COMP6248 Lab 8 Exercise

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1 VAE Latent Space

In the lab we trained a VAE on the Fashion-MNIST data set. The data was trained in a 2-D latent space, the map of which is illustrated in Figure 1, as dictated in the report. To represent our latent space we mapped 441 images (21x21).

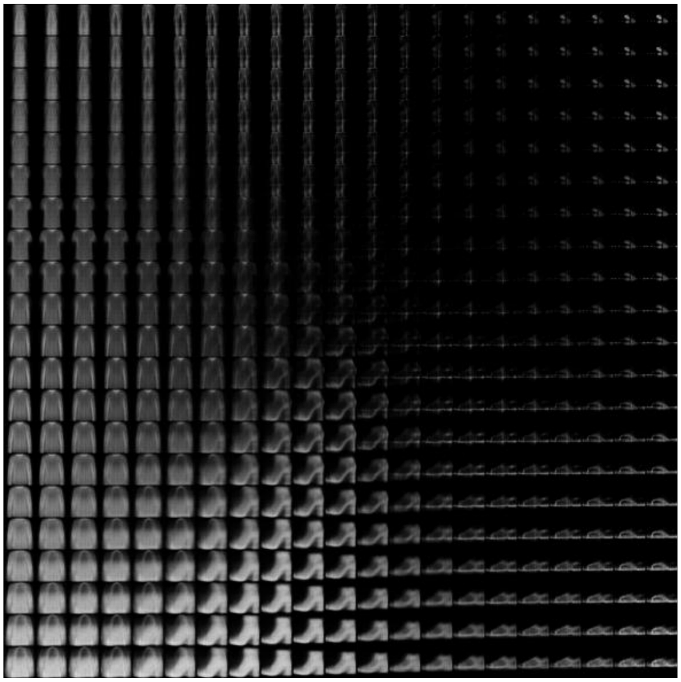

Fig. 1. Latent space of VAE

2 AE Latent Spave

Similarly, for the auto encoder we completed in part 1 of the lab, we adjusted a 2-D latent space and mapped a representation of this latent space in the same manner, illustrated in Figure 2

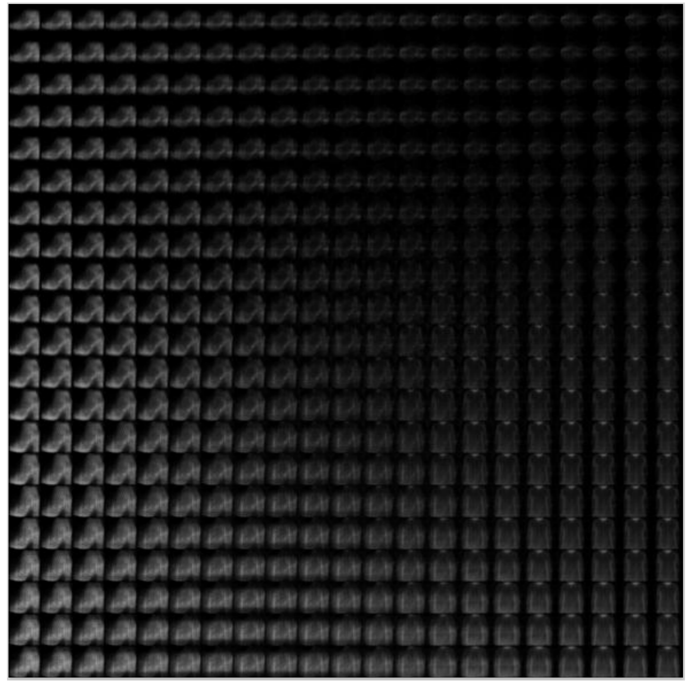

Fig. 2. Latent space of AE

3 Brief Discussion

Mapping a latent space allows us to understand how the generative capabilities of each version of the auto encoder we have tested. The VAE latent space most evidently shows better generalisation characteristics and is able to capture a large number of the pre-trained images than the AE. In addition, the transitions between pre-trained images are smoother than those provided in AE (notice the space occupied by transitioning between short sleeve shirt to long sleeve to a bag and then shoes on the bottom left hand side of the VAE map).

The difference between the two lies in the structure of the Encoder module for VAE and AE. While AE encodes images as singular points within some latent space, VAEs encode images as distributions (note the particular use of the `Log_sigma` module within the VAE Encoder design which handles this parameter for us). Hence, the outcome is a smoother transition between known states. By additionally regularising the VAE over training, it is able to better learn trained states hence the latent space is able to capture the trained states in more detail (wherever they appear). Combine these two realisations and we get a better defined distribution of potentially generated images.