Generative Experiments with Autoencoders and Variational Autoencoders

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Contents

1 Introduction

This report explores the generative properties of different autoencoder architectures on the MNIST dataset. We investigate the ability of standard, denoising, and variational autoencoders to generate images from random noise vectors, and evaluate the reconstruction quality of the VAE.

2 Task 1: Image Generation with Standard Autoencoder Decoder

2.1 Method

A standard autoencoder was trained on MNIST. After training, five noise vectors were sampled from a normal distribution with mean 5 and variance 1 ($\mathcal{N}(5, 1)$). These vectors were passed through the decoder to generate images.

2.2 Results

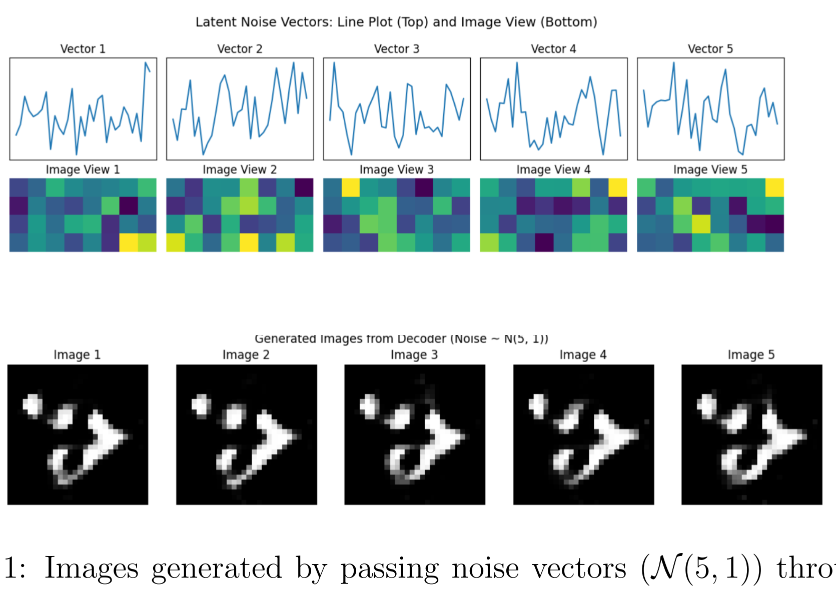


Figure 1: Images generated by passing noise vectors ($\mathcal{N}(5, 1)$) through the standard autoencoder decoder.

2.3 Discussion

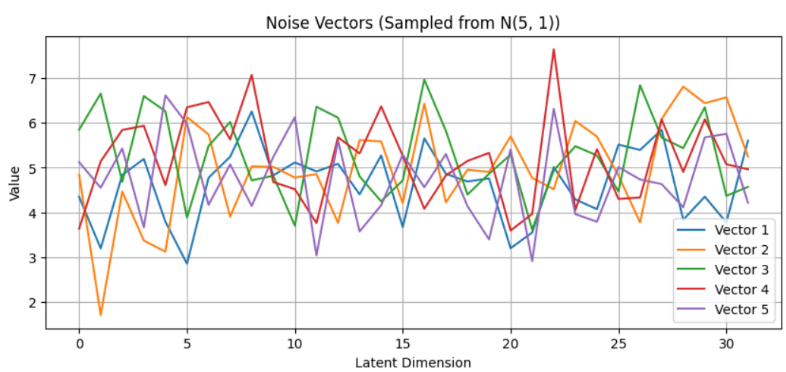
The images generated from random noise do not resemble real MNIST digits. This is expected, as the autoencoder's latent space is not regularized for generative sampling. The decoder is only trained to reconstruct images from latent codes produced by the encoder, not from arbitrary points in latent space.

3 Task 2: Image Generation with Denoising Autoencoder Decoder

3.1 Method

A denoising autoencoder was trained on MNIST, with Gaussian noise added to the inputs during training. Five noise vectors were sampled from $\mathcal{N}(5, 1)$ and passed through the decoder.

