Illustrative Session on Image Generative Models with Dall.E Mini

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Dall.E Mini — Text to Image

[Live Online Version of Dall.E Mini]

Part 1: Building Blocks of Dall.E Mini

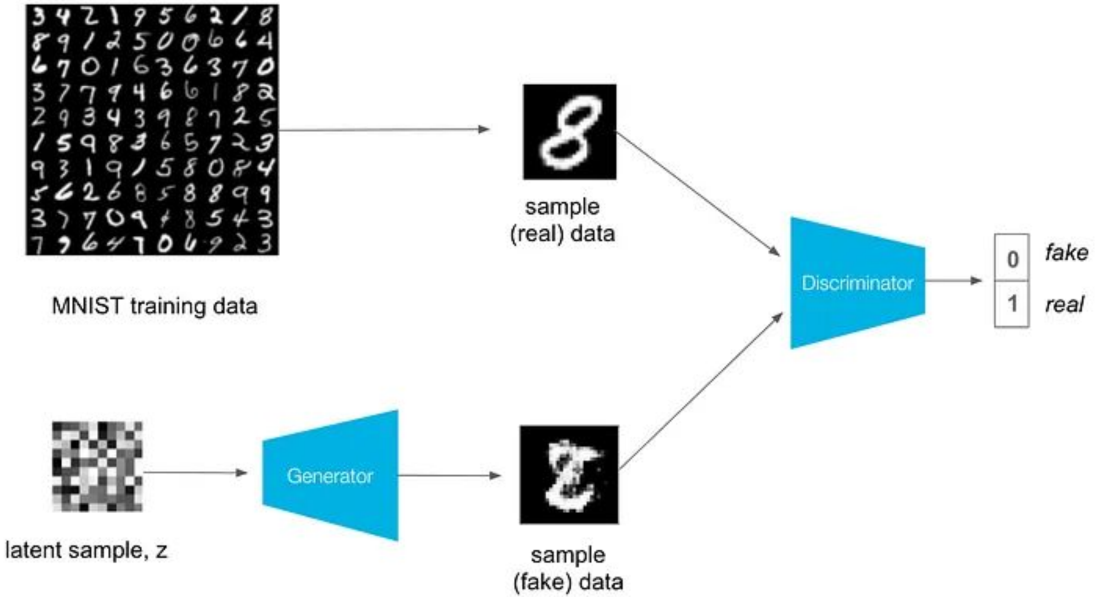
- **BART-based Encoder-Decoder**: Encodes captions as embedding vectors
- **VQ-GAN**: Decodes caption embeddings into Images
- **CLIP**: Evaluates caption-image relevance

Part 2: Generative Adversarial Networks (GANs)

- Dall.E Mini uses a variant of GANs called **VQ-GANs**.
- The evolution of VQ-GANs,
    - Vanilla GAN
    - **Autoencoders** (AEs)
    - **Variational** Autoencoders (VAEs)
    - **Vector Quantized** Autoencoders (VQ-AEs)
    - Vector Quantized **GAN**s (VQ-GANs)

