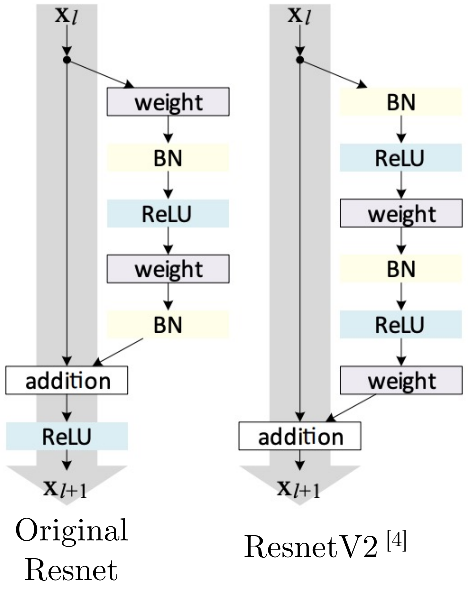
- Stage1:
  - Optimize lower bound w.r.t. $\theta$ and $\phi$
  - trains discrete VAE (dVAE) to learn image encoding

- Stage 2:
  - Optimize lower bound w.r.t. $\psi$
  - trains transformer to model conditional distribution of image tokens given text

# DALL·E Stage 1 - dVAE

- Encoder Output
  - Final embedding - 32 x 32 x 8192
  - ResnetV2 structure (improved over original Resnet)
- Decoder
  - Decoder block: ResnetV2 block + Nearest Neighbor upsampling



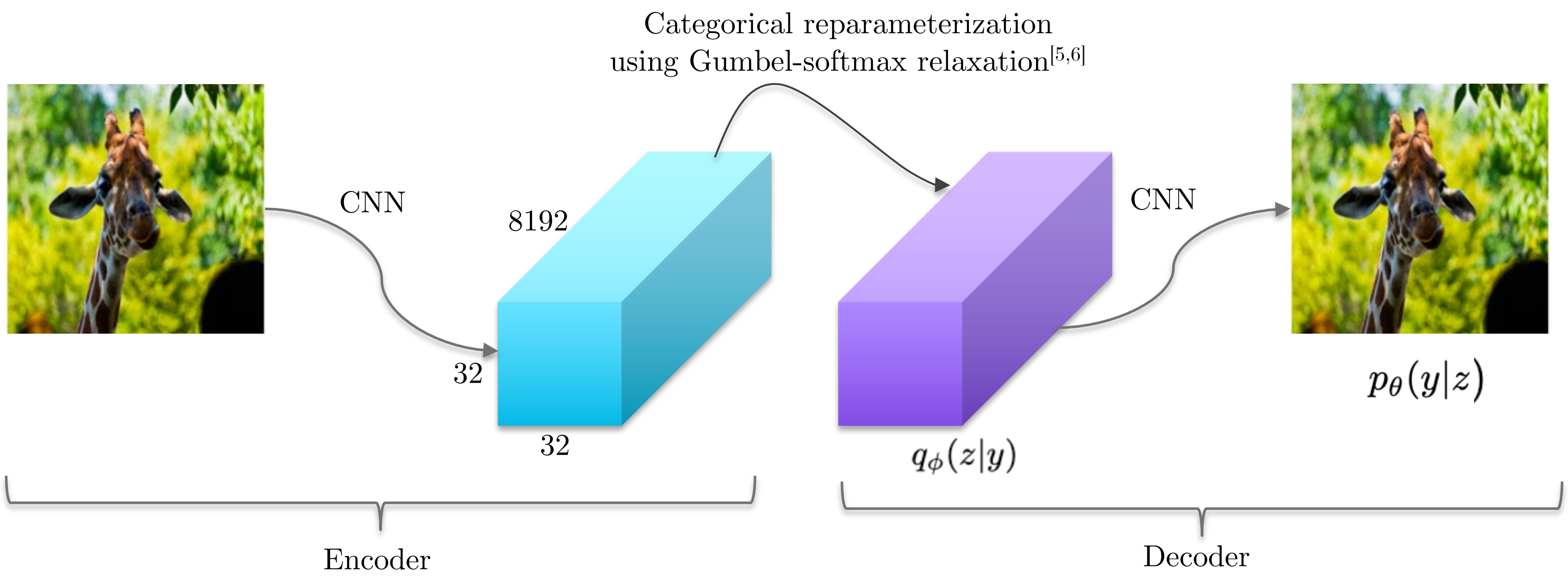



# DALL·E Stage 1 - dVAE

$$\hat{\theta}, \hat{\phi} = \underset{\theta,\phi}{\operatorname{argmax}} \; \mathcal{L}(\theta, \phi, \psi) = \mathbb{E}_{q_\phi(z|y)} \left[ \log p_\theta(y|z, x) \right] - \beta \, \mathbb{KL}\left[ q_\phi(z|y) \mid p_\psi(z|x) \right]$$

