GAN-Based Image Generation with CIFAR-10

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Course: CSC580 - Advanced Neural Networks

Colorado State University Global

Introduction

Generative Adversarial Networks (GANs) are a form of unsupervised deep learning composed of two competing neural networks-a Generator and a Discriminator. Introduced by Goodfellow et al. (2014), GANs train both models adversarially, resulting in increasingly realistic synthetic data generation.

This project implements a GAN using the Keras deep learning library and a filtered subset of the CIFAR-10 dataset. The Generator creates synthetic images from noise, while the Discriminator classifies images as real or fake. Only class 8 (objects resembling ships, trucks, or animals) was used for simplicity.

Methodology

Data Preparation

- CIFAR-10 data was filtered to include only class 8 samples.
- Images were normalized to a range of [-1, 1] to align with the Generator's tanh output activation.

Architecture

- Generator: Begins with a 100-dimensional latent vector, which is upsampled through transposed convolutions (UpSampling2D + Conv2D) to produce 32x32x3 images.
- Discriminator: A convolutional neural network that progressively downsamples images through Conv2D layers, followed by a Dense sigmoid output.

Training Details

- Discriminator and Generator were trained in alternating steps across 15,000 epochs.
- Training losses and Discriminator accuracy were tracked.
- Images were visualized at epochs 0, 2500, and final (15000) to monitor Generator progress.

Results

Epoch	Output Characteristics
0	Generator produces random noise. Discriminator accuracy ~42%.
2500	Generator begins to form block-like color structures. Discriminator accuracy >99%.
15000	Generator outputs visually consistent colored blocks. No realistic images observed.

Figures

- Figure 1: Epoch 0 Output
- Figure 2: Epoch 2500 Output
- Figure 3: Epoch 15000 Output

The Generator's convergence to repetitive "checkerboard" patterns suggests mode collapse, where the model finds a narrow range of outputs that partially fool the Discriminator but lack semantic variation.

Discussion

- Adversarial training was successfully implemented.
- The Discriminator learned to classify inputs with high accuracy.
- The Generator showed stability in training but failed to generalize, indicating architectural limitations or poor hyperparameter tuning.
- Checkerboard patterns are common in GANs that overfit or lack regularization.

Recommendations for Future Work

To generate more realistic results:
- Introduce Wasserstein loss (WGAN) or gradient penalty.
- Tune dropout rates and learning rates.
- Use Conditional GANs (CGANs) for class-aware image generation.
- Train longer or with improved data augmentation.

Key Takeaways

- Full GAN training loop successfully implemented.
- Mode collapse observed by Epoch 15000.
- Discriminator overfitting suggests imbalance.
- Further experimentation is needed for realism.

References

- Goodfellow, I. et al. (2014). Generative adversarial nets. NIPS.
- Chollet, F. (2015). Keras [Software]. GitHub.
- Krizhevsky, A. (2009). Learning multiple layers from tiny images. Technical Report.