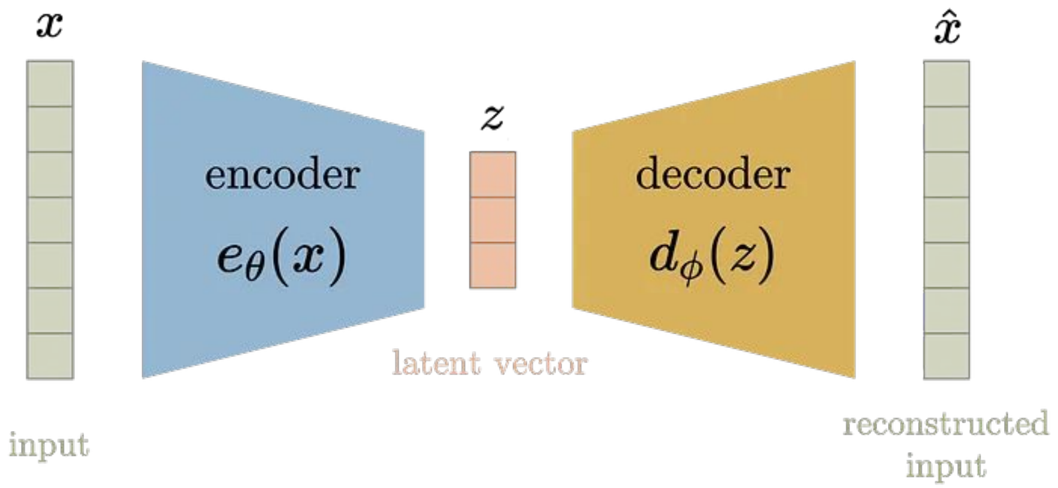
Python Code Demo

Vanilla GAN



Python Code Demo

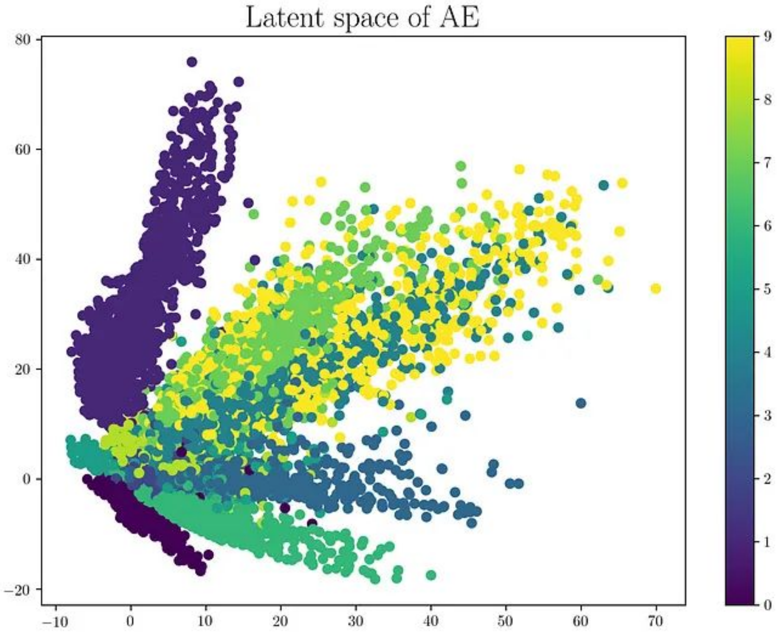
Autoencoder (AE)



$$loss = \|x - \hat{x}\|_2 = \|x - d_\phi(z)\|_2 = \|x - d_\phi(e_\theta(x))\|_2$$

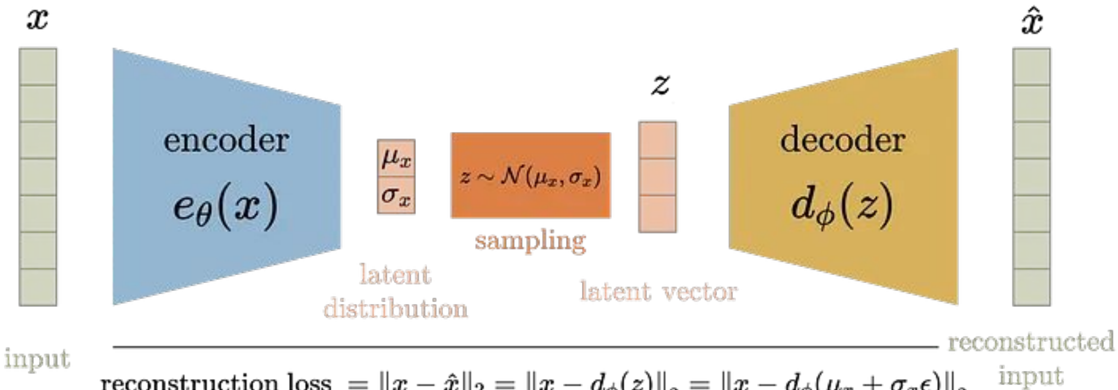
- The latent space is discontinuous and has significant “gaps”.

