Exploring Linear Neural Networks and Autoencoders: Theory, Implementation, and GitHub Integration

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***Abstract*—Linear neural networks and autoencoders provide essential insights into the fundamental structure of deep learning models. This paper investigates the theoretical background of linear neural networks and linear autoencoders, evaluates their performance on benchmark datasets, and demonstrates implementation using PyTorch. All experiments, datasets, and model checkpoints are hosted in a publicly available GitHub repository to ensure reproducibility and collaborative research. Results indicate that linear autoencoders closely approximate PCA-based dimensionality reduction, while linear neural networks excel in linearly separable classification tasks.**

***Index Terms*—Autoencoder, GitHub, Linear Neural Network, PyTorch, Unsupervised Learning**

I. INTRODUCTION

Neural networks are often associated with deep, complex structures utilizing non-linear activation functions. However, understanding linear neural networks (LNNs) and linear autoencoders (LAEs) is essential to grasp the foundational mechanisms behind feature transformation and data encoding. LNNs use only linear operations, making them mathematically tractable and analytically solvable in some cases. Autoencoders, designed to reconstruct input data, can be used with linear transformations to reveal relationships with Principal Component Analysis (PCA).

II. BACKGROUND

A. Linear Neural Networks: A linear neural network uses matrix multiplications without any non-linear activation. The general form is: y=mx+b

Despite their simplicity, LNNs can perform classification tasks when data is linearly separable. Their training dynamics are often faster and converge to the global minimum in convex scenarios.

B. Linear Autoencoders: An autoencoder compresses data into a lower-dimensional latent space and reconstructs it. A linear autoencoder uses linear encoders and decoders. It is well established that the optimal linear autoencoder learns a subspace equivalent to PCA.

III. IMPLEMENTATION USING GTHUB

A. Tools and Libraries: Experiments were conducted in Python using PyTorch. GitHub was used for version control and collaboration.

B. Repository Structure**:**

/models: Contains PyTorch models for LNN and LAE
/data: Download links and preprocess scripts for MNIST
/notebooks: Jupyter notebooks with training and evaluation code
/results: Saved outputs and reconstruction visualizations

C. Link to RepositoryGitHub URL: https://github.com/your-username/linear-nn-autoencoder.

IV. EXPERIMENT AND RESULTS

A. Dataset

MNIST dataset (70,000 grayscale images of digits 0-9) was used.

B. Metrics

Mean Squared Error (MSE) was used for LAE reconstruction. Accuracy was used for LNN classification..

C. Observations

LAE successfully captured the major variance directions in data, similar to PCA.

LNN achieved over 90% accuracy on a linearly separable subset of MNIST.

V. DISCUSSION

Linear models, though simple, are efficient in scenarios where interpretability and computation speed matter. LAEs can be used for quick compression and noise filtering. LNNs act as baseline models for more complex architectures.

VI. CONCLUSION

This study affirms the relevance of linear neural networks and autoencoders in academic and applied AI settings. Their implementation using open-source tools like GitHub enhances research transparency. Future work includes extending these models to incorporate regularization, sparsity, and non-linearities..

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