COL333 A3.2: Representation Learning

Poojan Shah 2022CS11594, Pritesh Mehta 2022CS11916

November 2024

$1 \quad VAE$

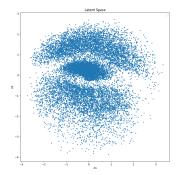
We used a CNN based architecture for the VAE. The following table and figure shows the architecture in detail. We observed that replacing the normal MLP with Convolutional layer allowed the VAE to pick up on essential image features. This allows good separation of the images into three distinct clusters. In all convolution layers, we use kernel size = 4 and stride = 2. Between each layer we use ReLU activation. We used $\beta = 0.55$ for the loss function. We obtained the following results:

Layer	Dimension
Conv2D	$1 \rightarrow 32$
Conv2D	$32 \rightarrow 64$
Conv2D	$64 \rightarrow 64$
FullConnect	$3136 \rightarrow 256$
FullConnect	$256 \rightarrow 128$
FullConnect	$128 \rightarrow 2$

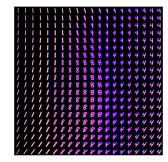
Encoder Architecture

Layer	Dimension
FullConnect	$2 \rightarrow 128$
FullConnect	$128 \rightarrow 256$
FullConnect	$256 \rightarrow 3136$
ConvTranspose2D	$64 \rightarrow 64$
ConvTranspose2D	$64 \rightarrow 32$
Convtranspose2D	$32 \rightarrow 1$

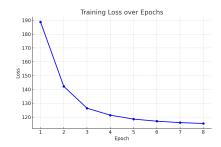
Decoder Architecture



Visualization of the latent space. Notice the 3 distinct clusters formed by the points



Manifold generation. We see a smooth transition between the three digits due to the generative ability of the VAE



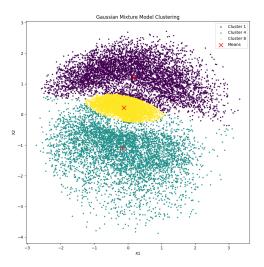
Loss function during training the VAE, We use $\mathcal{L}_{VAE} = \mathcal{L}_{Similarity} + \beta \mathcal{L}_{KL}$ with the hyperparameter $\beta = 0.55$



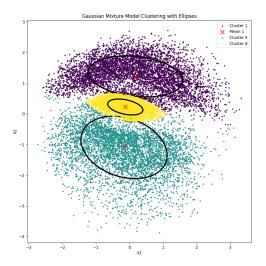
Reconstruction of Validation Images

2 Part 2 : GMM

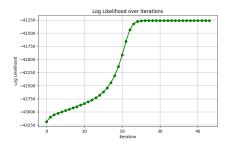
After applying the EM algorithm on the image clusters from VAE, we get the following results . We also show the progress of the EM algorithm for different iterations.



Results of EM algorithm on the dataset



Representing the clusters as mixtures of gaussians. We see that the ellipses are well separated with only a small misclassification rate.



Convergence of the log likelihood for the GMM.