Autoencoder (AE)



Python Code Demo

Variational Autoencoder (VAE)



$$\text{reconstruction loss} = \|x - \hat{x}\|_2 = \|x - d_\phi(z)\|_2 = \|x - d_\phi(\mu_x + \sigma_x \epsilon)\|_2$$

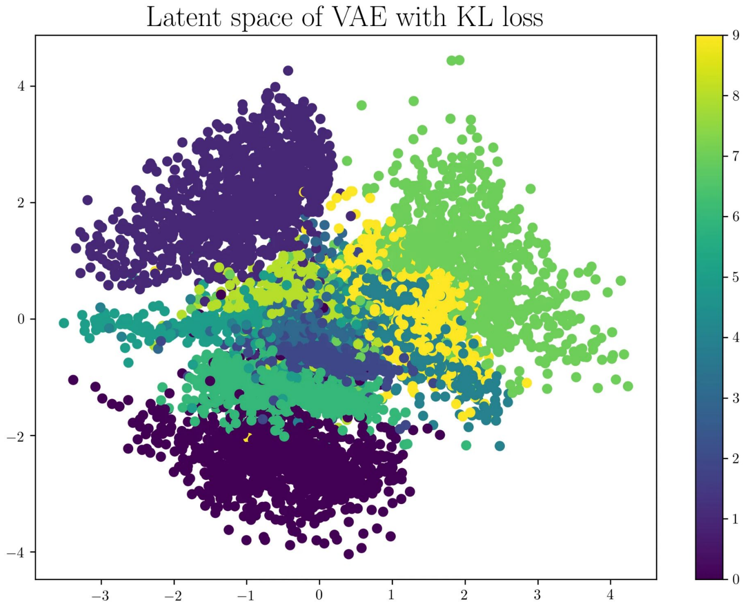
$$\mu_x, \sigma_x = e_\theta(x), \quad \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

$$similarity\ loss = KL\ Divergence = D_{KL}(\mathcal{N}(\mu_x, \sigma_x) \parallel \mathcal{N}(\mathbf{0}, \mathbf{I}))$$

$$loss = reconstruction\ loss + similarity\ loss$$

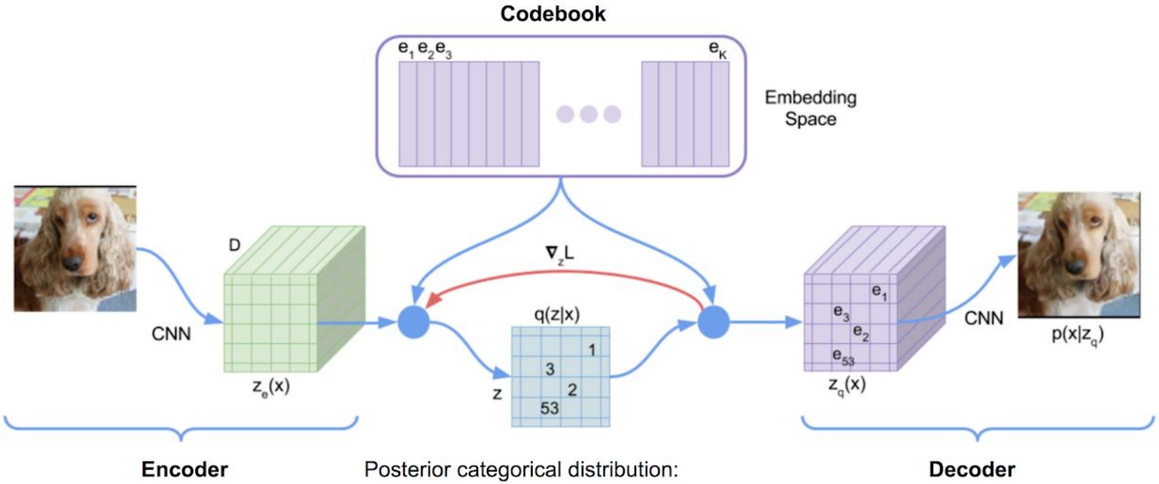
- The latent space is more cohesive — resembles the unit norm.
- Overlapping regions produce “morphed” images.

