Neural Discrete Representation Learning

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Introduction

Vector quantization variational autoencoder (VQ-VAE)

- VAE with discrete latent space

Why discrete?

- Many important real-world things are discrete (words, phonemes, etc.)
- Learn global structure instead of noise and details
- Achieve data compression by embedding into discrete latent space

Algorithm

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We define a latent embedding space $e \in R^{K \times D}$

(D is the dimensionality of each latent embedding vector)

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We define a latent embedding space $e \in R^{K \times D}$

(D is the dimensionality of each latent embedding vector)

To discretize $z_e(x)$: calculate a nearest neighbour in the embedding space

$$k = \text{argmin}_j \|z_e(x) - e_j\|_2$$

Algorithm

The posterior categorical distribution $q(z|x)$ -- deterministic!

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

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Reconstruction loss

$$L = \log p(x|z_q(x))$$

Model is trained as a VAE in which we can bound log p(x) with the ELBO.

Training

How can we get a gradient for this?

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(straight-through estimator)

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Main idea:

Gradients from decoder contain information for how the encoder has to change its output to lower the reconstruction loss.

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Embedding don’t get gradient from reconstruction loss $L = \log p(x|z_q(x))$

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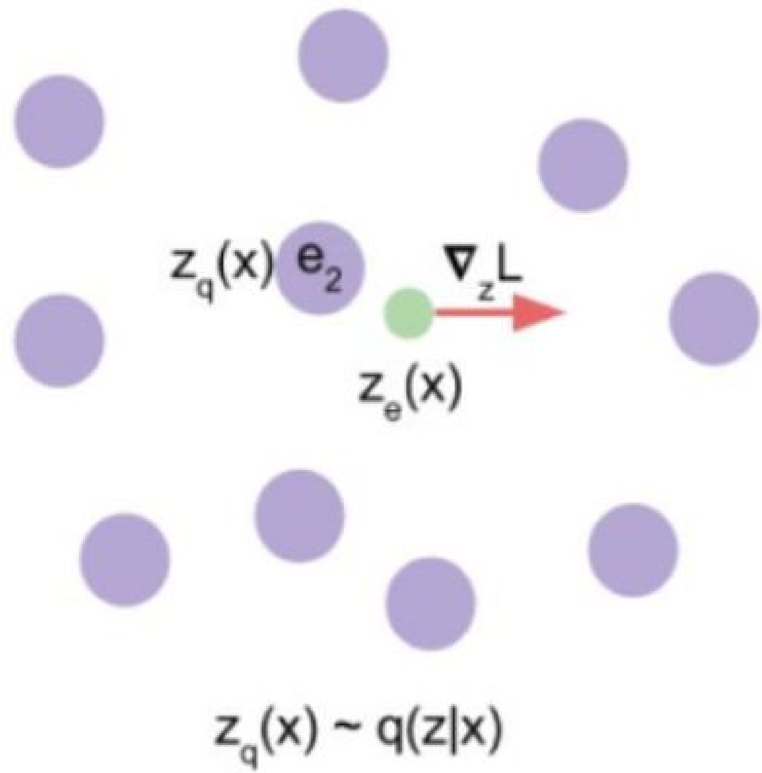
Use L2 error to move the embedding vectors e_i towards $z_e(x)$