3.2 Results



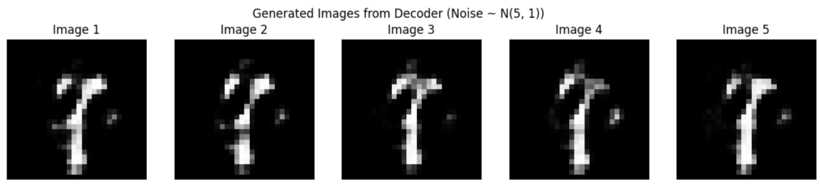


Figure 2: Images generated by passing noise vectors ($\mathcal{N}(5, 1)$) through the denoising autoencoder decoder.

3.3 Discussion

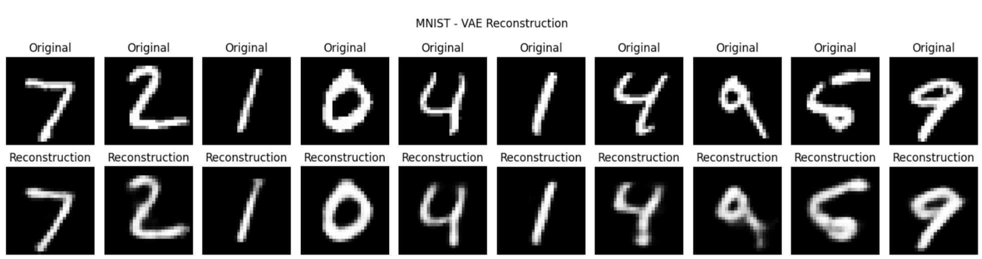
Similar to the standard autoencoder, the denoising autoencoder does not produce meaningful digits from random noise. The latent space is not structured for generative sampling, so the outputs are not realistic.

4 Task 3 and 4: Training and Evaluating a Variational Autoencoder

4.1 Method

A Variational Autoencoder (VAE) was implemented and trained on the MNIST dataset for 15 epochs. The encoder maps input images to a latent space characterized by a mean and log-variance, and the decoder reconstructs images from samples drawn from this latent space. The loss function combines binary cross-entropy (BCE) reconstruction loss and KL divergence regularization.

4.2 Results



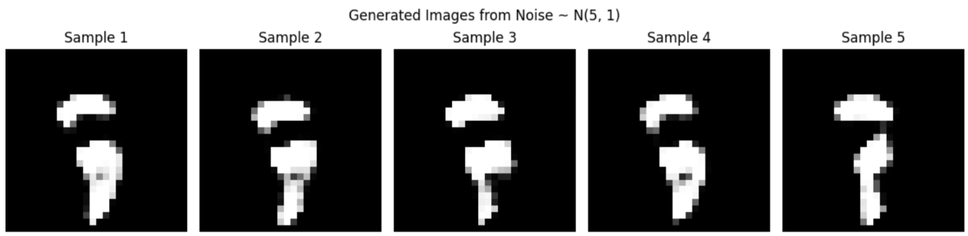


Figure 3: Top row: Original MNIST images. Bottom row: Corresponding VAE reconstructions.

Metric	Value
Mean Squared Error (MSE)	0.0116
Mean Absolute Error (MAE)	0.0364
R2 Score	-0.0922

Table 1: Evaluation metrics for VAE reconstructions on MNIST.

4.3 Discussion

The VAE is able to reconstruct MNIST digits with low error, as shown by the MSE and MAE metrics. The R2 score indicates the proportion of variance explained by the model. The reconstructions are visually similar to the originals, demonstrating the VAE's ability to learn a meaningful latent representation.

5 Conclusion

This study demonstrates that only the VAE, with its regularized latent space, is capable of generating realistic images from random noise. Standard and denoising autoencoders do not structure their latent spaces for generative sampling, resulting in unrealistic outputs when decoding random noise.

Code is in this link: Link