- $p_\psi(z|x)$ – uniform distribution over the K $=$ 8192 codebook vectors
- $q_\phi(z|y)$ – categorical distribution for each spatial position in 32 x 32 grid output by encoder
- $p_\theta(y|z, x)$ – evaluated using *logit-Laplace distribution*

$$f(x \mid \mu, b) = \frac{1}{2bx(1-x)} \exp\left( -\frac{|\operatorname{logit}(x) - \mu|}{b} \right)$$



# DALL·E Stage 2

$$\hat{\psi} = \underset{\psi}{\operatorname{argmax}}\ \mathcal{L}(\hat{\theta}, \hat{\phi}, \psi) = \mathbb{E}_{q_{\hat{\phi}}(z|y)}\left[\log p_{\hat{\theta}}(y|x,z)\right] - \beta\, \mathbb{KL}\left[q_{\hat{\phi}}(z|y) \mid p_{\psi}(z|x)\right]$$

- Learn prior distribution over text and image tokens
  - Text – 256 tokens (vocabulary size = 16384)
  - Image – 32 x 32 = 1024 tokens (codebook size = 8192)
- Model Architecture
  - autoregressive sparse transformer decoder (64 self-attention layers)

$$p_{\psi}(x, z) = \prod_m p_{\psi}(x_m | x_{<m}) \prod_i p_{\psi}(z_i | z_{<i}, x_i)$$

  - Masking
    - text-2-image attention – no mask
    - text-2-text attention – casual
    - image-2-image attention – row, column or convolutional attention masks
- Loss
  - Categorical cross entropy (weighted averaging for text (1/8) and image (7/8) – emphasize image modeling)

