**Critical Thinking**

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CSC525: Principles of Machine Learning

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08/10/2024

**Critical Thinking #4**

The example worked through for this assignment implements the Auto-Encoding Variational Bayes paper with ReLUs and the Adam optimizer. Variational Autoencoders (VAEs) are a type of generative model in machine learning, particularly within the family of autoencoders. They are used to learn a lower-dimensional latent representation of data and can generate new data points similar to the original dataset (GeeksforGeeks, 2023). VAEs are commonly used in unsupervised image generation, anomaly detection, data compression, and denoising.

In traditional autoencoders, an encoder network compresses the input data to a latent space representation, and a decoder network reconstructs the input from this latent space. However, in VAEs, the latent space is modeled as a probability distribution rather than a fixed point. VAEs differ from standard autoencoders by encoding the input as a distribution over the latent space, usually Gaussian (Rocca, 2021). Instead of encoding an input as a single point, VAEs encode the input as a mean vector and a standard deviation vector. To make the model differentiable, the reparameterization trick is used. This is key to make the model trainable using gradient-based optimization. The reparameterization trick works by restructuring the sampling process so that the randomness comes from a fixed, non-parametric distribution, such as a standard normal distribution, and the parameters are applied deterministically after the random sampling. This allows the gradients to flow through the deterministic part of the process. The reparameterization trick shifts the randomness in the sampling process to a fixed distribution, allowing the parameters of the variational distribution to be optimized via backpropagation. It is a key method for enabling the training of VAEs and other models that rely on continuous latent variables. (Baeldung, 2023). Without the reparameterization trick, backpropagation will not compute an estimate of the derivative through a random node generated by the VAE. Once trained, VAEs can generate new data points by sampling from the latent space distribution and passing these samples through the decoder.

The example implements a VAE to encode an image of a sequence of numbers into a latent space, then decodes and generates a new image of the sequence. The batch size for training is 128, and the number of epochs to train is 10. The dataset used to train this model consisted of randomly generated sequences of numbers. One way to improve this dataset would be to change the sequence to alphanumeric. Doing so would likely increase the number of trials needed to accurately train the model.

Figure 1 – Result after training.

A picture containing text, gauge, device

Description automatically generated

Figure 2 – Loss after training.

Text

Description automatically generated

VAEs are useful in NLP chatbots for dialogue generation, representation learning, and generative responses. VAEs can be used to generate diverse and creative responses in an NLP chatbot. By learning a latent space representation of dialogue, the chatbot can generate replies by sampling from this latent space. The reparameterization trick allows the chatbot to generate meaningful and coherent sentences based on learned patterns. Additionally, VAEs can help the chatbot learn to adapt its behavior in uncertain conversational environments, such as dealing with vague or unexpected user inputs. By representing the user's inputs as latent variables, the chatbot can shift its behavior based on the learned latent representations (Pykes, 2024).

Github: <https://github.com/khoiviet24/10.-Principles-of-Machine-Learning/tree/main/Module4>

**References**

*Baeldung. (2023, June 11). The reparameterization trick in variational autoencoders. Baeldung on Computer Science.* [*https://www.baeldung.com/cs/vae-reparameterization*](https://www.baeldung.com/cs/vae-reparameterization)

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*Pykes, K. (2024, August 13). Variational Autoencoders: How They Work and Why They Matter. DataCamp.* [*https://www.datacamp.com/tutorial/variational-autoencoders*](https://www.datacamp.com/tutorial/variational-autoencoders)

*Rocca, J. (2021, March 21). Understanding variational autoencoders (VAES). Medium.* [*https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73*](https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73)