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Assignment 1: Foundations Reflection

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Introduction

This report examines two main types of machine learning models discriminatory and genetic - MNIST applies to handwritten digit data sets. Discriminated models such as logistic regression focus on predicting class labels by learning direct decision limits from marked data. Generative models, such as generative conflicting networks (GAN), try to learn the underlying distribution of data to create new samples similar to training kits.

The main goal of this task is to compare the training processes, performance and observed the behavior of these models. While the logistical regression classification provides a base line for accuracy, GAN shows how generative approaches can synthesize images as new digits. This comparison illuminates stability, convergence, exit quality and their difference in the suitability of the real world.

Methods

Dataset

MNIST Data: 70,000 Grayscale Pictures (28 × 28 pixels) of digits.

Partition: 60,000 for training, 10,000 for tests.

Preprocessing:

Logistics regression: Pictures generalize (784 functions) and [0.1].

GAN: Generalized images for stability with TANH activation [–1,1].

Discriminative Model: Logistic Regression

- Architecture: Single linear layer mapping 784 → 10 output classes.
- Training: Adam optimizer, learning rate = 0.001.
- Loss Function: Cross-entropy.
- Epochs: 5.
- Evaluation Metrics: Accuracy, confusion matrix, and classification report.

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Generative Model: GAN

Generator:

Input: A Random noise vector (100 dimensions).

Layer: Fully connected layer [100 → 256 → 512 → 784], Tanh activation to produce 28 × 28 image.

Discriminator:

Input: Flattened image.

Layer: Fully connected layer [784 → 512 → 256 → 1], Sigmoid activation for real/false classification.

Training Setup:

Optimizer: Adam, Learning Rate = 0.0002, Betus = (0.5, 0.999).

Loss: Binary Cross-Entropy (BCE).

ERA: 5-10.

Strategy: Discrimination of each batch and alternative updates for generators.