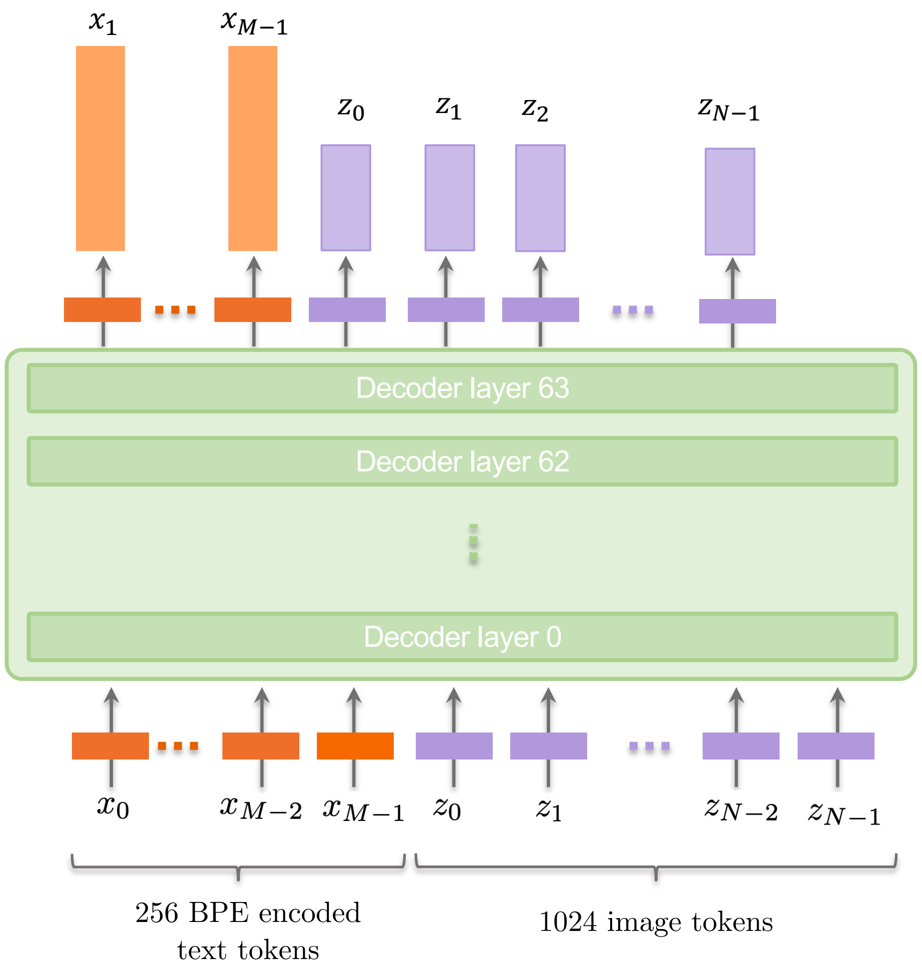
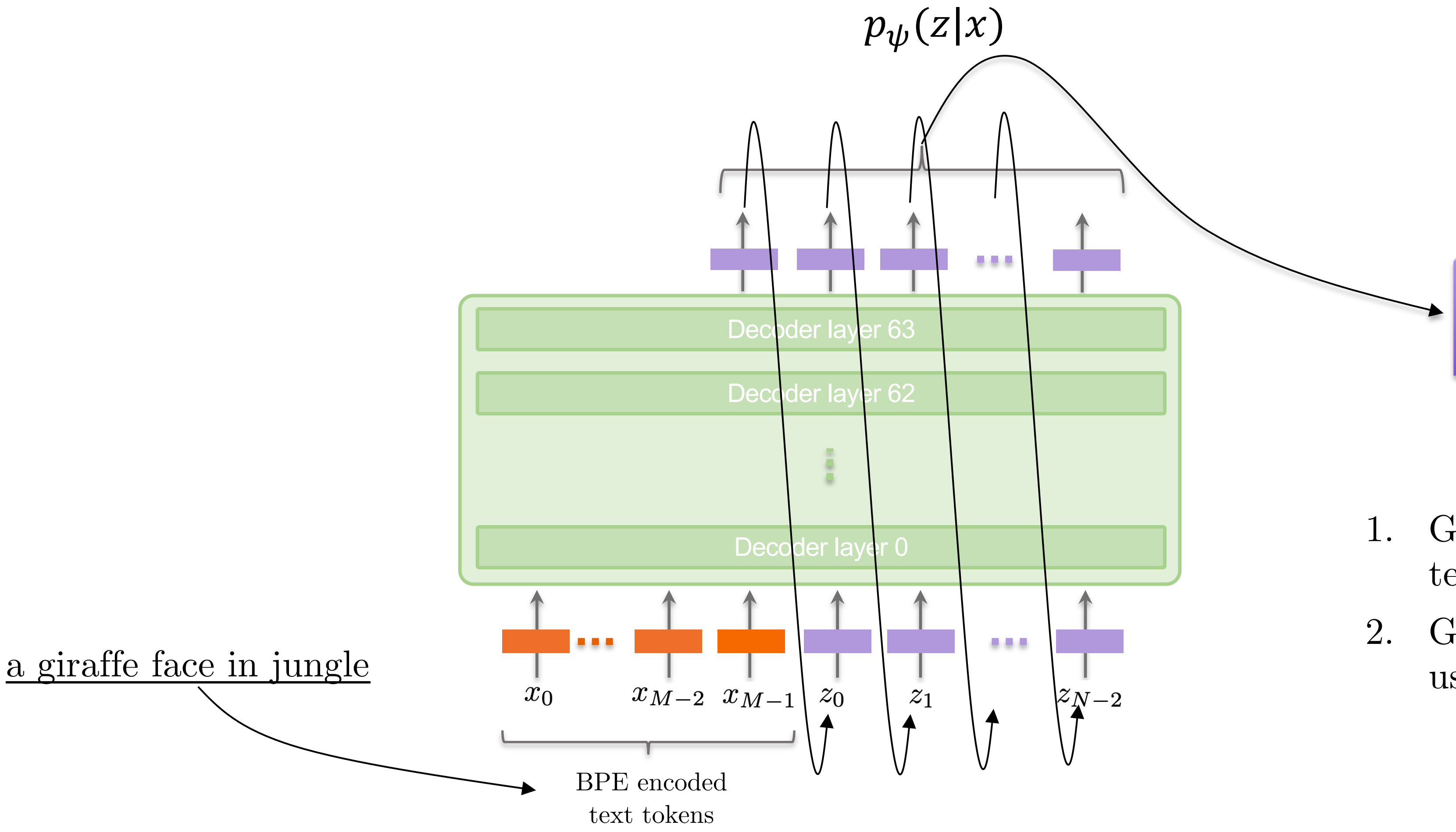
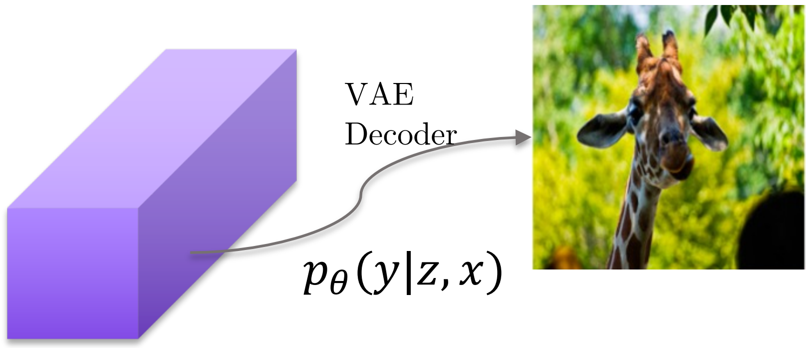



