Exploring the latent space of SEEG

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The manifold hypothesis posits that high dimensional data from nature lies on a reduced number of independent degrees of freedom. The Variational Autoencoder (VAE) is a Deep Learning architecture capable of encoding high-dimensional data into a reduced, fixed number of dimensions, known as the latent space, and reconstructing it back to its original form. Such properties make it an ideal tool to exploit the manifold hypothesis with several potential applications in Neuroscience, such as the analysis and understanding of data from several neuroimaging modalities and brain network models. In addition, VAEs may provide more interpretable results compared to other architectures by finding a relationship between latent dimensions and empirical properties in data.

In this study, we explore the usage of VAEs to analyze stereo-electroencephalography (SEEG) data and use its latent space to solve increasingly complex tasks. We begin by using synthetic data generated by an advanced neural mass model to predict the value of a model parameter from its latent representation, obtaining a predictive correlation of 0.993 using simple linear tools. Then, we move to seizure stage classification using synthetically generated epileptic seizure signals, obtaining a 99% accuracy with a linear classifier. We then trained the same system on empirical SEEG data, where we got a 90% linear classification accuracy. Finally, we developed a postprocessing algorithm to amplify prediction capabilities to label entire SEEG channels automatically, reaching at a mean accuracy per channel of 97.5%, with a False Positive Rate of 5.15%.