

Deep Generative Models

Lecture 14

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Recap of Previous Lecture

Outline

1. Latent Space Models

Score-Based Models

Autoregressive Models

2. The Worst Course Overview

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Outline

1. Latent Space Models

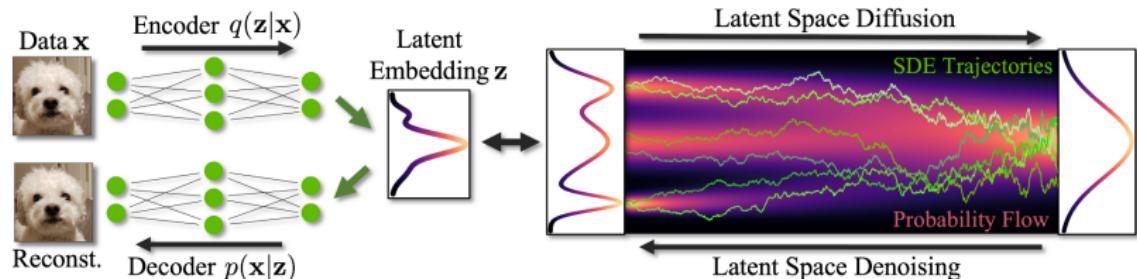
Score-Based Models

Autoregressive Models

2. The Worst Course Overview

Latent Space Models

Score-Based Models (Diffusion)

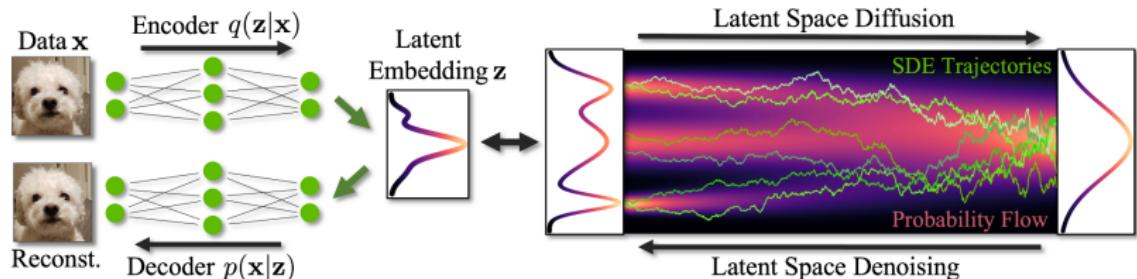


Dao Q. et al. *Flow Matching in Latent Space*, 2023

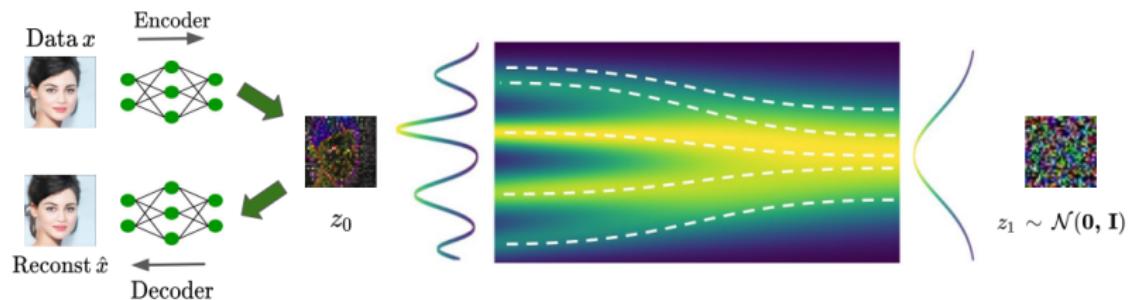
NeurIPS 2023 Tutorial: Latent Diffusion Models: Is the Generative AI Revolution Happening in Latent Space?

Latent Space Models

Score-Based Models (Diffusion)



Flow Matching



Dao Q. et al. *Flow Matching in Latent Space*, 2023

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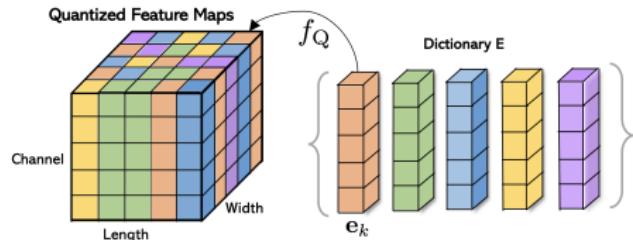
2. The Worst Course Overview