Fig: DALL-E Transformer

# Sample Generation Process




1. Generate image tokens by conditioning on text tokens using transformer
2. Generate image pixels from image tokens using VAE decoder

# Sample Evaluation

- Re-rank generated samples using a pretrained CLIP model

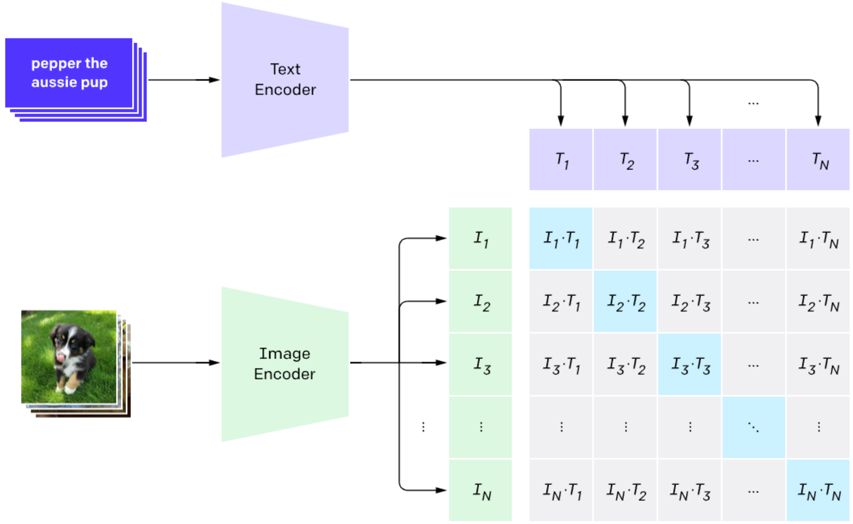



Fig: CLIP model[9]

# Evaluation

# Comparison

- DALL-E
- DF-GAN
- DM-GAN
- AttnGAN

# DALL-E v/s DFGAN Human Evaluation

- 5 independent human annotators (Amazon Mechanical Turk)