Variational Autoencoder (VAE)



Python Code Demo

Vector-Quantized Variational Autoencoder (VQ-VAE)



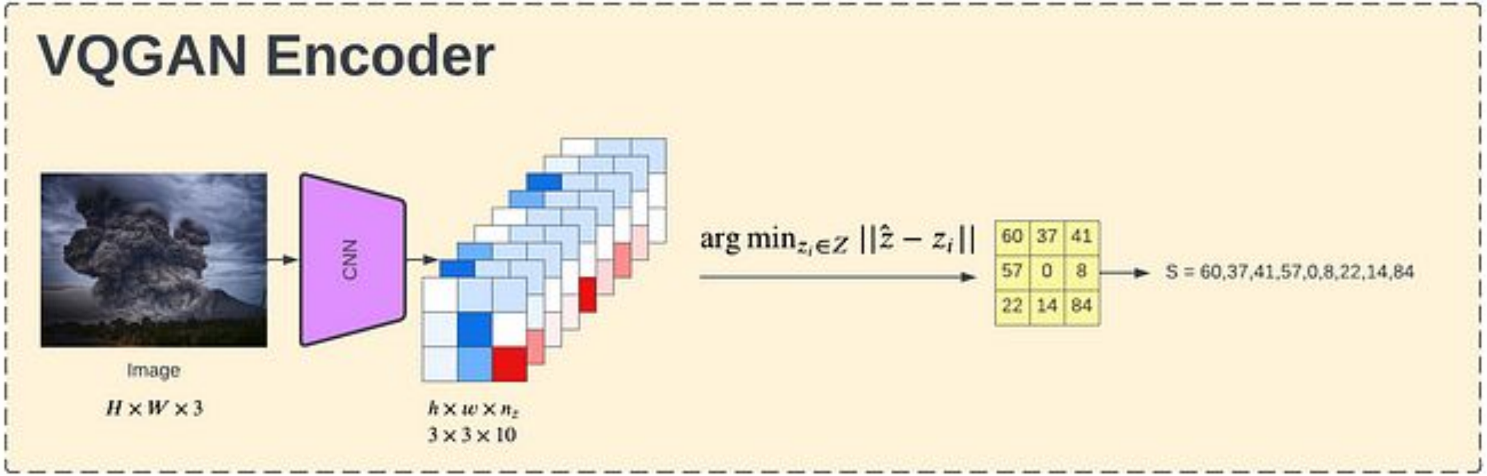
Posterior categorical distribution:

$$q(\mathbf{z} = \mathbf{e}_k|\mathbf{x}) = \begin{cases} 1 & \text{if } k = \arg\min_j \|\mathbf{z}_e(\mathbf{x}) - \mathbf{e}_j\|_2 \\ 0 & \text{otherwise.} \end{cases}$$

- The latent space is discrete.
- No “morphed” outputs.
- Latent space has same dimensions as codebook.