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3. Results and Observations

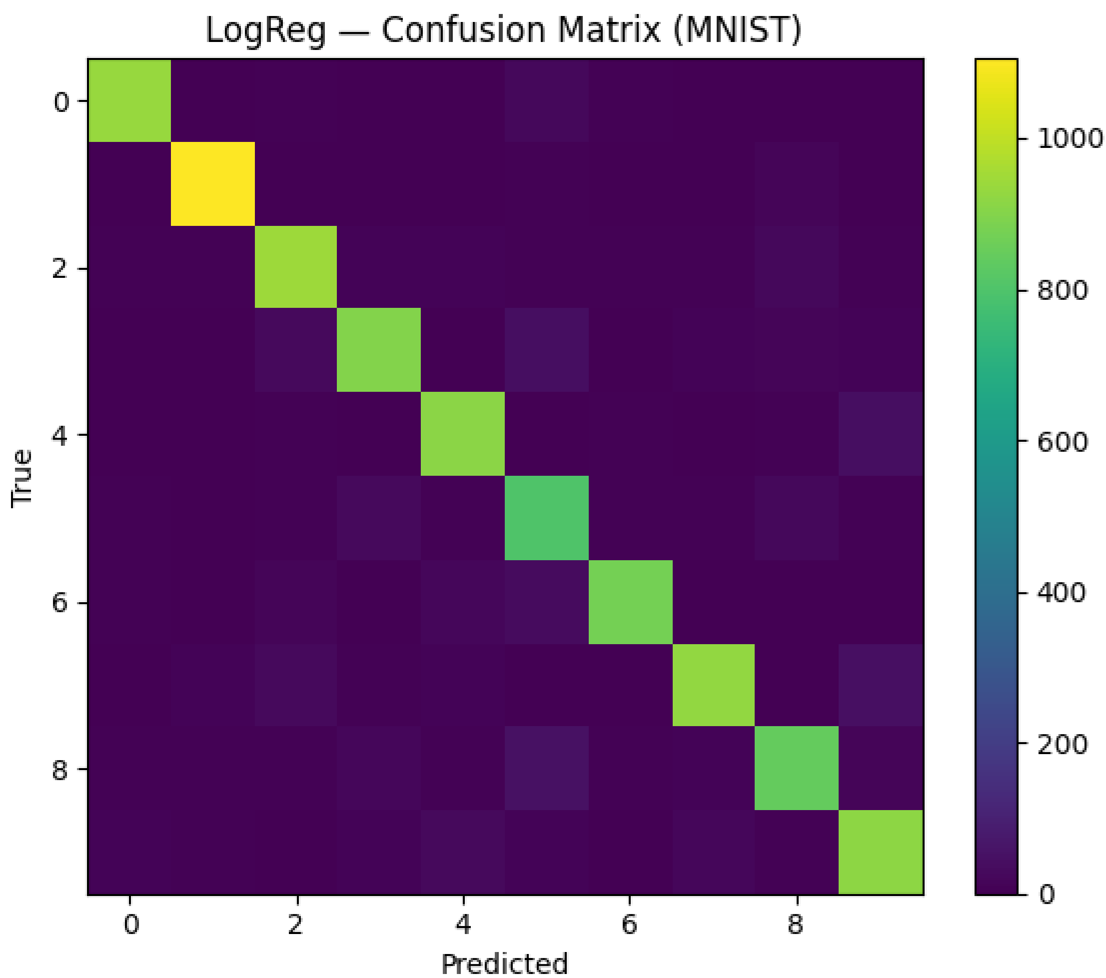
Logistic Regression

Accident: ~ 91–92% test accuracy within 5 ages.

Training mobility: The loss decreased evenly and continuously. The convergence was fast and stable.

Confusion matrix: Most of the errors came from the visually similar digits (eg 4 against 9, 3 vs 5).

Explanation: Weight visualization suggests that the model "1" for vertical rods or "8." For large stroke patterns that loops .



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	precision	recall	f1-score	support
0	0.959959	0.954082	0.957011	980.0000
1	0.966754	0.973568	0.970149	1135.0000
2	0.906040	0.915698	0.910843	1032.0000
3	0.915650	0.892079	0.903711	1010.0000
4	0.914830	0.929735	0.922222	982.0000
5	0.820329	0.895740	0.856377	892.0000
6	0.961581	0.914405	0.937400	958.0000
7	0.940223	0.902724	0.921092	1028.0000
8	0.897028	0.867556	0.882046	974.0000
9	0.879310	0.909812	0.894301	1009.0000
accuracy	0.916500	0.916500	0.916500	0.9165
macro avg	0.916170	0.915540	0.915515	10000.0000
weighted avg	0.917663	0.916500	0.916761	10000.0000

GAN

Generated Samples:

Epoch 1-2: Output noise and unfamiliar.

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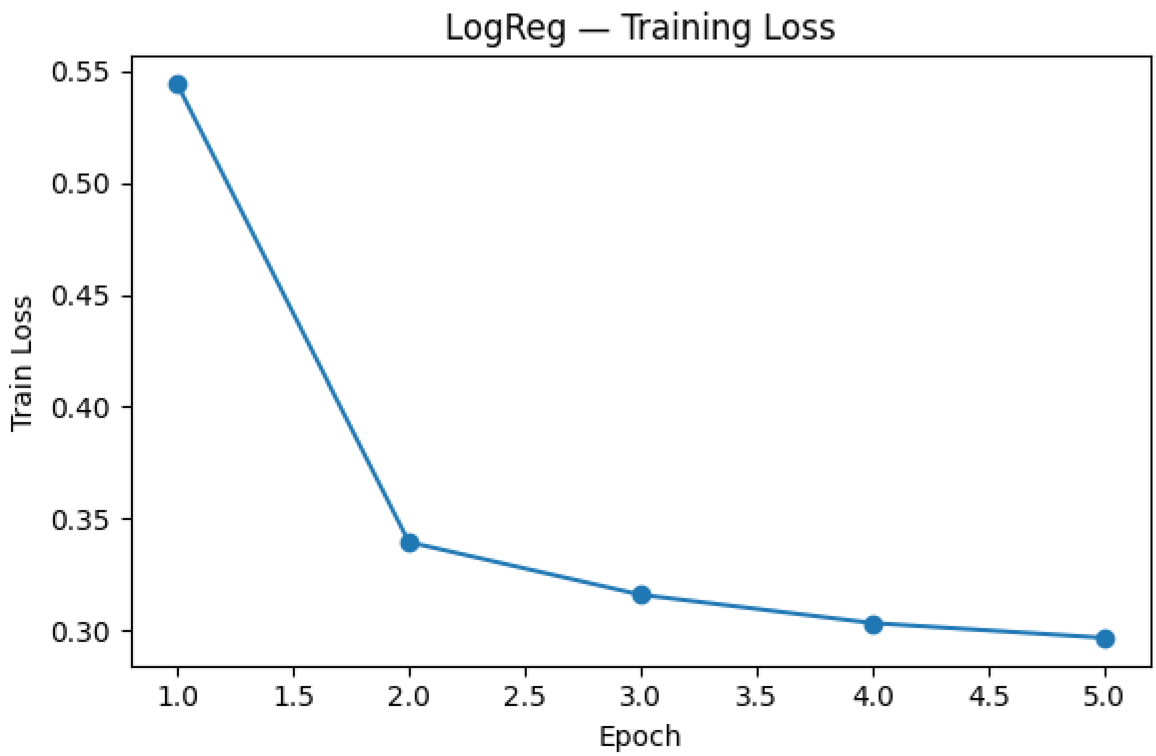
Epoch 5: Points began to be mixed with MNIST figures but lacked sharpness.

