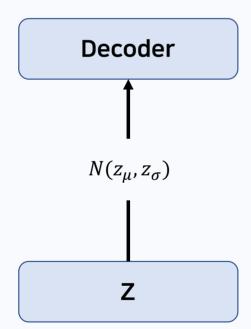
VQ-VAE (Neural Discrete Representation Learning)

https://arxiv.org/abs/1711.00937

Introduction

VAE (Variational AutoEncoder)

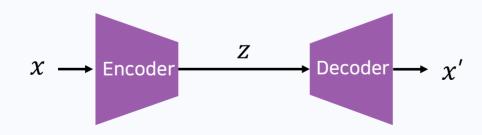


$$\log p(x) = \int \log p(x|z) \, p(z) dz$$

$$\log p(x) \ge \int \underbrace{\log p(x|z) \, q(z|x) dz - D_{kl} \, (q(z|x)) |N(0,1))}_{\text{Reconstruction term}}$$

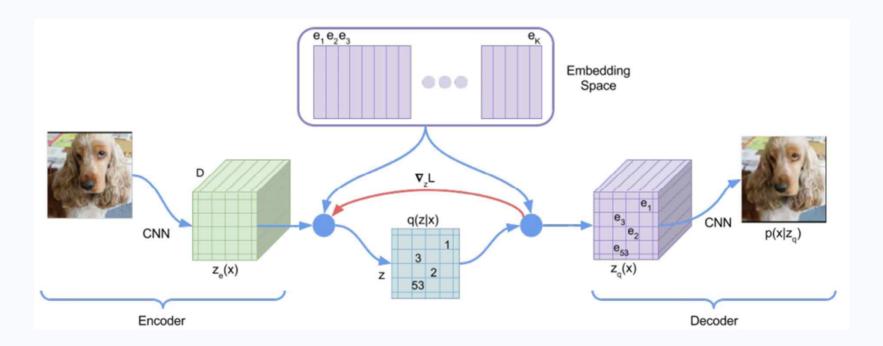
Introduction

- 왜 VQ(Vector Quantized) 이어야 하는가?
 - ✓ 현실 세계에 적합한 모델링 방법
 - 음성의 언어적 정보
 - 이미지 역시 Discrete한 표현으로 표현이 가능함
 - ✓ Posterior collapse 를 방지함.



Methodology

• 모델의 구조



Methodology

- 모델의 구조
 - ✓ Encoder
 - 입력된 x로부터 $z_e(x)$ 를 생성함.
 - ✓ Embedding Space

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

$$z_q(x) = e_k, \quad \text{where} \quad k = \mathrm{argmin}_j \|z_e(x) - e_j\|_2$$

Methodology

- Objective function
 - ✓ VQ-VAE log-likelihood

$$\begin{split} \log p(x) & \geq \int \log p(x|z) \, q(z|x) dz - D_{kl}(q(z|x)||p(z)) \\ \log p(x) & \geq \int \log p(x|z) \, q(z|x) dz - D_{kl}(q(z|x)||\frac{1}{k}), (k = \# \ of \ \ em \ bedding \) \\ D_{kl}(q(z|x)||1/k) & = \sum q(z|x) \log \left(\frac{q(z|x)}{p(z)}\right) \\ & = q(k|x) \log \left(\frac{q(z|x)}{p(z)}\right) \\ & = 1 * \log(\frac{1}{\frac{1}{k}}) = \log k \end{split}$$

Methodology

- Objective function
 - ✓ VQ-VAE 의 likelihood

$$p(x) = \int \log p(x|z) p(z) dz$$
$$p(x) \approx \log p(x|z_k) p(z_k)$$

✓ VQ-VAE 의 objective function

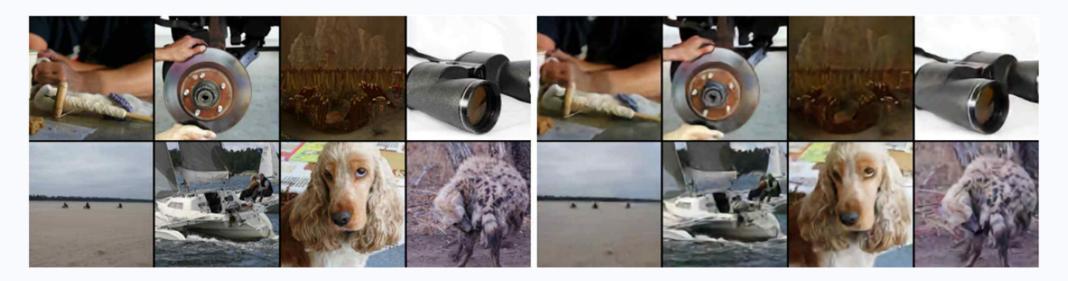
$$L = \log p(x|z_q(x)) + ||sg[z_e(x)] - e||_2^2 - \beta ||z_e(x) - sg[e]||_2^2$$

Reconstruction loss

Commitment loss

experiments

• 실험 결과 분석(Images)



experiments

• 실험 결과 분석(Images - pixelCNN prior + VQ-VAE Decoding)



kit fox, gray whale, brown bear, admiral (butterfly), coral reef, alp, microwave, pickup

experiments

• 실험 결과 분석(Audio)

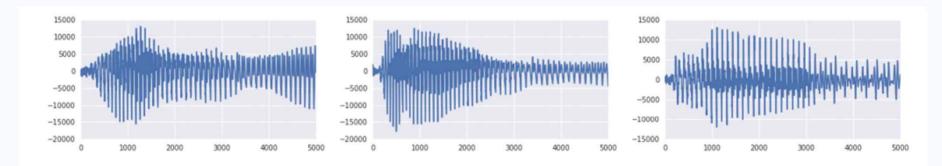


Figure 6: Left: original waveform, middle: reconstructed with same speaker-id, right: reconstructed with different speaker-id. The contents of the three waveforms are the same.