

Autoencoder Homework Report

Rishik Saha (2022CS11932)

Implementation Link

<https://github.com/17vali/COL775/blob/master/HW/HW8/autoencoder-hw.ipynb>

Ablation Study: Visual comparison

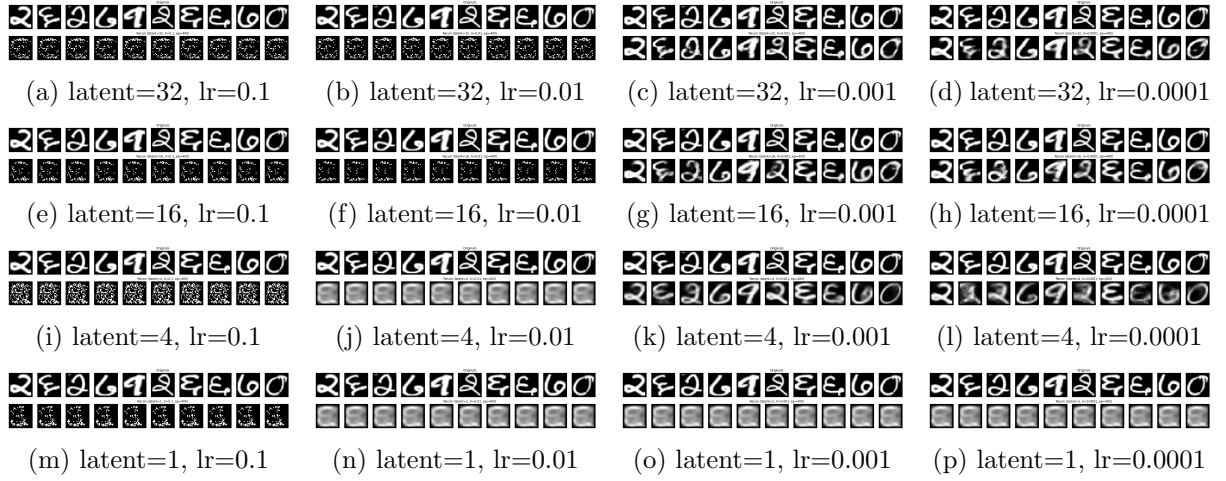


Figure 1: Full ablation grid: latent dimension (rows) vs learning rate (columns). All experiments use 400 epochs.

PCA Comparison (best autoencoder setting)

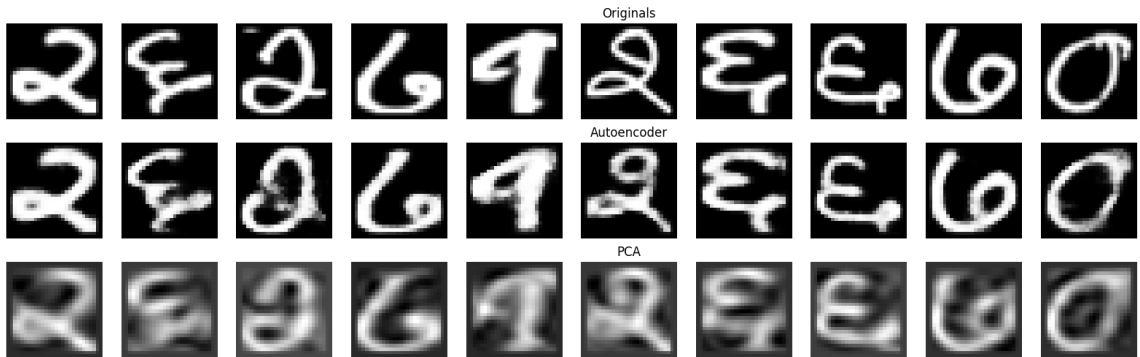


Figure 2: Autoencoder (latent=32, lr=0.001) vs PCA (n_components=32) reconstructions.

Qualitative comparison and discussion

- **Visual fidelity:** The Autoencoder reconstructions at latent=32 retain sharper strokes and finer handwritten details compared to PCA, which captures coarse shape but blurs fine structure.
- **Effect of latent dimension:** As latent size decreases ($32 \rightarrow 1$) reconstructions progressively lose detail; with latent=1 only gross digit shape remains.
- **Effect of learning rate:** Higher learning rates (e.g., 0.1) produces unstable training; very small rates (0.0001) may underfit within the same epoch budget. The grid helps identify stable settings (e.g. lr=0.001).
- **Linear vs nonlinear reduction:** PCA is linear and therefore cannot model nonlinear manifolds that handwritten digits inhabit; autoencoders can learn nonlinear mappings and thus reconstruct complex local strokes better.

Conclusion

The ablation grid summarizes the trade-offs between compression (latent dimension) and optimization (learning rate). For this dataset and architecture, an autoencoder with latent=32 and lr=0.001 (400 epochs) gave the best reconstructions; PCA at the same dimension produced blurrier outputs, illustrating the advantage of nonlinear dimensionality reduction for handwritten digits.