

Hackathon Project: IQ Data Stream Compression for Testing & Measurement

Problem Statement

Modern testing and measurement devices, such as oscilloscopes and signal generators, handle massive volumes of IQ (In-phase and Quadrature) data streams. These high-frequency signals require efficient storage and transmission, especially in remote processing applications.

The key challenges include:

- Handling large-scale IQ data transmission over limited bandwidth channels.
- Ensuring lossless or near-lossless compression to retain signal fidelity.
- Optimizing for real-time processing without overburdening the testing device.
- Enabling reconstruction of the original signal at the receiver end.

Hackathon Challenge (Hosted by Rohde & Schwarz)

The goal of this project was to develop an efficient **data compression algorithm** that minimizes the size of the IQ data stream while maintaining its usability for signal processing applications. The approach explored both **classical (PCA-based)** and **AI-driven (Autoencoder-based)** techniques to achieve optimal compression and reconstruction performance.

Approach: Implementing Compression Solutions

Two main approaches were tested:

1. Principal Component Analysis (PCA) for Data Compression

PCA is a classical **dimensionality reduction technique** that finds the most significant features in a dataset and removes redundant information.

- Applied PCA transformation to reduce data dimensionality while preserving variance.
- Selected the top principal components to retain essential signal information.
- Reconstructed the signal using inverse PCA transformation.
- Evaluated the compression ratio and reconstruction loss to optimize performance.

2. Autoencoder-Based Data Compression

An Autoencoder is a neural network architecture designed for unsupervised learning, capable of encoding and reconstructing data with minimal loss.

- Designed a deep learning model using TensorFlow/Keras.
- Implemented a bottleneck layer to compress the IQ data into a low-dimensional representation.
- Trained the network to minimize reconstruction loss using Mean Squared Error (MSE).
- Compared its efficiency to PCA in terms of compression ratio, accuracy, and processing time.

Results & Key Takeaways

Findings:

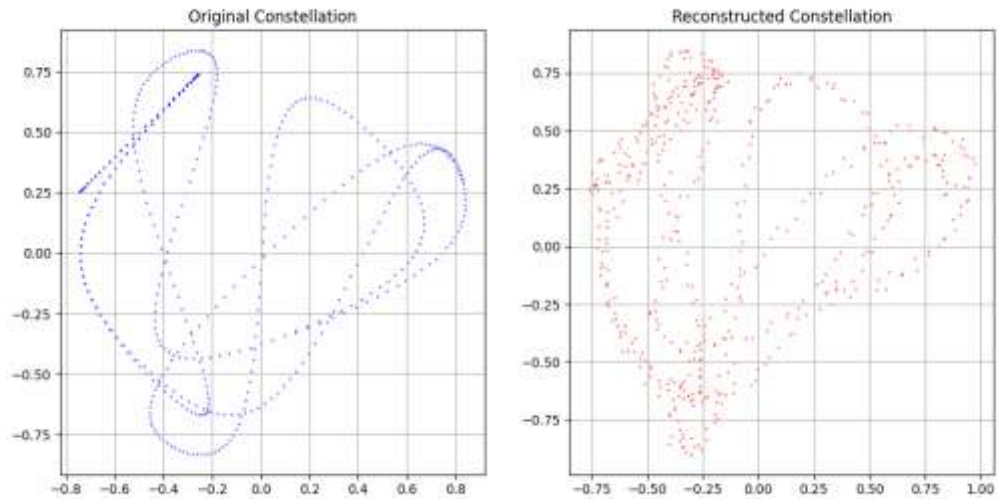
- PCA performed well for linear signal features, providing a straightforward compression technique with minimal computational cost.
- Autoencoder models captured more complex, nonlinear patterns, making them superior for handling more intricate IQ signal structures.
- A hybrid approach combining PCA for preprocessing and Autoencoder for final compression could be an optimal solution.

Future Directions

- Refining autoencoder models with advanced architectures like Variational Autoencoders (VAEs) or Transformer-based compression.
- Integrating real-world datasets for further validation.
- Deploying the solution in edge computing environments to enable real-time signal processing on low-power devices.
- Exploring adaptive compression techniques that dynamically adjust based on the channel conditions.