Vector Quantized VAE (VQ-VAE)

Define a dictionary space $\{\mathbf{e}_k\}_{k=1}^K$, where $\mathbf{e}_k \in \mathbb{R}^C$ and K is the dictionary's size.

$$\mathbf{z}_q = \mathbf{q}(\mathbf{z}) = \mathbf{e}_{k^*}$$

$$\text{Here } k^* = \arg \min_k \|\mathbf{z} - \mathbf{e}_k\|.$$

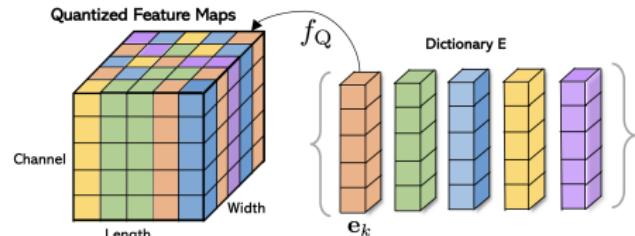


Vector Quantized VAE (VQ-VAE)

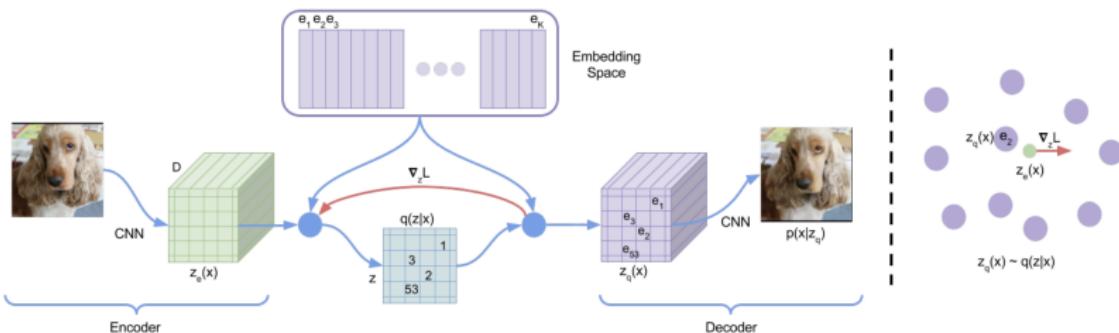
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$$\mathcal{L}_{\phi, \theta}(\mathbf{x}) = \log p_{\theta}(\mathbf{x} | \mathbf{z}_q) - \log K$$

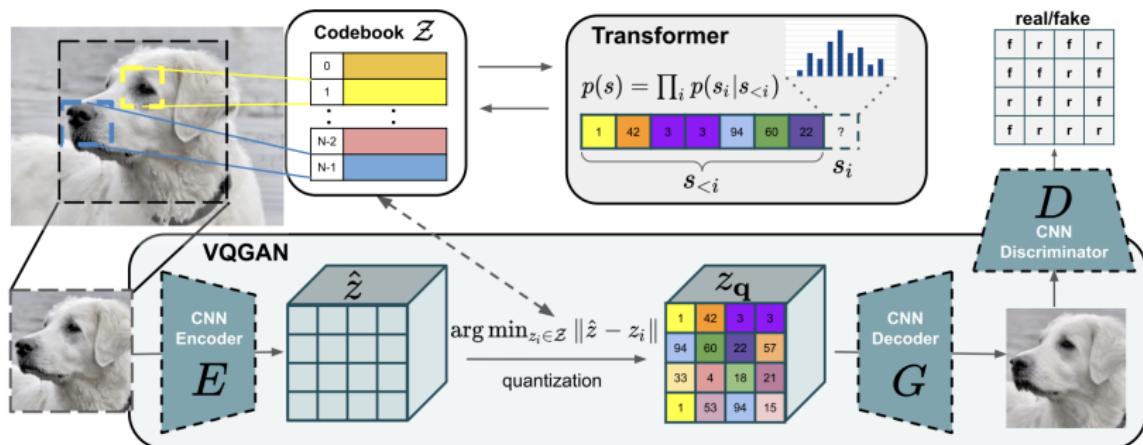


Zhao Y. et al. Feature Quantization Improves GAN Training, 2020

Oord A., Vinyals O., Kavukcuoglu K. Neural Discrete Representation Learning, 2017

Vector Quantized GAN

- ▶ We use a VQ-VAE model and its objective.
- ▶ We add an adversarial loss between generated and real images to further improve the visual quality of reconstructions.