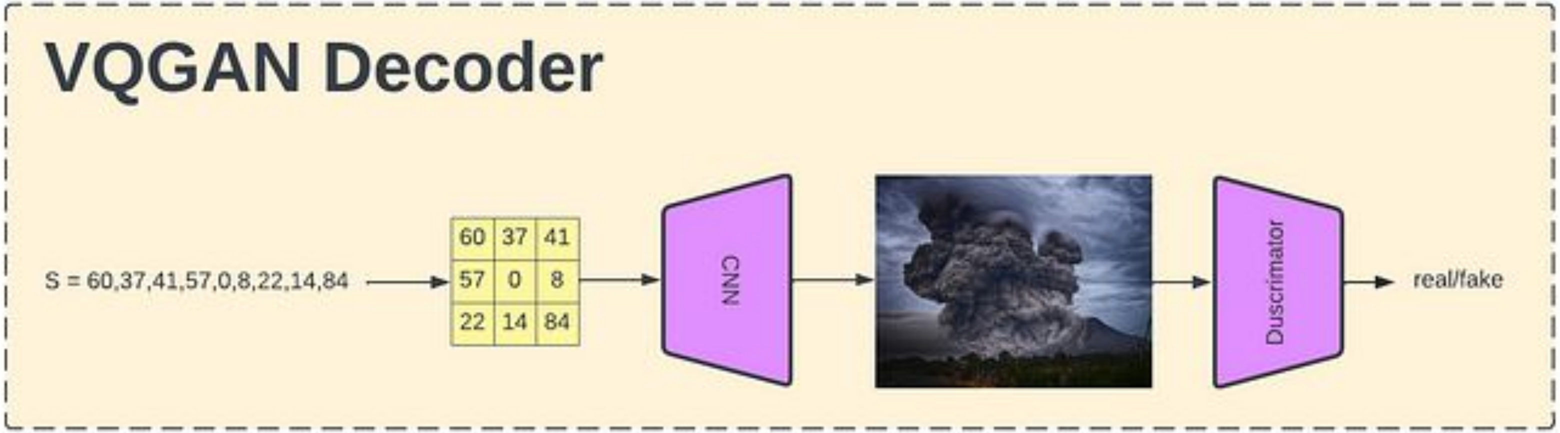
Python Code Demo

Vector-Quantized Variational GAN (VQ-GAN)



Python Code Demo

Vector-Quantized Variational GAN (VQ-GAN)

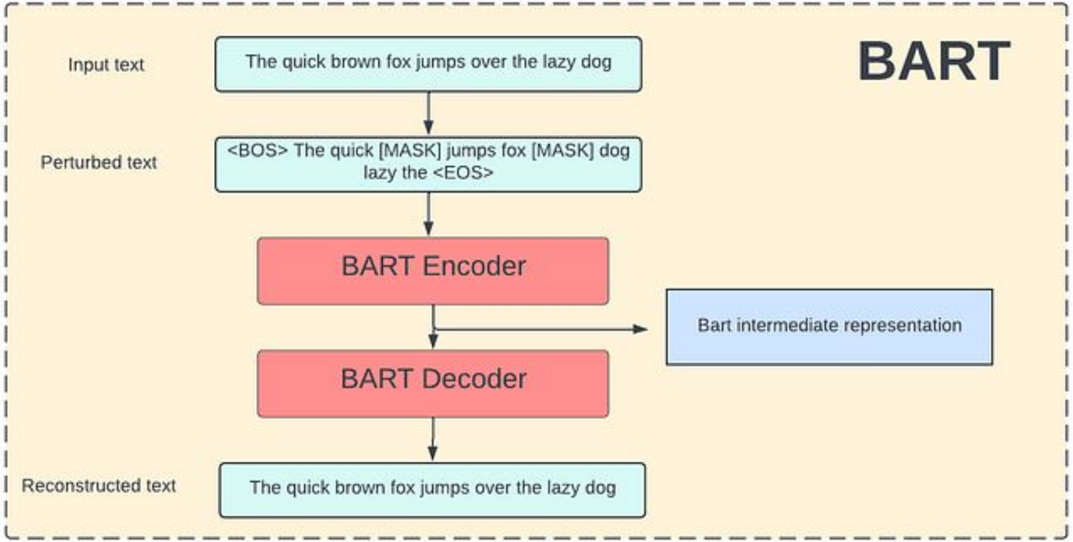


Part 3: BART Encoder-Decoder

- A BART model is pre-trained to “clean” text captions.
- For Dall.E Mini, the BART model **translates captions into the codebook vocabulary**.
- The codebook of VQ-GAN, in effect, maps text embeddings to image embeddings.

Python Code Demo

What BART does for Dall.E.



- Translates captions to codebook vocabulary.