Embedding loss = $\|\text{sg}[z_e(x)] - e\|_2^2$

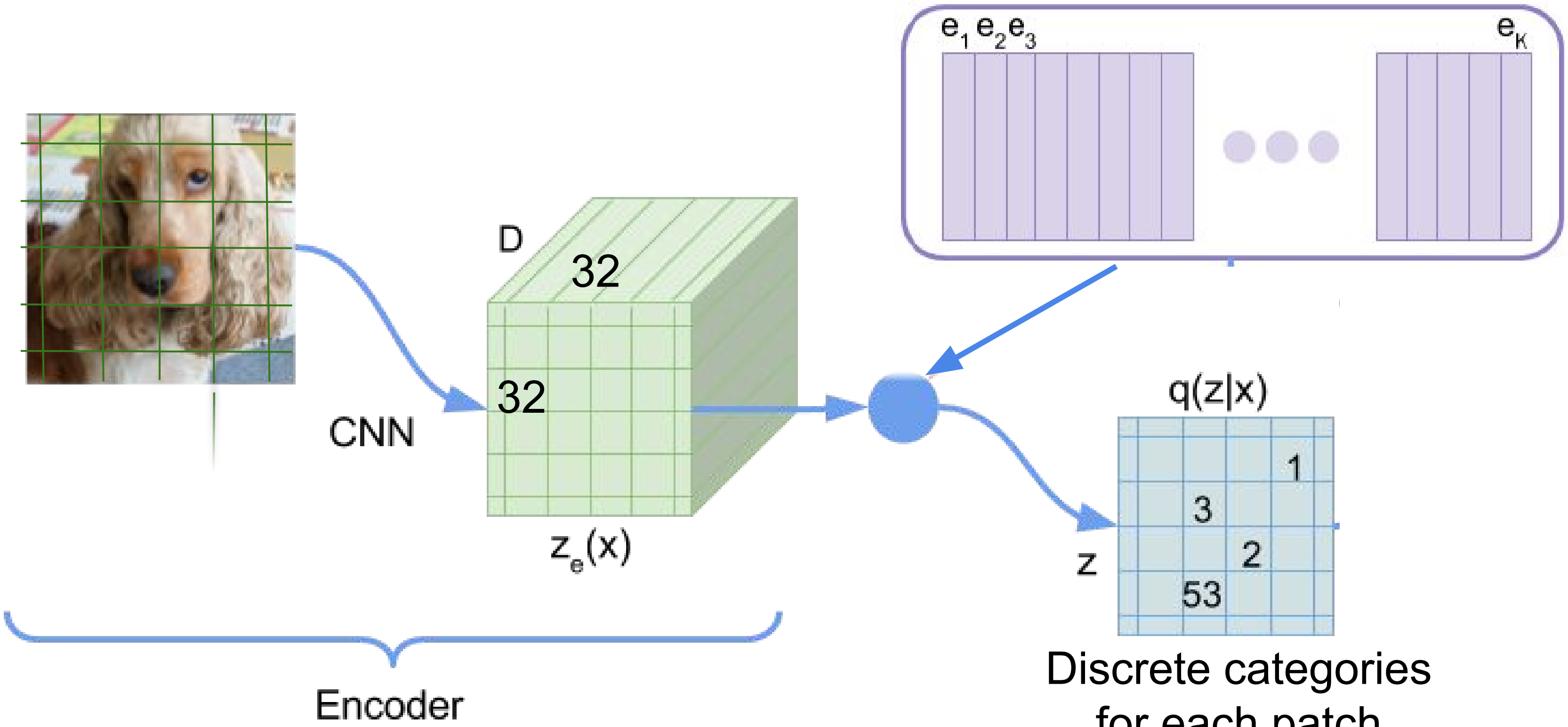
sg = stopgradient operator

Training



How to reconstruct an image?

Discrete z : a field of 32 x 32 latents (ImageNet), K=512



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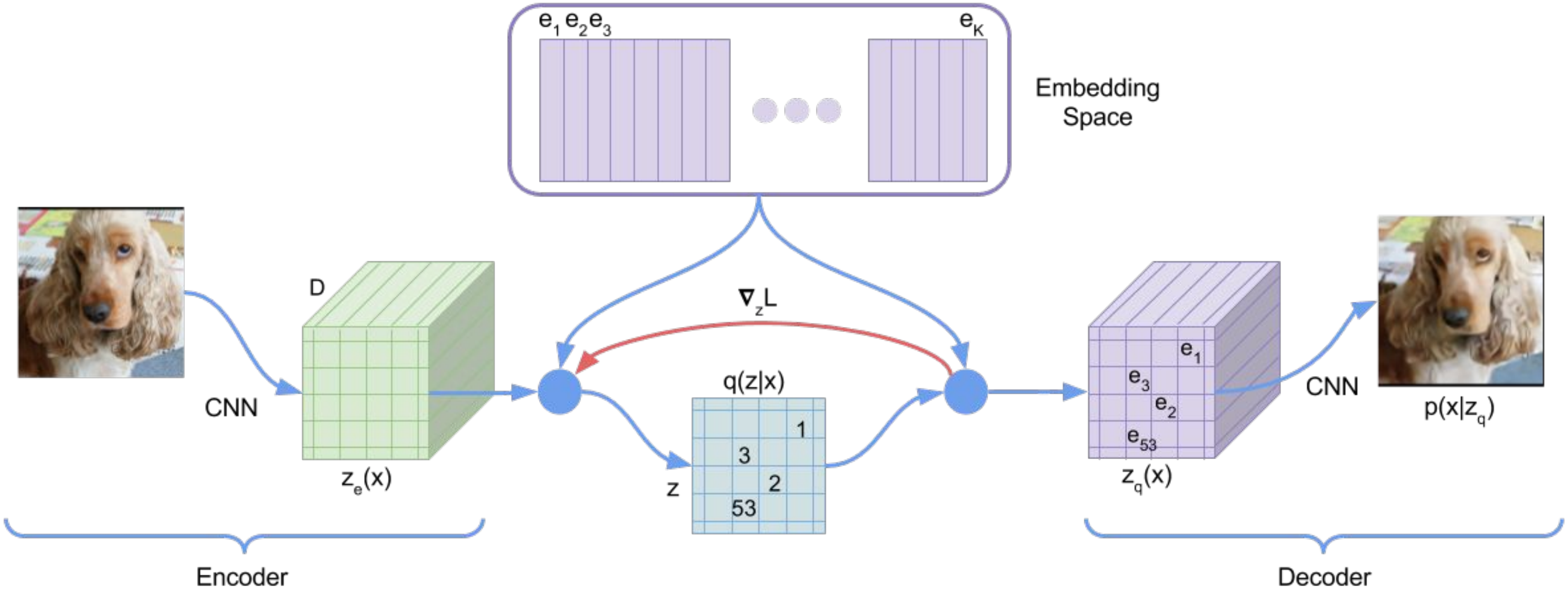

Experiments & Results

ImageNet - Reconstruction

128x128x3 images ↔ 32x32x1 discrete latent space (K=512)

Original

Reconstruction

ImageNet - Recon

128x128x3x(8 bits per pixel) / 32x32x(9 bits to index a vector)
= **42.6 times compression** in bits

128x128x3 images ↔ 32x32x1 discrete latent space (K=512)

