MLDS: Deep Learning
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Assignment 3 - Question 4

In the following report, I describe the model and experimental design choices in training the Vector-Quantized Variational Autoencoder as described in question 3. I have structured my response below to cover data processing, model architecture design and experimentation. Finally, I discuss the potential areas of improvements that I would have liked to explore given more time.

1 Data processing

The exploratory data analysis conducted in question 1 revealed that the Free Spoken Digit dataset contained the wide variety of recording lengths, amplitude values and prominent frequencies. My first priority for the project was therefore to preprocess the data to a format that is more conducive for deep learning.

As a first basic step, I set our to standardize the lengths of the audio entries by zero padding. Before doing this, I had to remove any files that outliers in terms of recording length, in order to avoid over dilution of the majority of the dataset with excessive zero padding. The amplitudes of the resulting data was then scaled by the standard deviation of the amplitude values.

Next, following the guidance provided in [1, 1], I transformed the waveform data into spectrograms using the Short Time Fourier transform function, implemented in the `tensorflow.signal` library. Spectrogram representations of sound display the spectral makeup of the signal in terms of frequencies (on the vertical axis) over time (on the horizontal axis). They can therefore reveal the specific patterns of sound frequencies that are present in an audio signal that may be more difficult to identify in a simple waveform (sound amplitude vs time) representation. The Short Time Fourier Transform was specifically chosen for this operation due to its robustness to scaling and linear transformations (meaning that they will be robust to image padding) as well as its revertability (meaning that the model outputs can be converted back to waveforms and played). The combination of these two properties have made the SFTF a popular tool in signal analysis and processing [2]. Figure 3 shows the magnitude and phase component spectrograms for one of the audio recordings in the dataset.

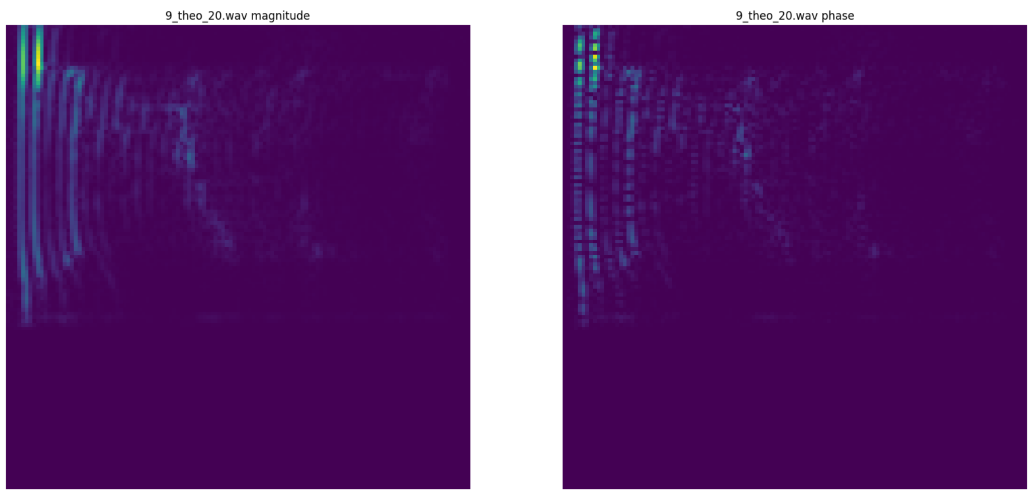


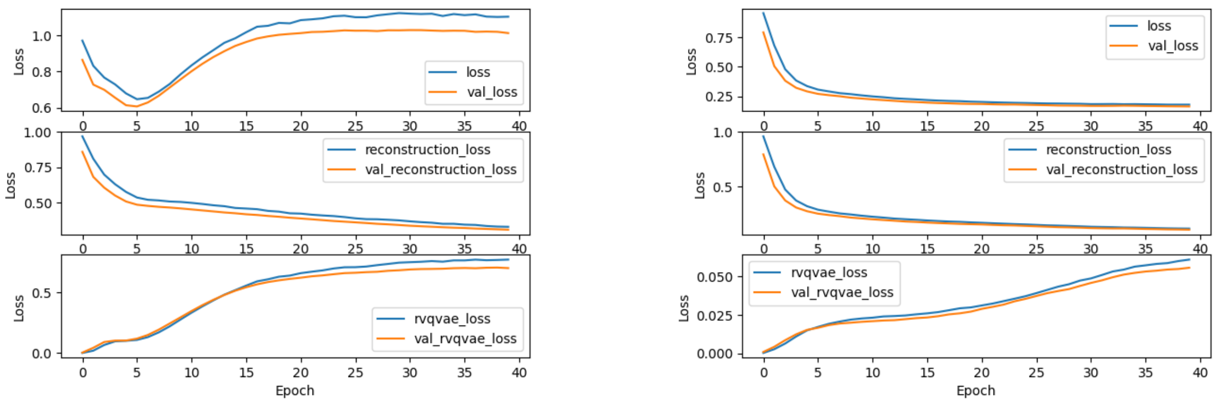
Figure 1: Recording for digit “nine”, converted to spectrogram by STFT. Left frame shows frequency magnitude, right shows phase.