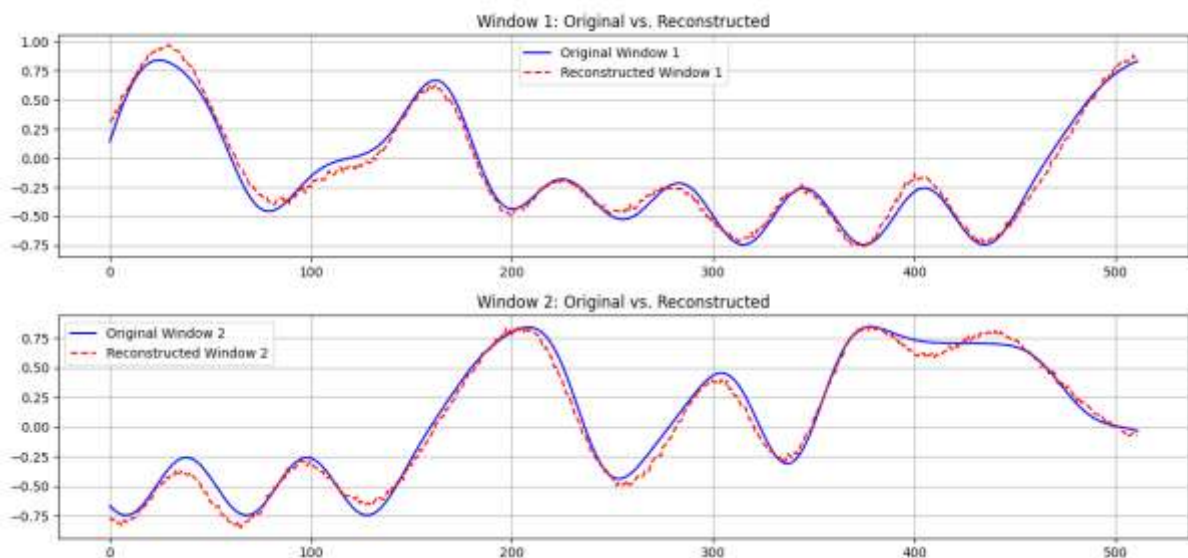
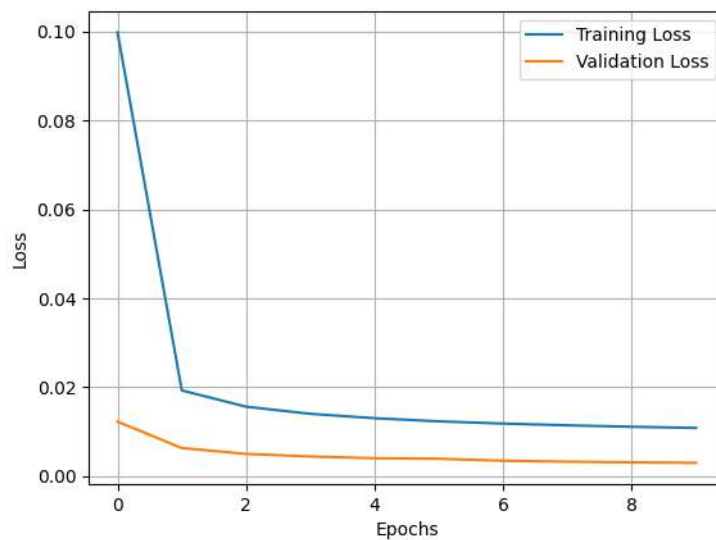
Figures

Constellation Diagram, EVM metric, Train Loss and Validation loss and input signal and reconstructed signal



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Epoch 4/10
5497/5497 ————— 233s 42ms/step - loss: 0.0143 - val_loss: 0.0044
Epoch 3/10
5497/5497 ————— 257s 47ms/step - loss: 0.0162 - val_loss: 0.0050
Epoch 4/10
5497/5497 ————— 233s 42ms/step - loss: 0.0143 - val_loss: 0.0044
Epoch 5/10
5497/5497 ————— 263s 48ms/step - loss: 0.0132 - val_loss: 0.0040
Epoch 6/10
5497/5497 ————— 259s 47ms/step - loss: 0.0125 - val_loss: 0.0039
Epoch 7/10
5497/5497 ————— 249s 45ms/step - loss: 0.0119 - val_loss: 0.0035
Epoch 8/10
5497/5497 ————— 259s 47ms/step - loss: 0.0115 - val_loss: 0.0033
Epoch 9/10
5497/5497 ————— 270s 49ms/step - loss: 0.0112 - val_loss: 0.0031
Epoch 10/10
5497/5497 ————— 238s 43ms/step - loss: 0.0109 - val_loss: 0.0030
1833/1833 ————— 15s 8ms/step - loss: 0.0030
Test loss: 0.003001
1833/1833 ————— 11s 6ms/step
Compression Ratio: 16.0:1

EVM: 0.1182 (11.82%) | -18.55 dB
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Fundamentals: PCA & Autoencoders

Principal Component Analysis (PCA) Overview

- Reduces dimensionality while retaining most data variance.
- Uses Eigen decomposition of the covariance matrix.
- Best suited for linear, structured data.
- Computationally efficient but lacks adaptability for nonlinear data.

Autoencoders Overview

- Neural network architecture with encoder (compression) and decoder (reconstruction) components.
- Learns complex, nonlinear transformations in data.

- More powerful than PCA but requires training data and higher computational cost.
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Conclusion

This project demonstrated the power of AI-driven and classical compression techniques for IQ data stream optimization. The findings from this Hackathon pave the way for scalable solutions in the testing & measurement industry, optimizing data transmission and storage without compromising signal integrity.

By leveraging machine learning, deep learning, and classical signal processing, future solutions can achieve higher compression ratios, lower latency, and improved adaptability to real-world conditions.