Statistical Data Analysis II

Lab 10

Exercise 1

Identify all the occurrences of sampling in training a variational autoencoder.

Hint. Analyze the Evidence Lower Bound of a VAE.

Exercise 2

Let $\mathcal{D} = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$ be a training dataset. In fitting a VAE, a common practice is to approximate the reconstruction loss $\mathbb{E}_{q_\psi(\mathbf{z}|\mathbf{x})}[p_\theta(\mathbf{x} \mid \mathbf{z})]$ with a one sample estimate $p_\theta(\mathbf{x}_n \mid \mathbf{z}_n)$, where $\mathbf{z}_n \sim q_\psi(\mathbf{z} \mid \mathbf{x}_n)$. Modify your implementation of VAE to use $K \in \mathbb{N}$ many samples instead.

Plot the learning curve with $-ELBO$ for different values of K.

(Optional)

Is comparing $-ELBO$ a good strategy for model selection? Try with FID[1] instead.

Exercise 3

Can importance weighting be prove useful in training a VAE? It was observed[2] that using importance weighting, a strictly tighter log-likelihood lower bound can be obtained. This comes with multiple benefits for training a VAE.

Your task is to implement an Importance Weighted AutoEncoder.

Prove that it is useful, as compared to a standard VAE. One empirical argument is enough, e.g. compare the latent spaces or reconstruction quality etc.

Hint. It should be enough to add a few lines to your existing implementation. See D.4 in `https://arxiv.org/pdf/2206.08309.pdf`*.*

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[1] https://github.com/mseitzer/pytorch-fid

[2] https://arxiv.org/pdf/1509.00519.pdf