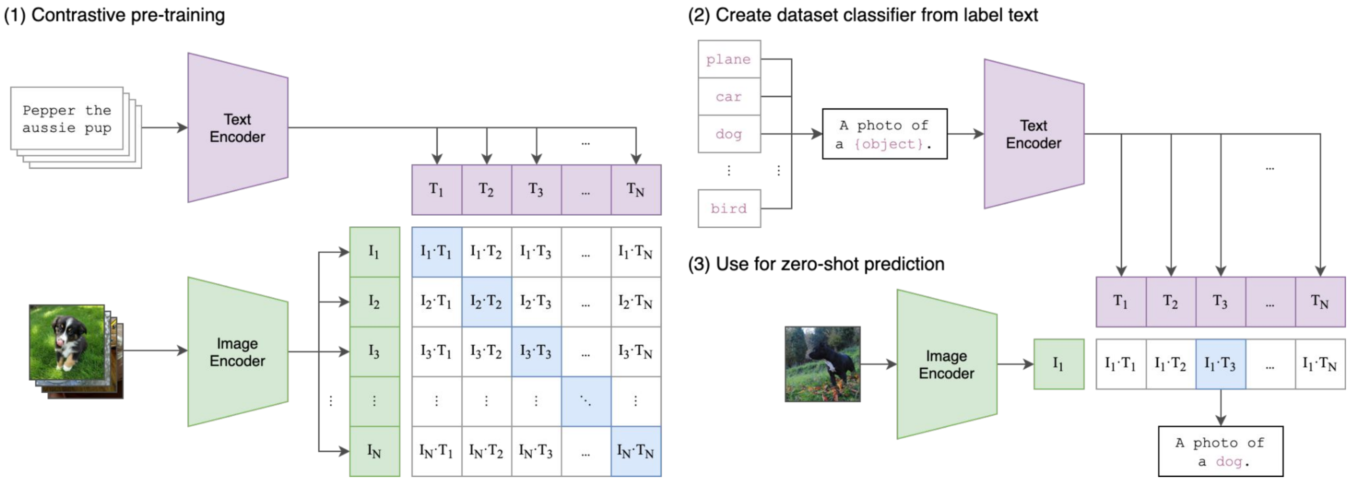
Part 4: CLIP to Rank Images by Relevance

Python Code Demo

- CLIP is a neural network trained on a variety of (image, text) pairs
- It can be instructed in natural language to predict the most relevant text snippet, given an image (and vice versa), without directly optimizing for the task
- CLIP is thus similar to the zero-shot capabilities of GPT-2 and 3
- CLIP matches the performance of the original ResNet50 on ImageNet “zero-shot” without using any of the original 1.28M labeled examples

