Vector Quantized-VAE

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Introduction

- Vector Quantized-VAE (VQ-VAE)
- Encoder outputs quantized rather than continuous codes
- Prior is learnt rather than static

Goal

- Achieve a model that conserves the important features of the data in its latent space while optimizing for maximum likelihood

Approach

- Vector Quantization

$$q(z=k|x)=\begin{cases}1 & \text{for } \mathrm{k}=\operatorname{argmin}_j \|z_e(x)-e_j\|_2, \\ 0 & \text{otherwise}\end{cases},$$

$$z_q(x)=e_k, \text{where } k=argmin_j \left|\left|z_e(x)-e_j\right|\right|_2$$

Commitment Loss

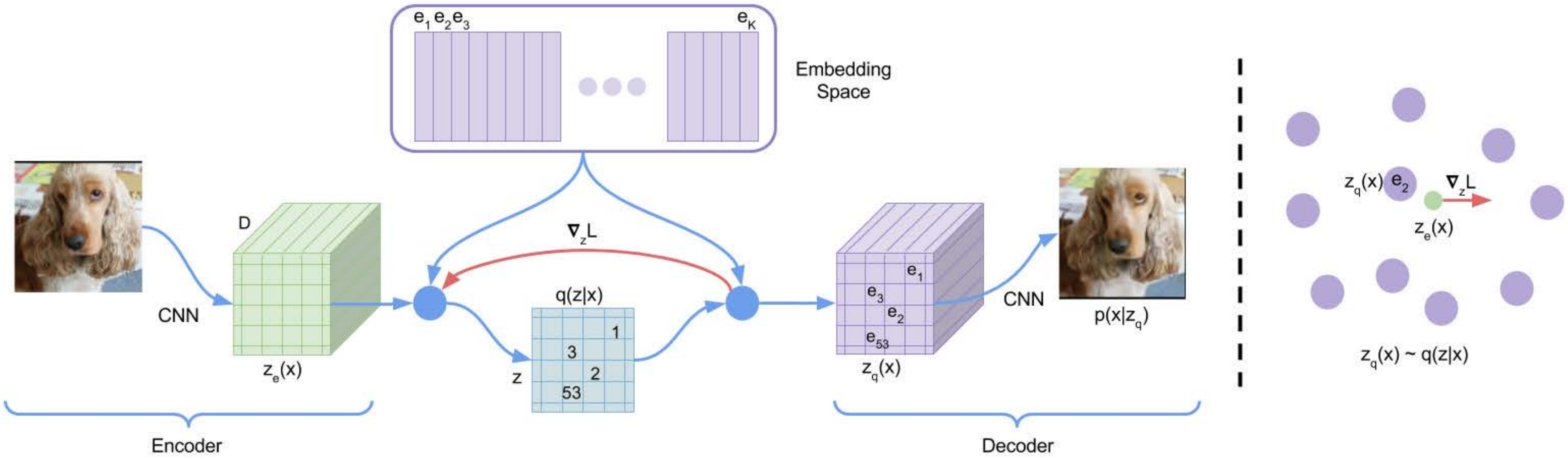
- Objective

$$L=\boxed{\log p\left(x\middle|z_q(x)\right)}+\boxed{\left|\left|sg[z_e(x)]-e\right|\right|_2^2}+\boxed{\beta\left|\left|z_e(x)-sg[e]\right|\right|_2^2}$$

Reconstruction Loss

VQ Objective

Model Architecture



Advantage of model

- Simple to train
- Circumvent *Posterior Collapse*
- Low variance

Experiments: Reconstruction

Experiments: Sampling