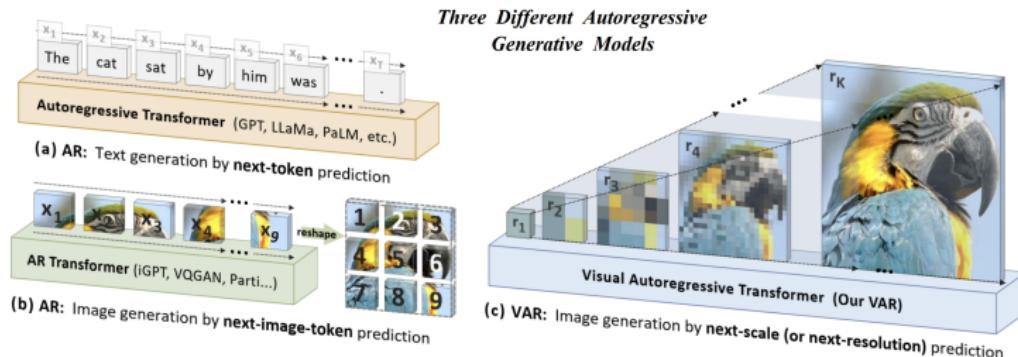


LlamaGen: Pure Autoregression

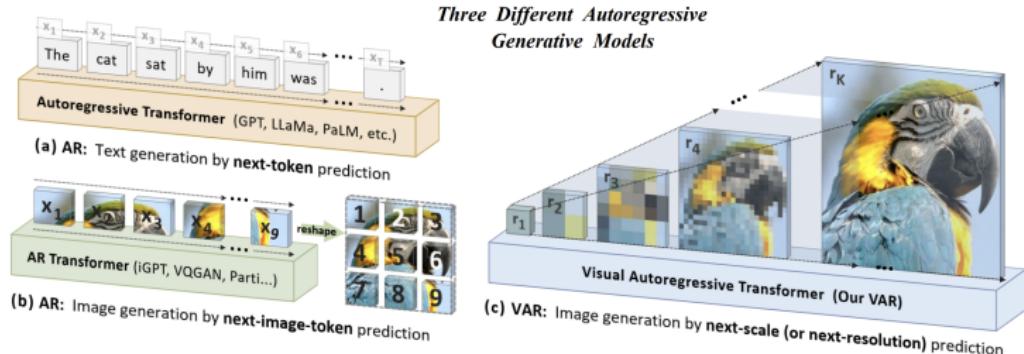
- ▶ Use a VQ-GAN encoder for mapping images into the discrete latent space (codebook vectors).
- ▶ Train a pure autoregressive model (Llama-based) in the latent space.
- ▶ Use the VQ-GAN decoder to map discrete tokens back to image space.



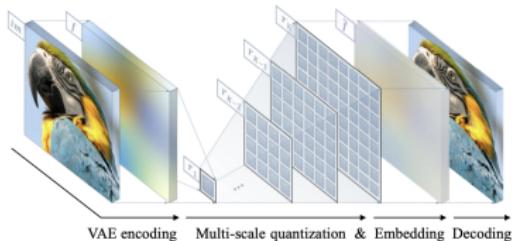
Visual Autoregressive Modeling (VAR)



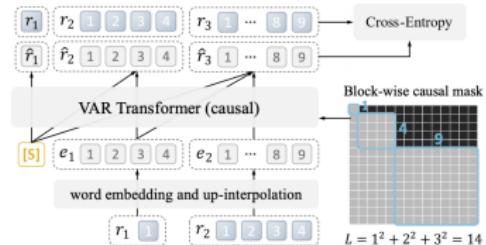
Visual Autoregressive Modeling (VAR)



Stage 1: Training multi-scale VQVAE on images
(to provide the ground truth for training Stage 2)



Stage 2: Training VAR transformer on tokens
($\$$ means a start token with condition information)