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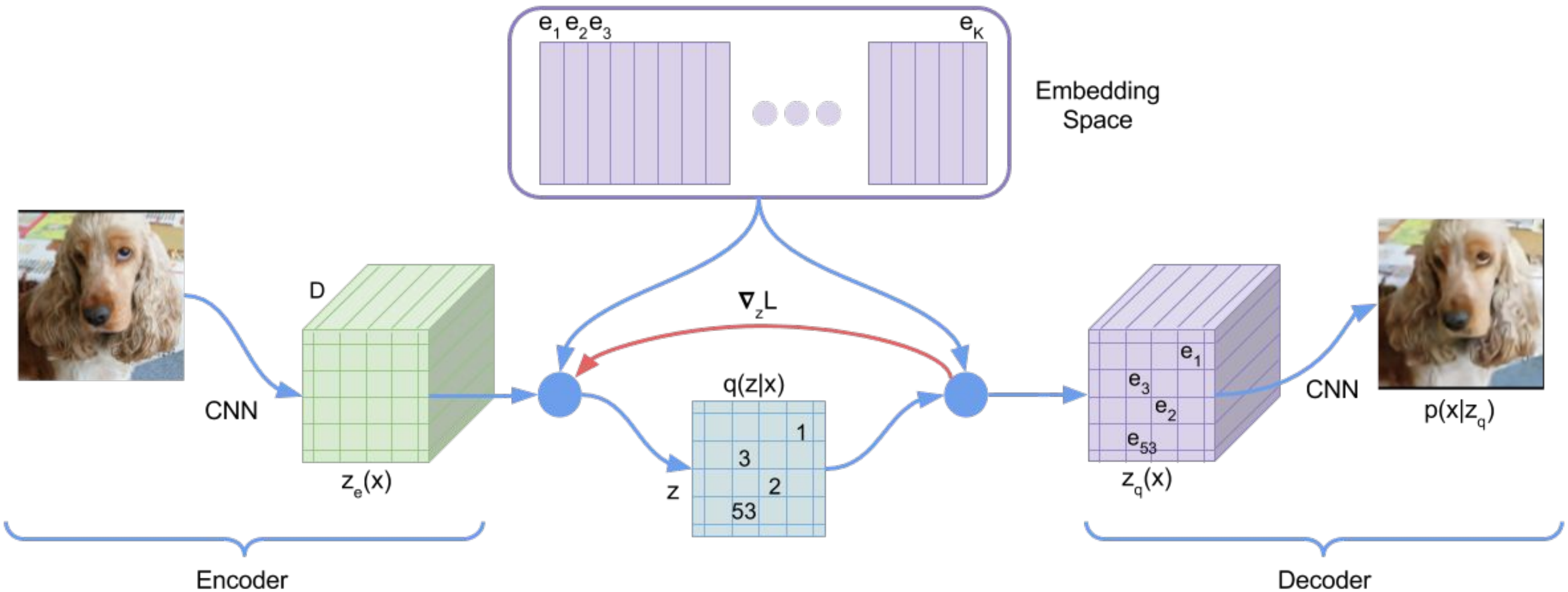
ImageNet - Samples

Train PixelCNN on the 32x32x1 discrete latent space. Sample from PixelCNN, decode with VQ-VAE decoder.



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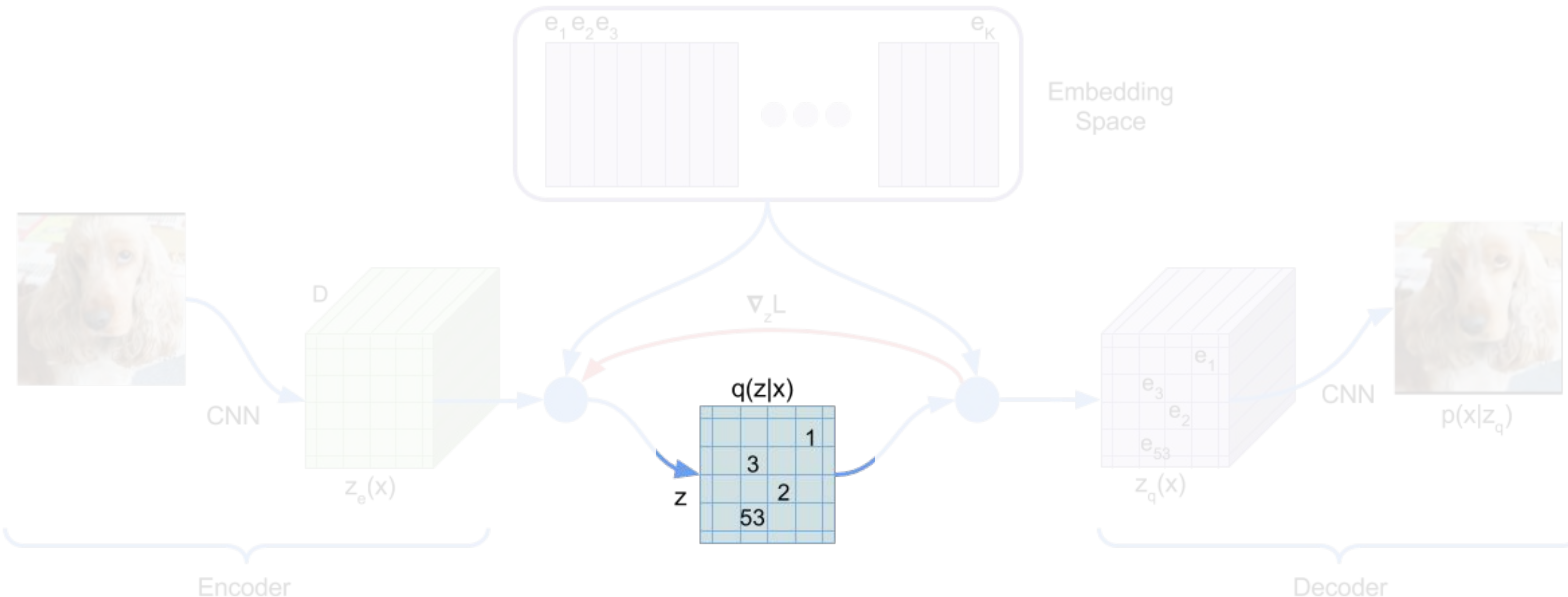

