Deep-Learned Compression for RF Modulation Classification

First Report

1 Introduction

We evaluate the effectiveness of a hierarchical vector-quantized autoencoder model, HQARF, in compressing complex-valued radio-frequency (RF) signal samples for the task of modulation classification. A deep learning classifier trained on uncompressed data is used to assess the impact of the lossy compression performed by HQARF on classification accuracy at various compression levels. The goal is to determine the feasibility of reducing data transmission and storage requirements for RF machine learning applications [2].

2 Dataset and Experimental Setup

2.1 6 Modulations Dataset

The experiments utilize a synthetic dataset with 6 different Modulations of signals, generated using the open-source torchsig library [1]. It contains high SNR, clear-channel samples of six digital modulation schemes:

1. 4-level Amplitude Shift Keying (4ASK)
2. 8-level Pulse Amplitude Modulation (8PAM)
3. 16-level Phase Shift Keying (16PSK)
4. 32-level Quadrature Amplitude Modulation (32QAM-cross)
5. 2-level Frequency Shift Keying (2FSK)
6. 256-carrier Orthogonal Frequency Division Multiplexing (OFDM256)

All the modulation numbers are referred in 2b. Each datapoint consists of a sequence of 1024 complex in-phase/quadrature (I/Q) samples. The shape of a single signal is 2x1024 (2 channels and 1024 features).

2.2 Other Parameters

We decided to use the hierarchial structure for the model as it will be much easier to compare the results with different levels of compression simultaneously. Also each layer of compression has its own hyper parameters like no of residual blocks (these increase the complexity of model), Cosine loss coefficient (weight of the cos loss), cos reset (which removes the cosine loss for deeper layers) and finally the codebook reset type which helps in better convergence of the model.

2.3 HQARF Compression Model

The HQARF model compresses the RF datapoints using a hierarchy of vector-quantized variational autoencoders (VQ-VAEs) [4]. It has 5 layers, L0 through L4, providing 5 levels of lossy compression. We increased the compression ratio by a factor of 2 at each successive layer.

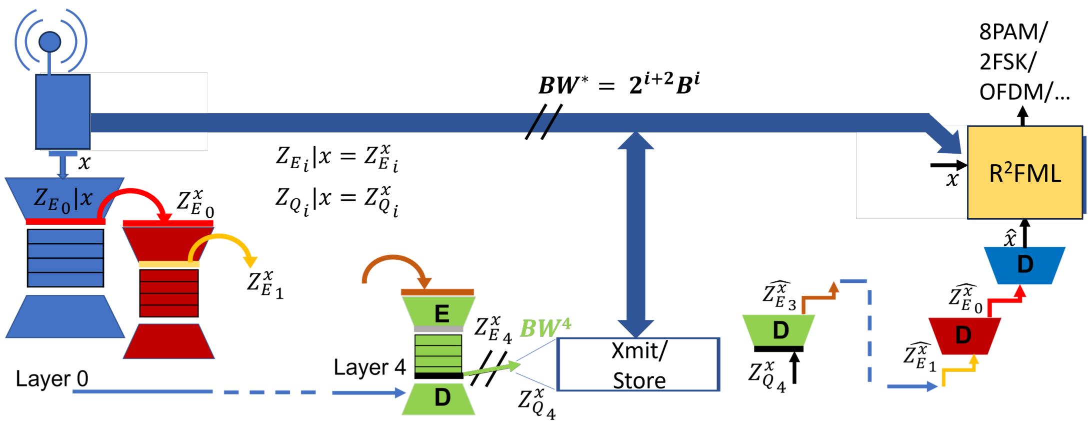


Figure 1: HQARF Architechure [2]

The encoders and decoders at each layer are composed of 1D convolutional and deconvolutional neural networks respectively. The latent space is quantized using a learnable codebook.

HQARF is first trained as a regular hierarchical autoencoder (HAE) to minimize reconstruction loss. The learned weights are then used to initialize the HQARF training which includes the quantization and generative losses [5].

2.4 EfficientNet Classifier

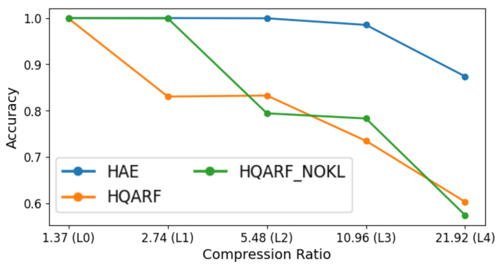
An EfficientNet-B4 neural network [3] pre-trained on the uncompressed dataset is used as the modulation classifier. It achieves approximately 100% classification accuracy on the test set. This model is used to evaluate the classification accuracy on the HQARF reconstructions at each compression level.

3 Results

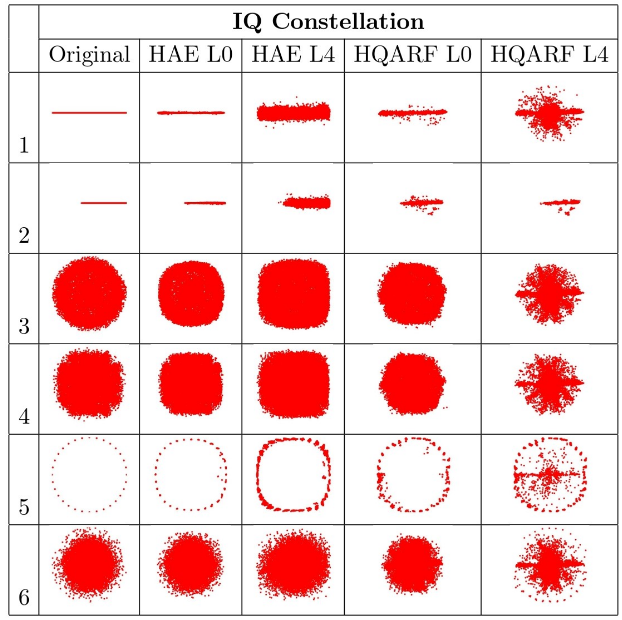
Fig. 2a plots the modulation classification accuracy of reconstructed signals vs. the compression ratio for the HQARF model at different layers, with and without the generative loss term. The accuracy of the HAE model along with the HQARF with and without Generative loss is shown for reference.

The classification accuracy remains close to 100% up to a compression ratio of 8 at layer 3 (L3). At 16x compression (L4), the accuracy drops to around 80%.

The quality of the reconstructed signal constellation diagrams and spectrograms Fig. 2 progressively degrades at higher compression levels. However, the key modulation characteristics are preserved adequately



(a) Classification Accuracies vs Compression Ratio



(b) Constellations for the Signals and the reconstructions

Figure 2: Results from [2]

for classification up to L3/L4.

4 Conclusions

The proposed HQARF model can compress complex-valued RF signal data by up to 8-16x while maintaining modulation classification accuracy close to that achieved with uncompressed data. This shows the potential for significant reduction in data transmission bandwidth and storage requirements for RF deep learning applications.

The current HQARF design still leaves room for improvement compared to the theoretical compression bound based on SVD analysis of the dataset. Avenues for future work include optimizing the HQARF architecture, training methodology and hyperparameters. This includes deciding on the best codebook dimensions, length of Ze, number of residual blocks present in the encoder and decoder for a specific layer.

References

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