Outline

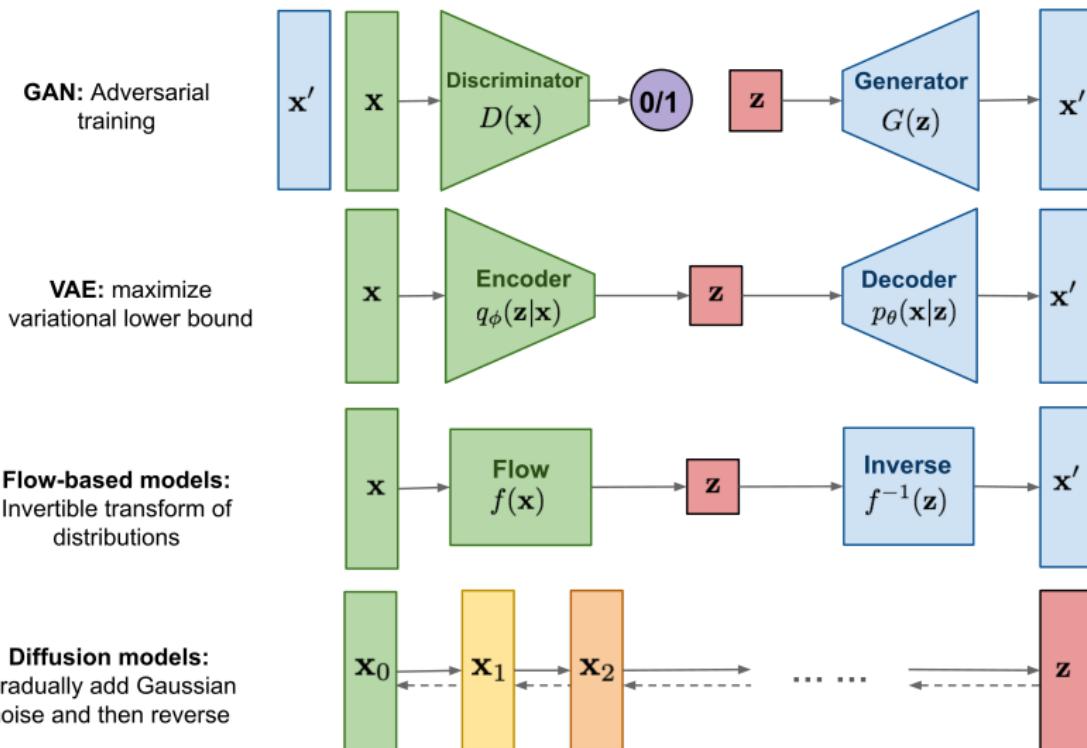
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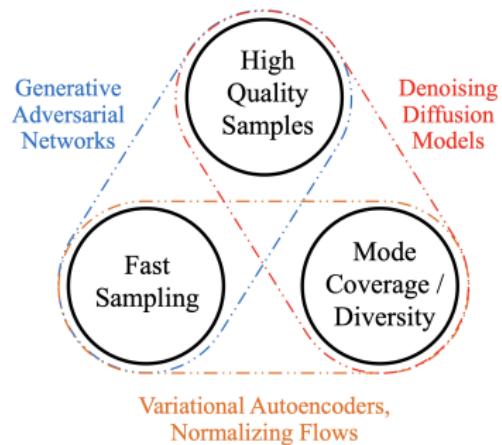
Autoregressive Models

2. The Worst Course Overview

The Worst Course Overview :)



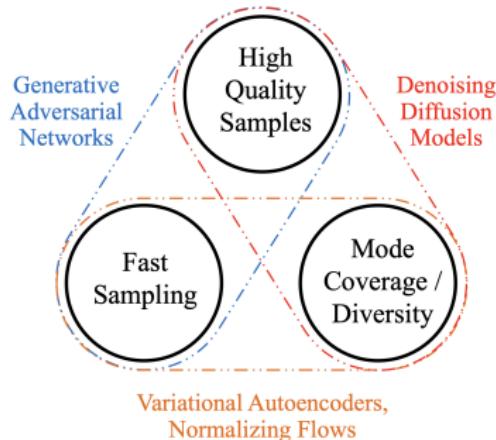
The Worst Course Overview :)



Xiao Z., Kreis K., Vahdat A. *Tackling the generative learning trilemma with denoising diffusion GANs*, 2021

Simon J.D. Prince. *Understanding Deep Learning*, 2023

The Worst Course Overview :)



Model	Efficient	Sample quality	Coverage	Well-behaved latent space	Disentangled latent space	Efficient likelihood
GANs	✓	✓	✗	✓	?	n/a
VAEs	✓	✗	?	✓	?	✗
Flows	✓	✗	?	✓	?	✓
Diffusion	✗	✓	?	✗	✗	✗

Xiao Z., Kreis K., Vahdat A. *Tackling the generative learning trilemma with denoising diffusion GANs*, 2021

Simon J.D. Prince. *Understanding Deep Learning*, 2023

Summary

- ▶ Most state-of-the-art generative models are latent variable models with either continuous or discrete latent spaces.