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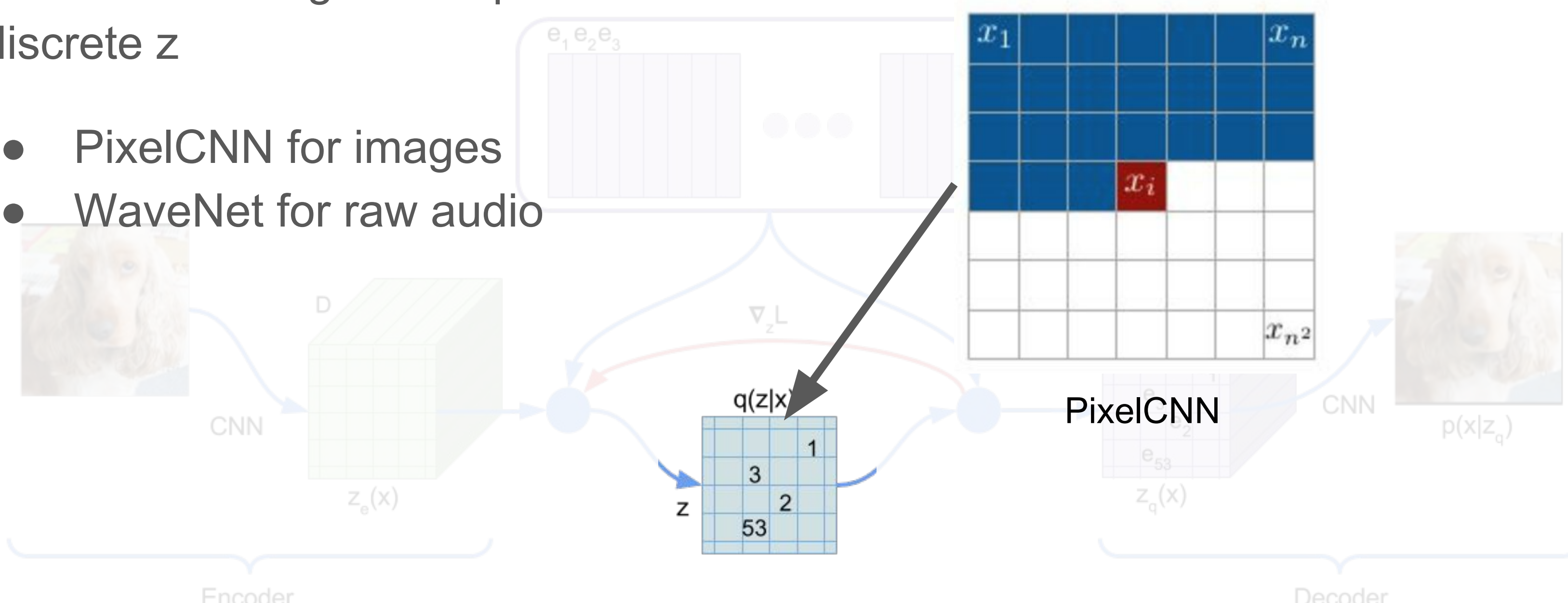
Learn an autoregressive prior over discrete z

- PixelCNN for images
- WaveNet for raw audio



PixelRNN Image Source: https://towardsdatascience.com/summary-of-pixelrnn-by-google-deepmind-7-min-read-938d9871d6d9