**Task:** Evaluate the two images and answer the questions below.

Image 1


Image 2

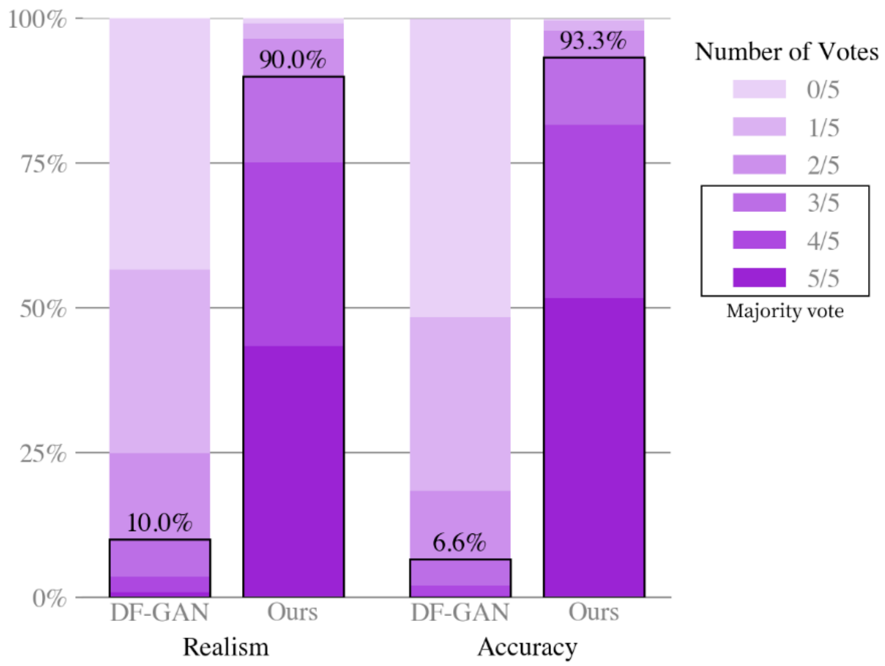
Which image is more realistic?

○ Image 1 is more realistic ○ Image 2 is more realistic

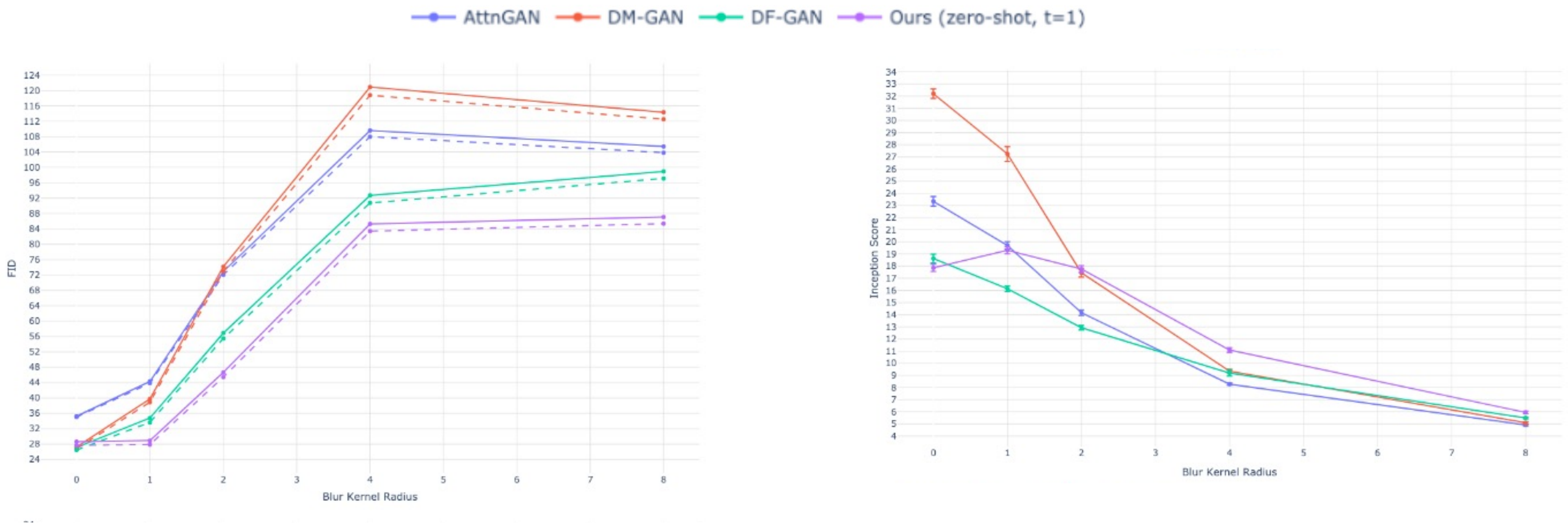
Which image matches with this caption better? **Caption:** "a man walks across a street with a stop sign in the foreground."