Some points are shown more often than others, the partial mode suggests collapse.

Loss Curves : The generator and discriminatory losses are swung instead of changing. This reflects the adverse nature of the training.

Latent Space Behavior: Small changes in the noise vector resulted in gradual changes in number forms, showing that Gana learned a constant latent place.



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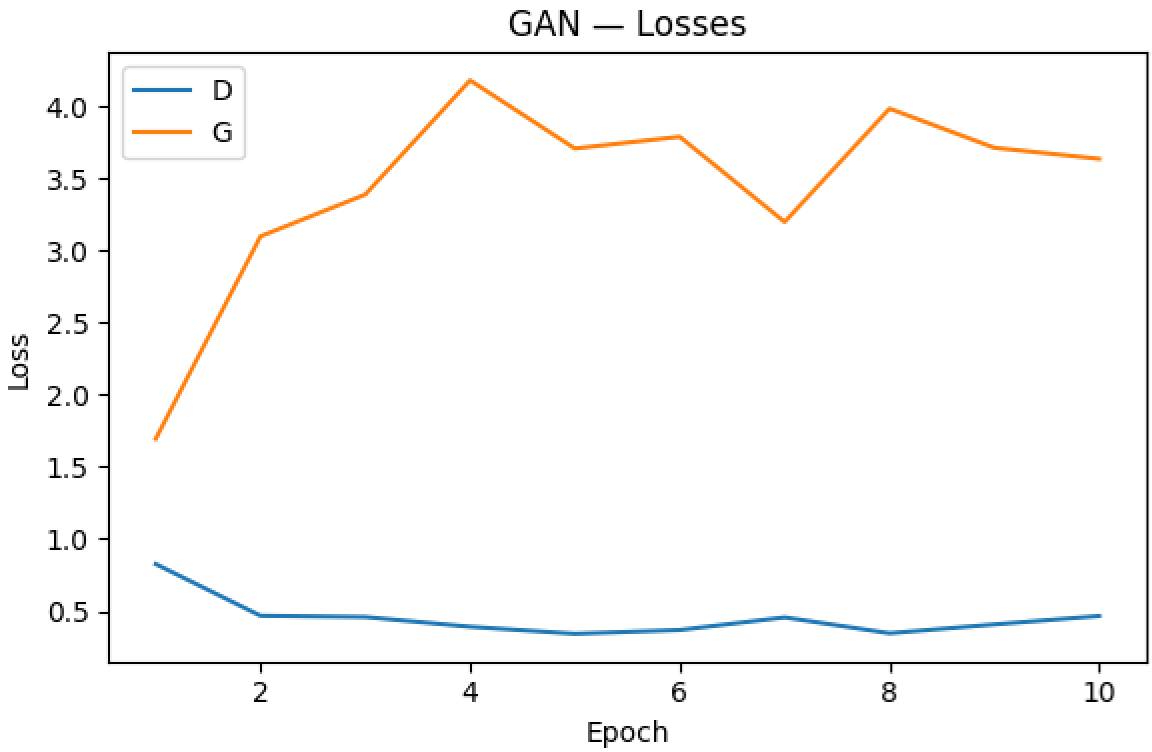