2 Model architecture design

The transformation of the image into $128 \times 128 \times 2$ tensors meant that the dataset was transformed to a convenient format in order to be processed by a two-dimensional Convolutional Neural Network, enabling us to make use of the local connectivity and equivalence properties of CNNs to help the model identify local features and patterns that are important for the overall representation of the audio file.

For question 3a, I therefore start by adapting the CNN encoder and decoder architecture implemented in [3] to suit the shape of the spectrogram tensor outputs from the data processing stage. The encoder for this architecture is first comprised of a two 2D Convolutional layers, the first with 32 filters and the second with 64. Both layers have a 3-by-3 kernel, "same" padding and a stride of 2. Finally, the resulting output is then passed on a final 2D Convolutional layer with the number of filters equal to our chosen latent dimension of 128, a kernel size of 1, "same" padding and linear activation. The structure of the decoder is equivalent to the transpose of the encoder architecture. The outputs of the decoder were then fed into the `RVQVectorQuantizer` layer, which was implemented changeable hyperparameter inputs for Residual Vector Quantization embedding layers and γ. In the next section, I describe the experiments conducted in changing these values.

3 Experimentation



(a) Model 1 - $\gamma = 0.99$, 5 RVQ layers

(b) Model 1 - $\gamma = 0.998$, 10 RVQ layers

Figure 2: Basic and best models from Q3a experimentation

In figure 2a, I show the training and validation loss for the basic model architecture as describe in the previous section, with $\gamma = 0.99$ and 5 RVQ layers. The loss curves immediately revealed that the commitment loss tends to increase rapidly in the early epochs and then plateau later on. The issue specifically was that increase in commitment loss exceeded the rate of optimization of the reconstruction loss, leading to an increasing loss for the majority of the training. For the next few model iterations, I therefore attempted to find ways in which to improve the optimization of the commitment loss.

My first attempt in doing was to improve the initialization method of the latent embeddings for the VQVectorQuantizer layer by the use of the Glorot Normal initialization (Model 2). The reasoning for this was that improved initialization would lower the rate of commitment loss increase throughout training. The change did result in an improvement, albeit marginal.

The next attempt was to experiment with the incorporation of a probabilistic output layer for the decoder model (Model 3), with the reasoning that a stochastic output may help with regularization throughout training. This however was not the case as the additional noise created by the probabilistic layer resulted in a deterioration in loss optimization and quality of reconstructions. Seeing this as a failed attempt, I ultimately scrapped this approach.

Finally, I sought to improve performance by increasing the latent embedding learning momentum γ parameter and number of Residual Vector Quantization layers (in models 4 then 5 respectively). The combined effect of these two changes were significant. In figure 2b, we see that the training and validation loss improve continuously throughout all the epochs, a marked improvement in comparison to figure 2a. As a result, the quality of the audio reconstructions produced by the model were relatively high; not only was the original audio identifiable in the reconstruction, but the background interference was also minimal.

4 Further modifications to explore

In question 3b, I implemented the RealNVP multiscale framework for producing a sampling model for the quantized output of the RVQVectorQuantizer layer. Unfortunately, my efforts were not particularly successful. As shown in figure 3, the resulting model failed to produce outputs that captured the local variations in the audio spectrograms. If I were given more time on this assignment, I would use this to explore the possible causes for this. Firstly, it is apparent that the data preprocess bijection suggested in the original paper for image data is not suitable for RVQVectorQuantizer output, since the range of values for the latter are not constrained to 0 to 255 pixels. I attempt to account for this in the model by introducing an extra Sigmoid bijector step or altogether bypassing the preprocess bijector, but this did not fully solve the issue. The second possible improvement that I would explore is to increase the size of the model by introducing more affine-squeeze-affine blocks, to improve the models' ability to capture low and high level features. Lastly, I would explore the impact of introducing a multi-modal distribution to replace the unimodal base Gaussian distribution, to reflect the fact that the outputs of the RVQVectorQuantizer layer are discrete.

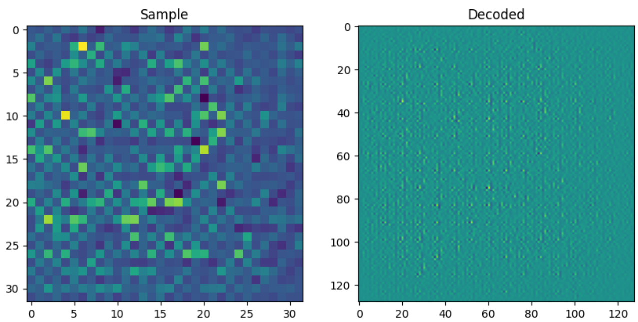


Figure 3: Sample from the Real NVP model trained on quantized outputs (left) and corresponding output of VQ-VAE decoder (right)

References

[1] Ketan Doshi. *Audio deep learning made simple (Part 1): State-of-the-art techniques*. 2021. URL: https://towardsdatascience.com/audio-deep-learning-made-simple-part-1-state-of-the-art-techniques-da1d3dff2504 (visited on 04/19/2024).

[2] L. Durak and O. Arikan. "Short-time Fourier transform: two fundamental properties and an optimal implementation". In: *IEEE Transactions on Signal Processing* 51.5 (2003), pp. 1231–1242. DOI: 10.1109/TSP.2003.810293.

[3] *Vector-Quantized Variational Autoencoders*. 2021. URL: https://keras.io/examples/generative/vq_vae/ (visited on 04/19/2024).