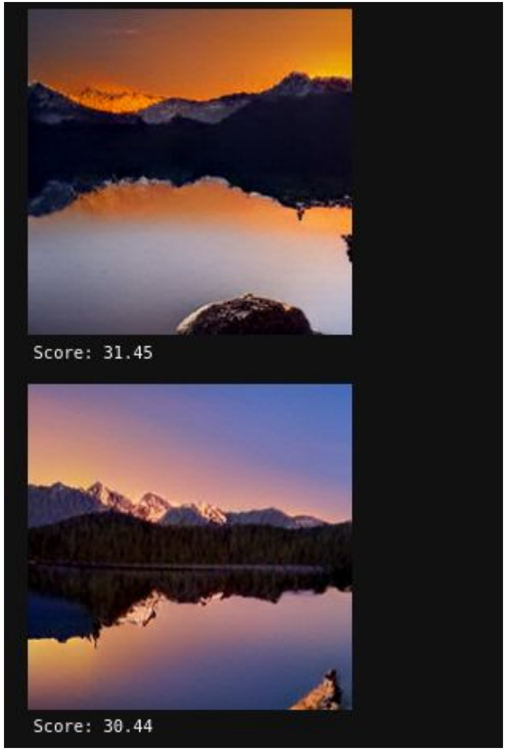
CLIP Architecture

Python Code Demo

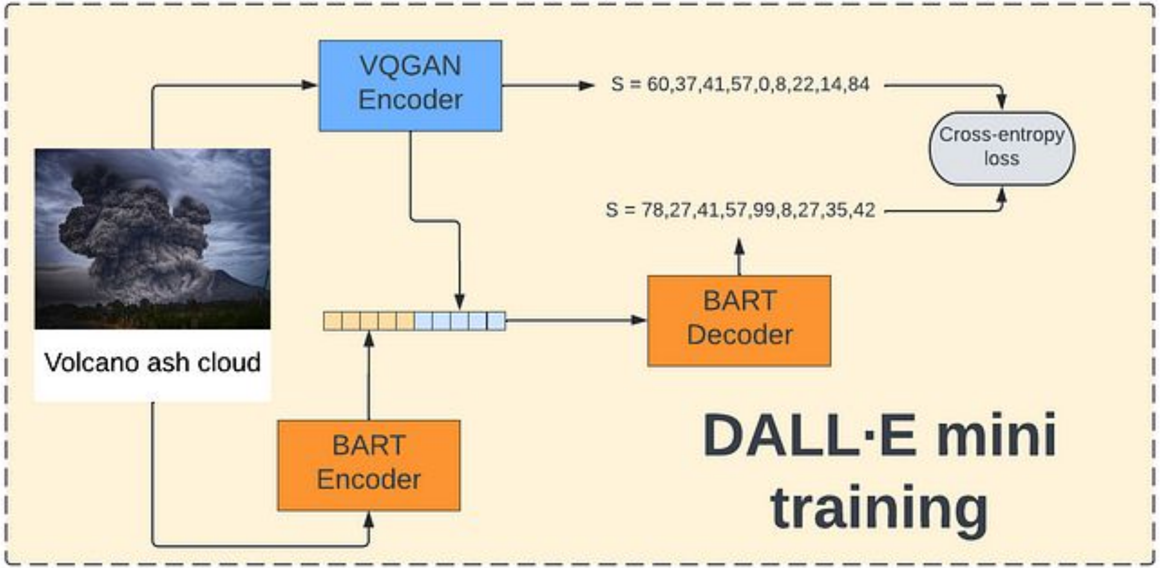


Contrastive pre-training is a type of self-supervised learning technique to learn representations of data that are useful for downstream tasks, such as image classification or natural language processing.

Relevance Scores

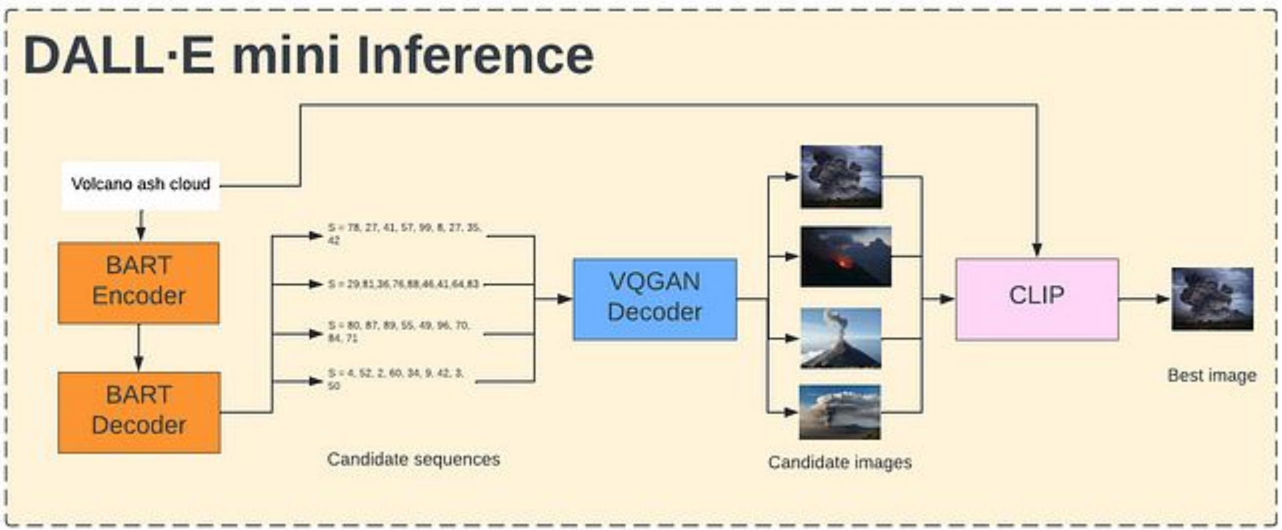


Part 5: Piecing the blocks together.



Python Code Demo

The Dall.E Mini Text-to-Image Pipeline.



Thank you for listening!

Questions?

Examples of Generated Images

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