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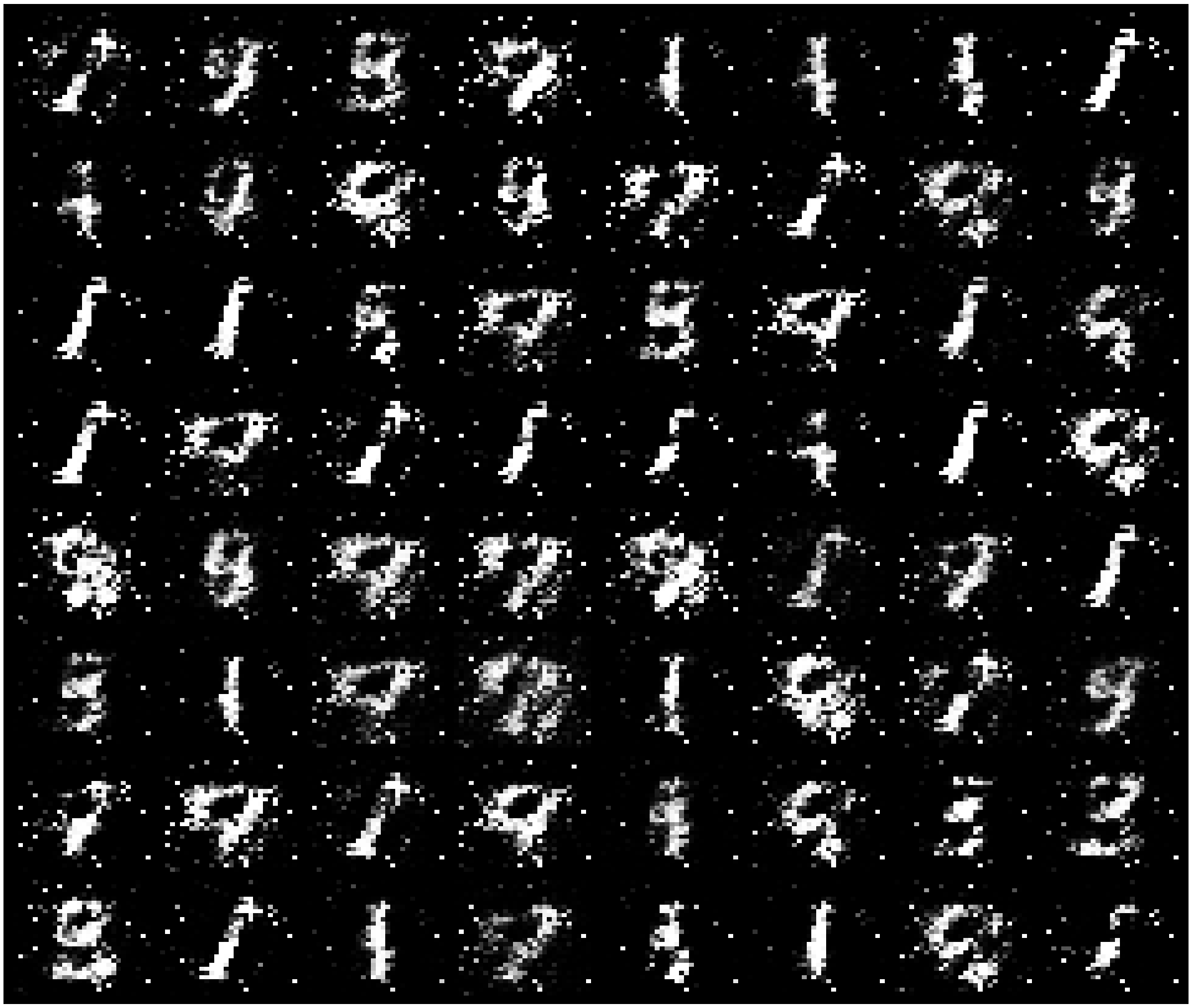

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4. Reflection and Analysis

Comparison illuminates the fundamental difference between discriminatory and generous modeling:

Training stability: The logistical region is convex and stable, well converted with minimal setting. GAN -s are unstable due to unwanted layouts, and often require model capacity and careful balance of hyperparameters.

Performance: Logistic regression gained high classification accuracy on actual data, while GAN tests were visually commendable but incomplete after some ages.

Lecturer: Logistic regression provides explicit strain and clear assessment measurements (accuracy, F1). Gans trust more on visual inspection, which makes the evaluation less right.

hyperparameters. sensitivity: GAN has changed significantly with small adjustment in performance learning speed or network size, sometimes leading to mode collapse.

Application:

Discriminated models are best suited for tasks with marked data where the classification or prediction target is (eg spam detection, medical image classification).

Excel in tasks required by generative model synthetic or creative production (eg image synthesis, data text, privacy data data).

5. Conclusion

Discriminated models such as logistic regression provide faster, reliable classification with strong interpretation, making them ideal for monitored learning functions. Generative models such as GAN, while exercise are more difficult to exercise, enable powerful abilities in data generation, creativity and simulation.

In real applications:

When accuracy and lecturer are important, use the logistics region of specially structured branded data.

Use GAN -er when new data generation or creativity is needed, but expect high calculation costs and instability.

Overall, this task shows trade ties between stability and creativity, and shows why both models are central to modern AI.