

The Variational Autoencoder(VAE) is a generative model — it estimates the probability density function (PDF) of the training data. It can also sample examples from the learned PDF, which is able to generate new examples that look similar to the original dataset. Hence it can be a powerful tool on data augmentation.

A. Part One

As can be seen in both figures below, the autoencoder(AE) of a single layer will perform as what the principal component analysis does. If there is no non-linear function that will be used in the AE, the number of neurons in the hidden layer is of smaller dimension that of the input then PCA and AE can yield the same result. Otherwise, the AE may find a different subspace. One thing to note is that the hidden layer in an AE can be of higher dimensionality than that of the input. In such cases, AE's may not be making dimensionality reduction. Additionally, by making a comparison between them, we can tell that variational autoencoder can provide a clearer subspace.

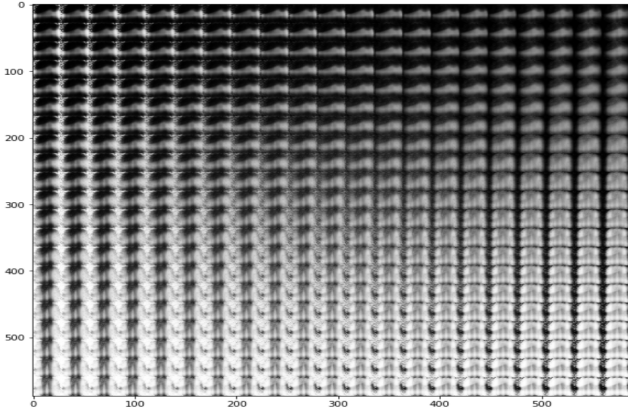


Figure 1: Visualisation of the autoencoder.

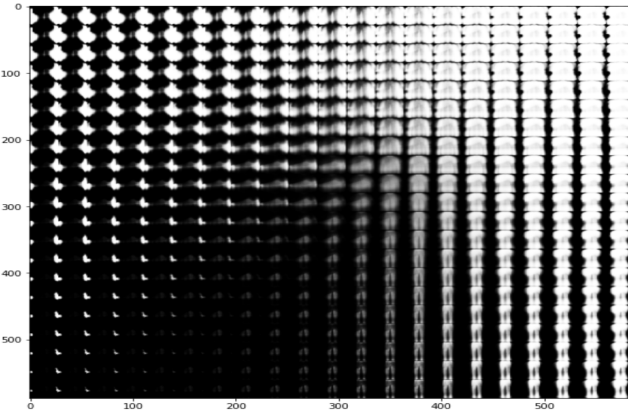


Figure 2: Visualisation of the variational autoencoder.

While an autoencoder has to reproduce its input, a variational autoencoder has to reproduce its output for keeping its hidden neurons to a specific distribution. This means the output of the network will inevitably get used to the hidden neurons outputting based on a distribution. Therefore we can generate new images, just by sampling from that distribution, and inputting it into the network's hidden layer.

B. Part Two

I trained my VAE model for 20 epochs with the Adam optimiser and the MSELoss, and its loss curve, as well as the visualisation result on the FashionMNIST, are namely shown below.

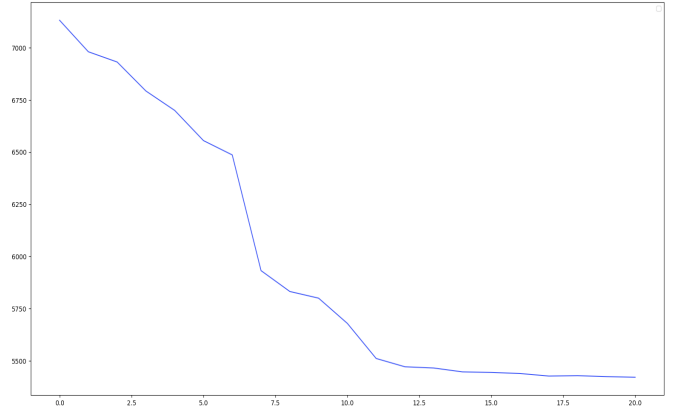


Figure 3: Loss curve of VAE model, epochs = 20, batch_size = 128, lr=5e-4.

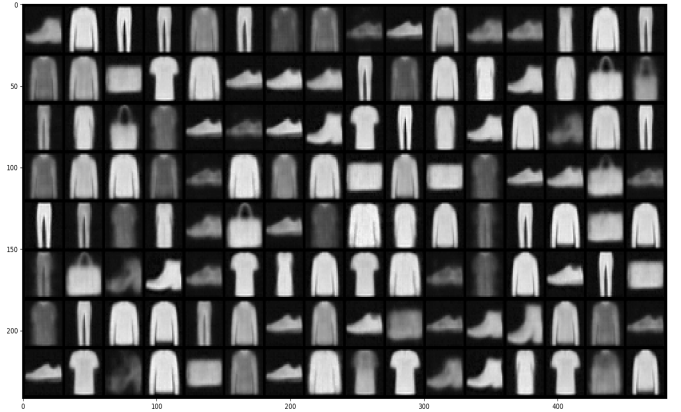


Figure 4: Visualisation of the results while exerting VAE on the testset, 16*8 samples.

After a few epochs the model converges and gives reasonable results. Notice that FashionMNIST doesn't disentangle quite as nicely as on the MNIST, probably because of the larger variation and higher complexity in the images. Although, adding a bit of hyper-parameters tuning may be useful for further improving its performance.