○ Image 1 matches better ○ Image 2 matches better ○ Neither 1 nor 2 match

**Submit**



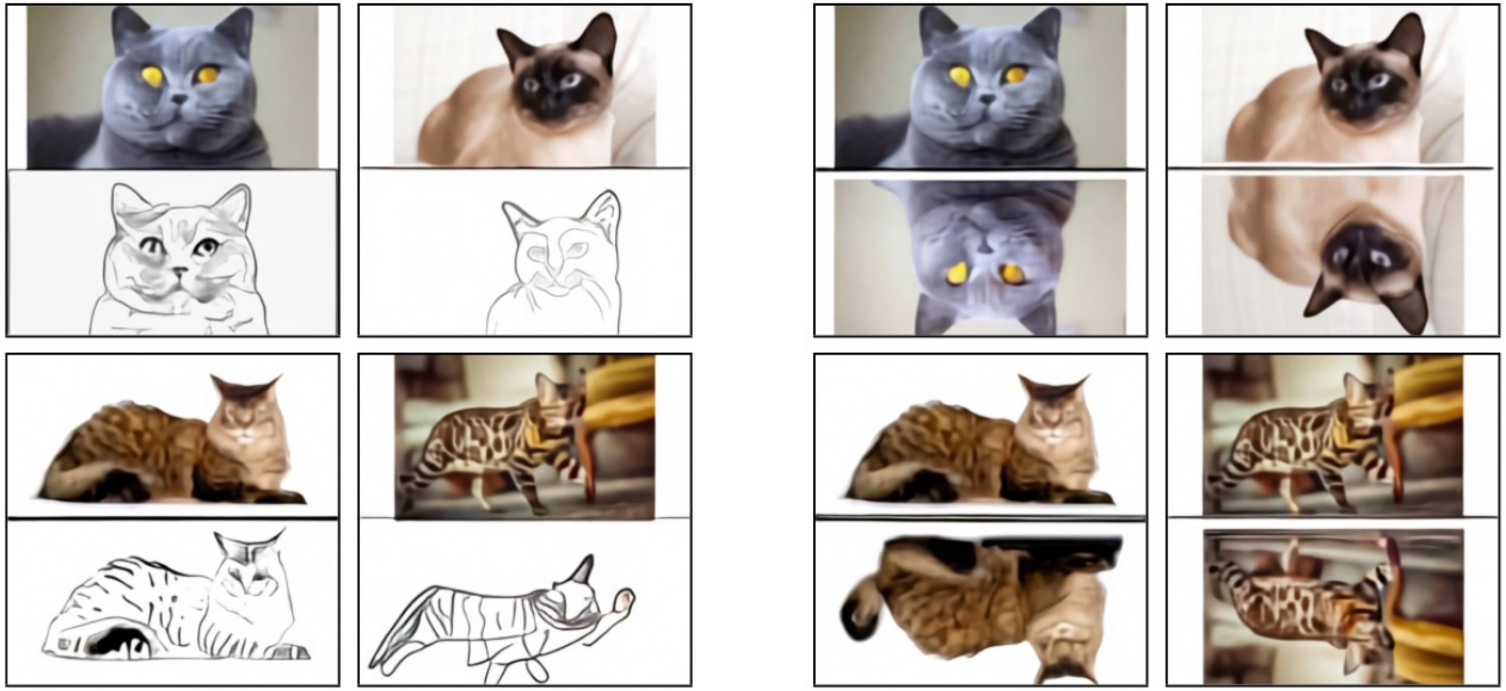
# DALL-E v/s DFGAN Comparison




(a) FID and IS on MS-COCO as a function of blur radius.

# Zero Shot Image to Image Translation

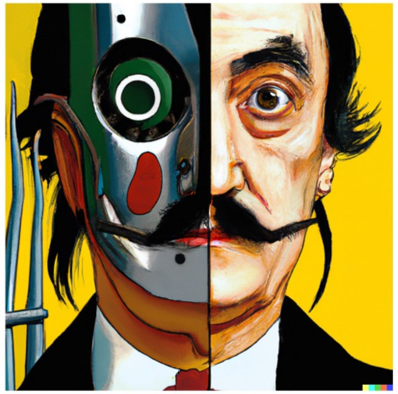
- Unanticipated and no explicit modification in training
- Emerged during test



(a) "the exact same cat on the top as a sketch on the bottom"

(b) "the exact same photo on the top reflected upside-down on the bottom"

# Recent Works



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

DALL-E 2[8] (OpenAI)

Make-A-Video[7] (meta)

# Thank you!

# References

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