ImageNet - Generation

Microwave pickup tiger beetle coral reef brown bear

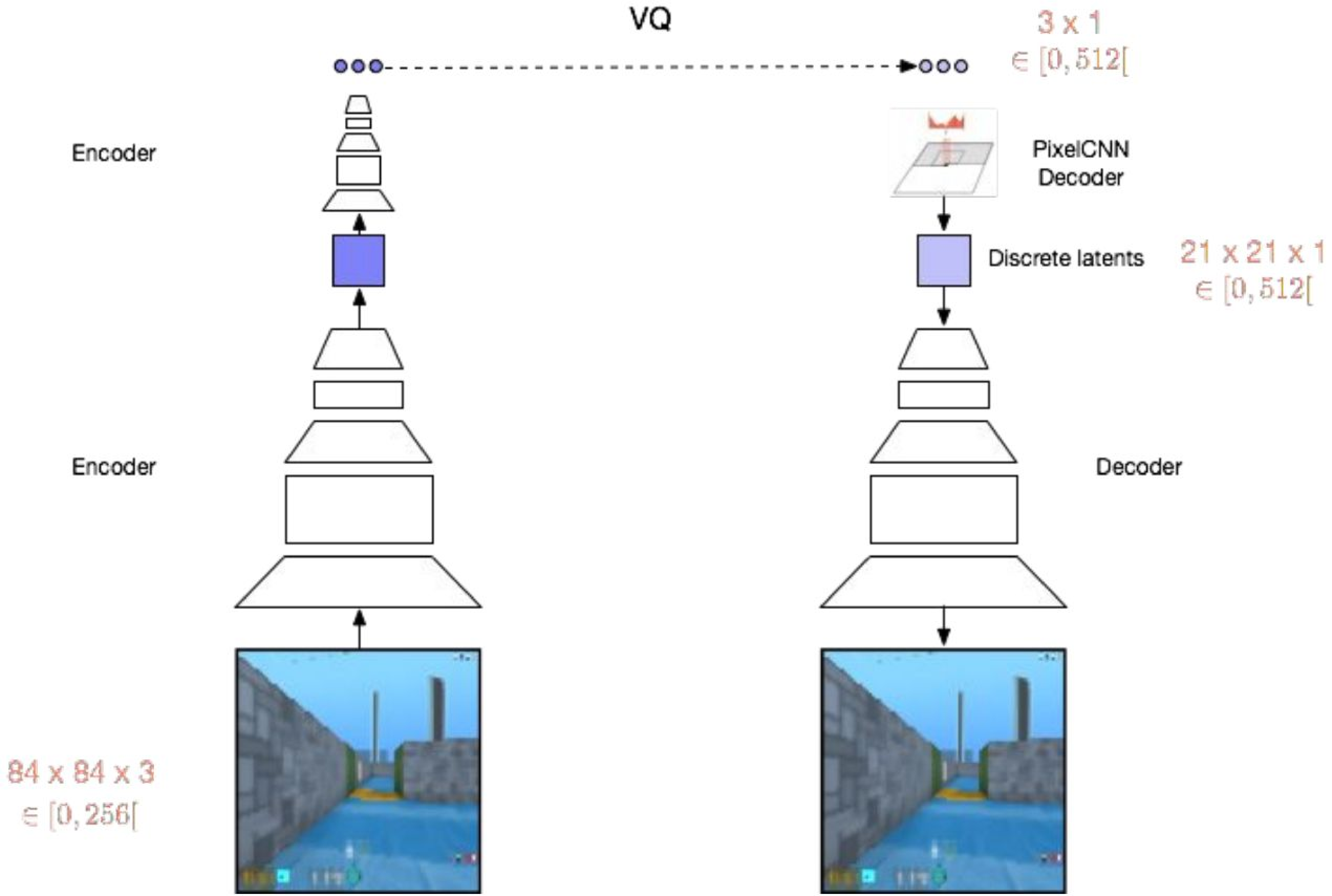
DeepMind Lab - Reconstruction

84x84x3 images
↔ 21x21x1 discrete latent space (K=512)
↔ 3x1 discrete latent space (K=512)

Two VQ-VAE layers!

3x9 = 27 bits in latent representation.

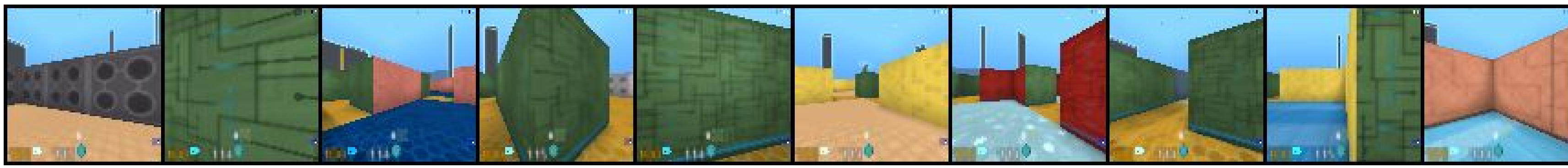
Can’t reconstruct exactly, but does capture global structure.



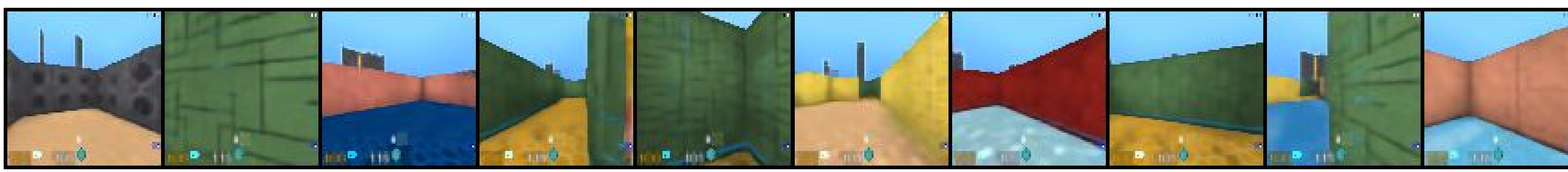
Source: https://avdnoord.github.io/homepage/slides/SANE2017.pdf

