Conclusion

In the initial stages of this research, the exploration of Conditional Variational Autoencoders (CVAE) commenced with the MNIST dataset. This foundational step allowed for a comprehensive understanding of CVAE, its mechanics, and its capabilities in capturing latent structures within a dataset using the PyTorch framework. As proficiency with CVAE was established, the investigation seamlessly transitioned to the integration with the Koopman operator.

The incorporation of the Koopman operator introduced a dynamic dimension to the latent space. Unlike traditional approaches, the Koopman operator facilitated the transformation of the latent space into a probability distribution using both PyTorch and Keras. This transformation enriches the expressiveness of the latent space, capturing the underlying dynamics of the system in a probabilistic manner.

In essence, the collaboration between CVAE and the Koopman operator, implemented using PyTorch and Keras, not only enables the generation of conditioned data but also imbues the latent space with a probabilistic structure. This innovation extends the capabilities of generative models, presenting a robust framework for understanding and representing complex dynamical systems.

This research lays the groundwork for future endeavors at the intersection of deep learning and control theory, offering a nuanced perspective on the generative capabilities of Conditional Variational Autoencoders enhanced by the transformative power of the Koopman operator, utilizing PyTorch and Keras.