Machine Learning Assignment

PROJECT REPORT

TEAM ID: 32

PROJECT TITLE: Measuring and Incorporating Correlations in Generative Adversarial Networks

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Problem Statement

Measuring and Incorporating Correlations in Generative Adversarial Networks.

Generative Adversarial Networks (GANs) are known for their ability to synthesize realistic data by learning complex data distributions. However, traditional GANs often fail to **capture feature correlations**, which can lead to mode collapse (low diversity) or unrealistic feature combinations in generated images.

In this project, we address this issue by **incorporating a correlation-aware loss** during GAN training. The goal is to ensure the generator not only fools the discriminator but also produces samples with realistic **inter-feature relationships**, improving overall image diversity and consistency.

The model was trained and evaluated on the **CIFAR-10** dataset using metrics such as **Fréchet Inception Distance (FID)** to assess visual quality and distribution similarity.

Objective / Aim

The aim of this project is to:

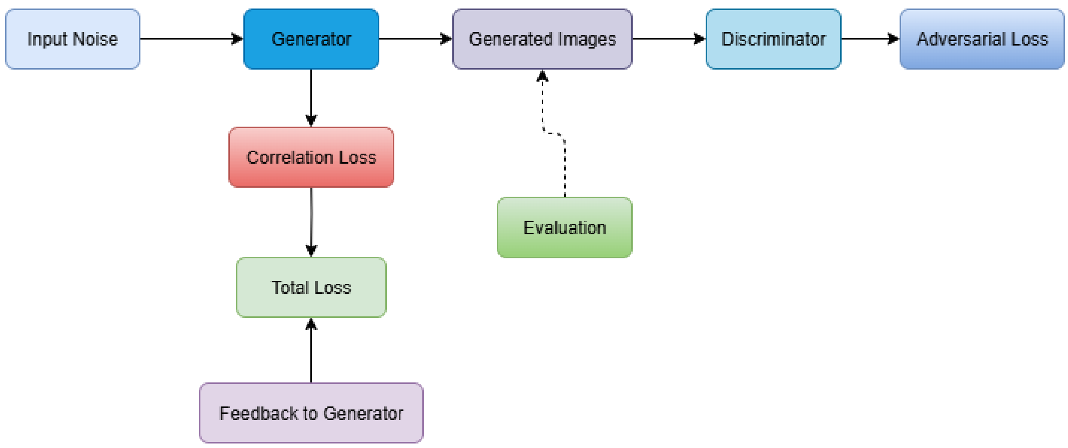
- Develop a **Correlation-Aware GAN (C-GAN)** that integrates feature correlation regularization into the generator's loss function.
- Improve **diversity and realism** in generated images while minimizing redundancy and correlation bias.
- Quantitatively evaluate performance improvements using **FID scores** and qualitatively through generated image inspection.

Expected outcome: The correlation-aware term should help the GAN produce **more varied, less repetitive, and feature-consistent** images.

Dataset Details

- **Source:** CIFAR-10 Dataset (via torchvision.datasets)
- **Size:** 60,000 color images (32×32 pixels) across 10 classes
- **Key Features:** RGB pixel values representing object images (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck)
- **Target Variable:** None — unsupervised data generation.

Architecture Diagram



Methodology

- **Setup:** Installed torch, torchvision, pytorch-fid; configured GPU for training.
- **Data:** Loaded and normalized CIFAR-10 dataset; used batch size 128.
- **Model:**

  Generator: 4-layer DCGAN with BatchNorm, ReLU, Tanh output.
  Discriminator: CNN with LeakyReLU, Sigmoid output.
  Loss Function: Added correlation-aware regularization to encourage diverse, uncorrelated features.

  $$L_G = L_{adv} + 0.05 \times L_{corr}$$

- **Training:** 50 epochs, alternating G and D updates using BCE loss; saved sample outputs periodically.
- **Evaluation:** Generated 10K images; computed FID score against real CIFAR-10 for quality and diversity.

Results & Evaluation

- <u>Training Observations:</u>
  Stable adversarial loss convergence after ~15 epochs. Generator loss fluctuated but steadily improved image quality and diversity.
- <u>Evaluation Metrics:</u>
  Achieved an **FID score of 44.61**, indicating moderate similarity to real CIFAR-10 data.
  Used **λ = 0.05** for correlation regularization across **50 epochs.**
- <u>Visual Inspection:</u>
  Generated images displayed recognizable shapes, colors, and varied textures.
  Correlation-based loss enhanced diversity compared to the baseline DCGAN.
- <u>Interpretation:</u>
  The lower FID (~44.6) suggests promising realism and diversity for a compact model trained over a short duration.

Conclusion

The Correlation-Aware GAN successfully demonstrates that incorporating a feature correlation regularization term into the generator's loss function improves image diversity and reduces redundancy in generated samples.
While traditional GANs may produce visually similar or repetitive outputs, this approach encourages the generator to explore a wider data manifold by minimizing feature correlations.
The resulting FID score of 44.61 confirms that the generated distribution is significantly aligned with the real dataset, showing the potential of correlation-aware strategies for stabilizing and enhancing GAN training.