DeepMind Lab - Reconstruction

Original

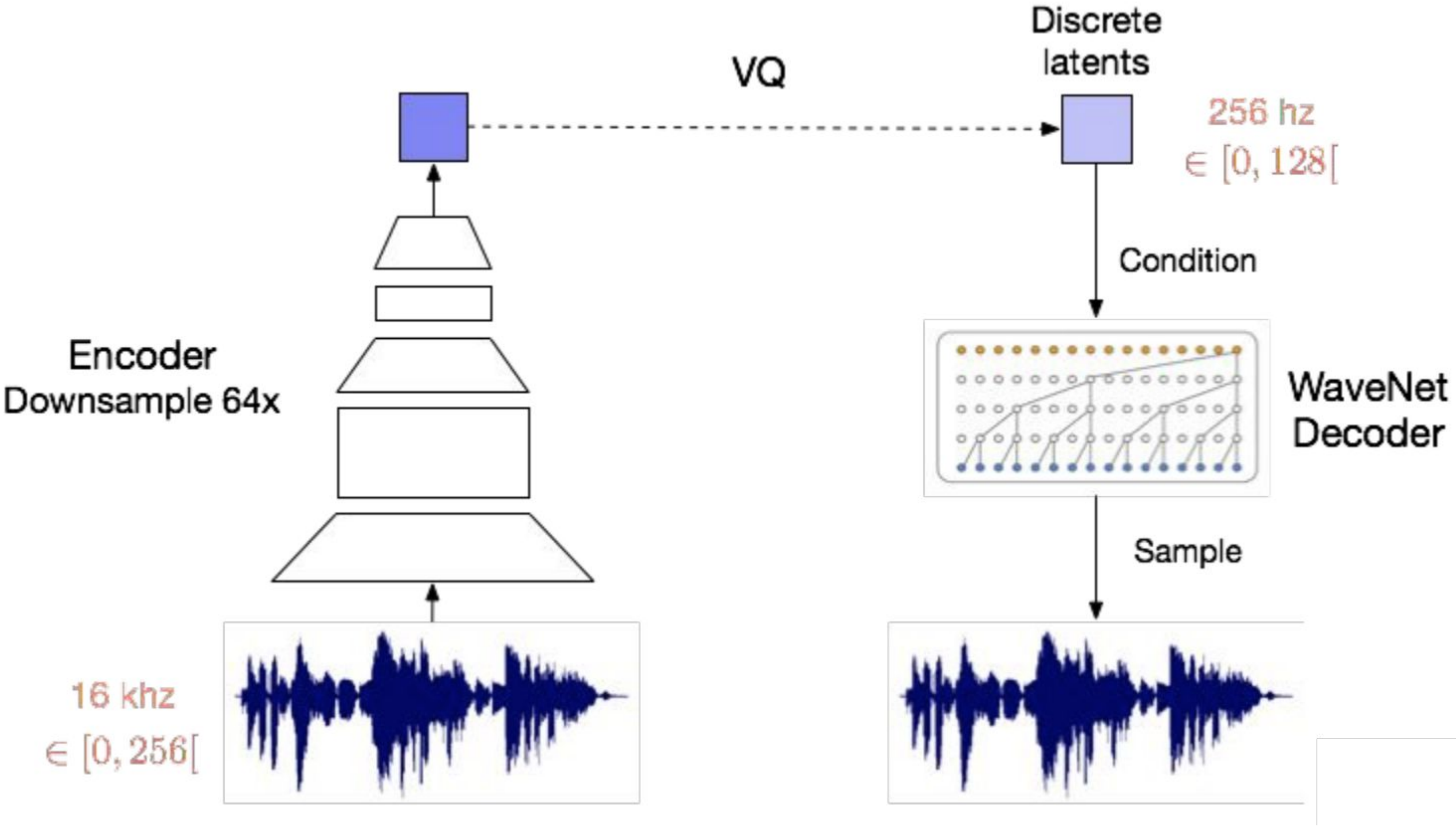


“Reconstruction”



Audio (VCTK) - Reconstruction

Use WaveNet decoder.



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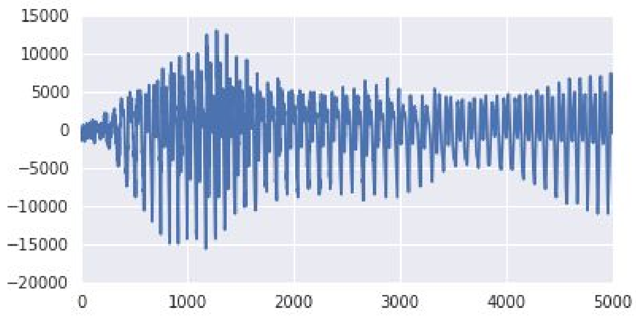
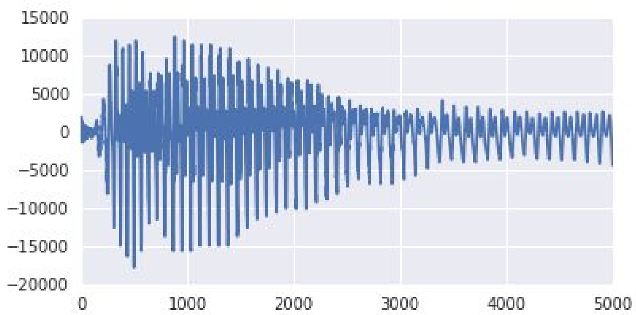
Audio (VCTK) - Reconstruction

