**Option #1: Working with a Generative Adversarial Network**

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**Abstract:**

This paper presents a detailed analysis of a Deep Convolutional Generative Adversarial Network (DCGAN) implemented for image generation from the CIFAR-10 dataset. The code utilizes the Keras library to train a generator and discriminator model iteratively. The discriminator aims to differentiate real and generated images, while the generator’s objective is to produce images that can deceive the discriminator. The training process involves updating the models’ weights using the adversarial training paradigm. The paper examines the code implementation, discusses the model architecture, and provides an analysis of the training progress and generated images.

**Deep Convolutional Generative Adversarial Networks for Image Generation: A Case Study on CIFAR-10 Dataset**

Deep Convolutional Generative Adversarial Networks (DCGANs) have emerged as powerful models for generating realistic images. In this paper we focus on training a DCGAN to generate images of class 5 from the CIFAR-10 dataset. The goal is to analyze the code implementation and evaluate the quality of the generated images through a detailed examination of the training progress.

**Methods:**

The code is written in Python using the Keras library. It starts by loading the CIFAR-10 dataset and selecting images of class 5 for training. The generator and discriminator models are constructed using the Sequential API in Keras. The generator takes random noise vectors as input and generates images, while the discriminator classifies images as real or fake. The models are compiled with appropriate loss functions and optimizers. The training loop updates the models’ weights by iteratively training the discriminator and generator on batches of real and fake images. The progress is visualized by displaying generated images and plotting the losses.

**Results:**

The training progress is analyzed by examining the discriminator and generator losses, accuracies, and the quality of the generated images. The initial discriminator loss is relatively high, indicating that it struggles to differentiate real and fake images. However, as the training progresses, the discriminator loss decreases significantly, approaching zero, and the discriminator accuracy reaches 100%.

This suggests that the discriminator becomes proficient in distinguishing real and fake images. The generator loss steadily decreases, indicating improvement in its ability to generate realistic images. The generated images, displayed at different epochs, show a progression towards more visually coherent and class-relevant images.

**Discussion:**

The DCGAN model successfully learns to generate images of class 5 from the CIFAR-10 dataset. The decreasing discriminator loss and increasing accuracy demonstrate the effectiveness of the discriminator in detecting real and fake images. The decreasing generator loss indicates that the generator learns to generate more realistic images as the training progresses. However, it is important to note, that after a certain point (around 10,000 epochs), the discriminator loss and accuracy reach optimal values, while the generator loss fluctuates. This suggests that the generator has already learned to generate realistic images, and further training might not yield significant improvements.

**Conclusion:**

The analysis of the DCGAN training process on the CIFAR-10 dataset demonstrates the effectiveness of the model in generating images of a specific class. The code implementation successfully trains a discriminator and generator, achieving realistic image generation. The training progress shows the convergence and improvement of the models over epochs. The findings of this study contribute to the understanding of image generation using DCGANs and provide a foundation for future research in this area.