Proc. The International Conference on Quantum Information, Comp

Co-evolutionary Asymmetry vs. Modular Design

Optimization Trade-offs in Quantum Denoising Autoencoders

Jacob L. Cybulski[1,5][0000−0002−9061−9389] ✉, Jakub Zwoniarski[2], Artur Strąg[3], and Sebastian Zając[4][0000−0001−6616−8744]

[1] Deakin University, School of IT, Melbourne, Australia
jacob.cybulski@deakin.edu.au
[2] Institute of Spintronics and Quantum Information, Faculty of Physics and Astronomy, Adam Mickiewicz University, Poznań, Poland
jakzwo1@st.amu.edu.pl
[3] Primary School No. 306, Warsaw, Poland
[4] Military University of Technology, Faculty of Electronics, Warsaw, Poland
Sebastian.zajac@wat.edu.pl
[5] Enquanted, Melbourne, Australia
✉jacob@enquanted.com

Abstract. In Quantum Machine Learning (QML), modularity, symmetry-awareness, and pretraining are standard heuristics used to mitigate barren plateaus in deep variational circuits. While effective for symmetric tasks like noiseless data compression, we demonstrate that these intuitions falter in asymmetric tasks such as chaotic time series denoising. This paper investigates the denoising of chaotic Mackey–Glass sequences across a spectrum of Quantum Autoencoder (QAE) architectures, contrasting the performance of co-evolutionary asymmetric designs (Monolith) against multi-stage modular models with pre-trained, synchronized latent spaces (Mirror, Sidekick, and Stacked). Our experiments characterize the "Curse of Asymmetry," where extensively pretraining a decoder on clean data carves a rigid latent manifold that prevents the subsequent encoder from generalizing to high-entropy noise. Consequently, the baseline Monolith QAE – optimizing an unconstrained, independent encoder and decoder – significantly outperforms all pretrained modular variants in both denoising capacity and parameter efficiency. Furthermore, our complexity analysis identifies a structural "instability zone" for modular designs, proving that pre-trained models require deeper circuits merely to overcome their initial structural biases. By mapping these failures, this work challenges the presumed safety of modularity and fixed structural priors in quantum time series processing, demonstrating that models leveraging co-evolutionary asymmetry can offer superior performance in this context.

Keywords: Quantum Machine Learning · Quantum Autoencoder · Signal Denoising · Curse of Asymmetry