Original



Reconstruction

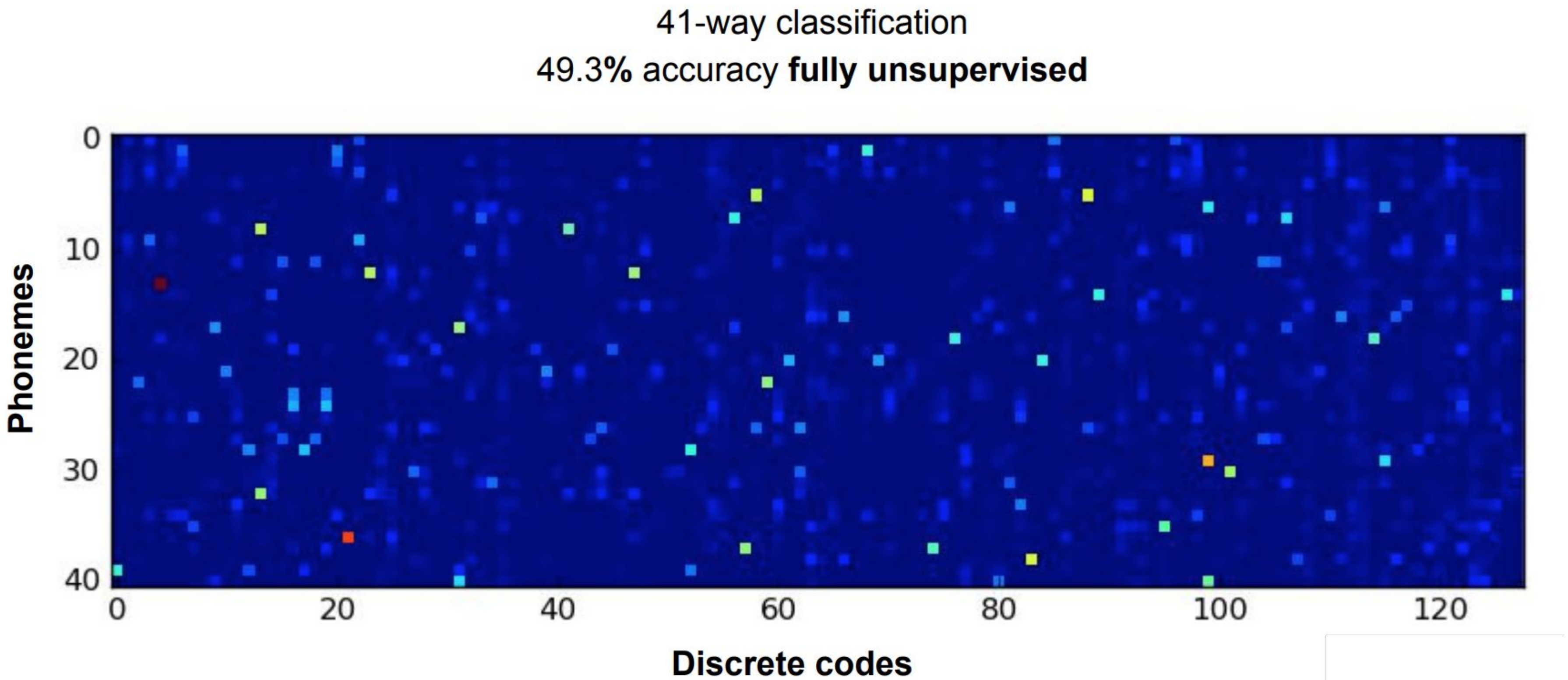


Again, not exact reconstruction, but captures global structure.

(More examples at https://avdnoord.github.io/homepage/vqvae/)

Audio (LibriSpeech) - Latents == phonemes?

It turns out discrete latent variables roughly correspond to phonemes.
Note that the semantics of discrete codes could be dependent on previous codes;
so it's interesting that individual discrete codes actually hold meaning!



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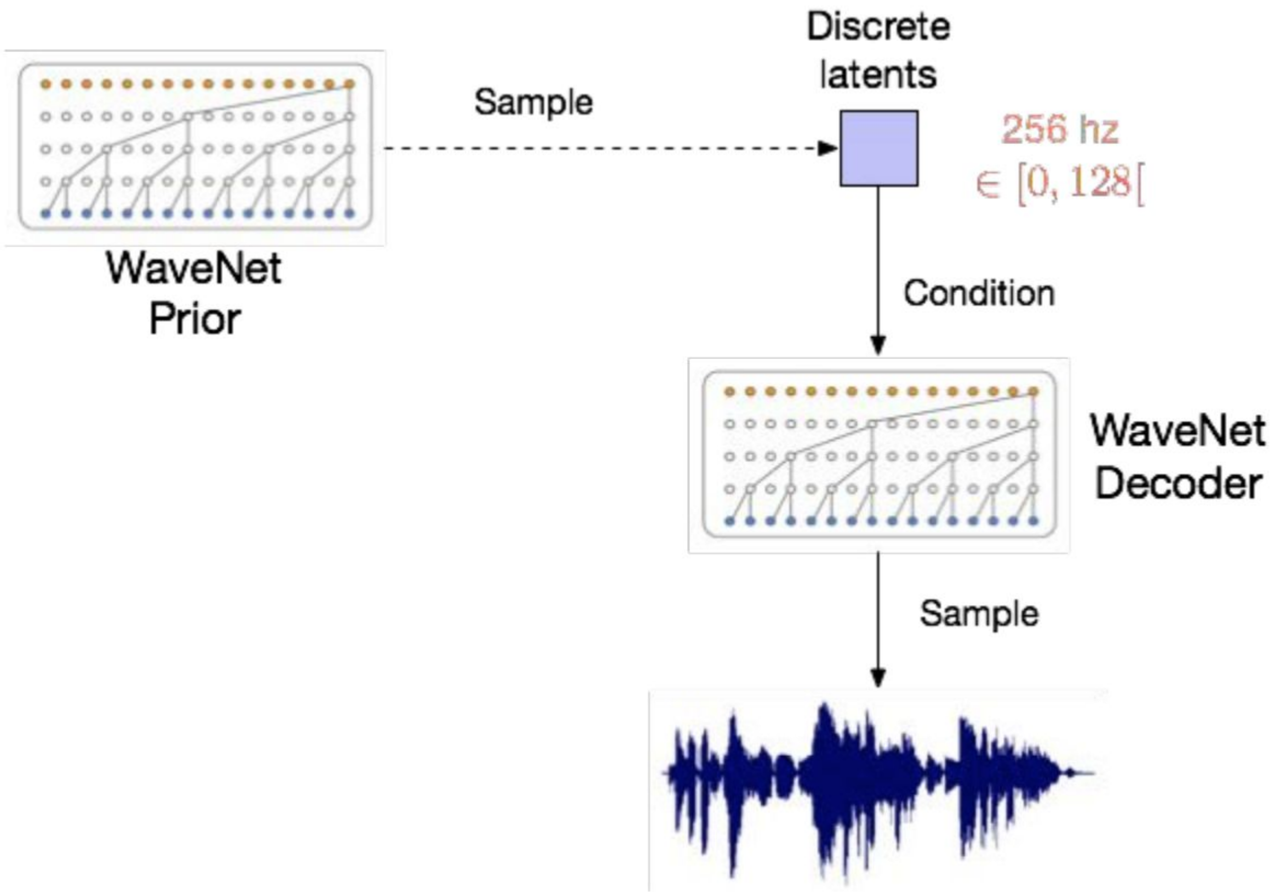
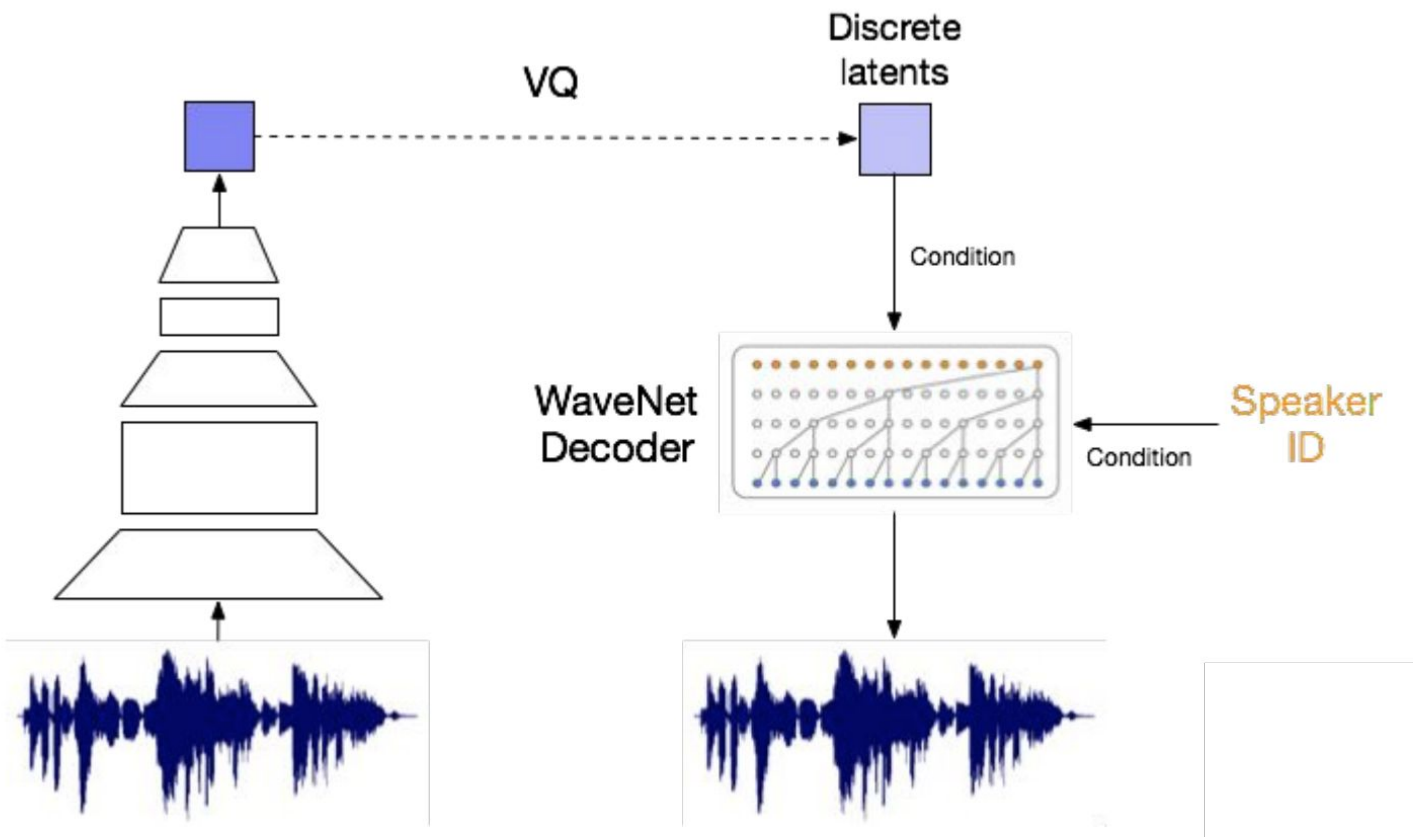
Audio (LibriSpeech) - Sampling



[Example]()

Source: https://avdnoord.github.io/homepage/slides/SANE2017.pdf

Audio (LibriSpeech) - Change Speaker Identity



[Original](#)

[Transferred](#)

=> Discrete latent variables are not speaker-specific!

Source: https://avdnoord.github.io/homepage/slides/SANE2017.pdf

Summary

- Pros:
  - Learn meaningful representations with global information
  - Can model long range sequences
  - Fully unsupervised
  - Avoids “posterior collapse” issue
  - Model features that usually span many dimensions in data space
- Cons:
  - Straight-through estimator is biased
  - Compression relies on large lookup tables