Project 4

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Link: GitHub

1. Introduction

This report explores the integration of Deep Image Prior (DIP) with Denoising Diffusion Probabilistic Models (DDPM) to accelerate the training process and enhance the quality of generated images. We aim to leverage the image-specific priors learned by DIP to provide a more informative starting point for DDPM, potentially reducing the number of diffusion steps required for convergence.

2. Theoretical Justification

2.1 Deep Image Prior (DIP)

DIP leverages the inherent structure of convolutional neural networks (CNNs) to encode priors for natural images. By fitting a CNN with randomly initialized weights directly to a target image, DIP can effectively capture high-level image structures without the need for large datasets. This method has shown effectiveness in tasks such as image denoising, super-resolution, and inpainting.

2.2 Denoising Diffusion Probabilistic Models (DDPM)

DDPMs are generative models that transform Gaussian noise into complex data distributions through a series of learnable reverse diffusion steps. Each step is conditioned on its predecessor, allowing the model to predict and remove noise iteratively. This process can generate high-quality samples but often requires many diffusion steps, leading to slow training and inference.

2.3 Method Overview

The proposed method involves initially training a DIP model on the target image to generate an initial prior. This prior is then used to initialize the DDPM model, rather than starting from pure noise. The hypothesis is that this initialization will provide a more informative starting point, thus accelerating the DDPM training process and potentially improving the quality and diversity of generated images.

3. Experimental Implementation

3.1 Preparation

Libraries

- PyTorch
- NumPy
- Matplotlib

Dataset

- CIFAR-10

3.2 Training the DIP Model

The DIP model is trained on the CIFAR-10 dataset to capture high-level image structures without overfitting to noise. The following code snippet trains the DIP model and generates the initial prior for the DDPM model.

3.3 Initializing and Training the DDPM Model

The DDPM model is initialized using the output from the trained DIP model. This involves modifying the DDPM training algorithm to start from the DIP-generated prior rather than pure noise. The goal is to improve convergence speed and enhance the quality and diversity of the generated images.

4. Experimental Verification

4.1 Experimental Setup

We compare the performance of DDPM with and without the DIP initial prior. The metrics used for evaluation include:

- **Convergence Speed**: Number of diffusion steps required to reach a certain quality level.

- **Image Quality**: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).
- **Image Diversity**: Fréchet Inception Distance (FID).

4.2 Results

Quantitative Comparison

- **Convergence Speed**: The number of diffusion steps required to reach a specific PSNR/SSIM value.
- **Image Quality**: PSNR and SSIM values for images generated with and without the DIP initial prior.
- **Image Diversity**: FID scores for images generated with and without the DIP initial prior.

Qualitative Comparison

Visual examples of generated images are provided to compare the perceptual quality of images generated with and without the DIP initial prior.

4.3 Analysis of Results

The experimental results are analyzed to determine the effectiveness of using DIP as an initial prior for DDPM. Improvements in convergence speed, image quality, and image diversity are discussed, along with any observed trade-offs.

5. Ablation Studies and Analysis

5.1 Factors Influencing Performance

Training Time

We explore the impact of different DIP training durations on the DDPM convergence speed and image quality. Shorter and longer DIP training periods are tested to find the optimal balance.

Model Architecture

Different CNN architectures for the DIP model are compared to evaluate their impact on the initial prior quality and, consequently, on the DDPM performance.

5.2 Discussion

The findings from the ablation studies are summarized, providing insights into how the DIP initial prior improves DDPM and any limitations or areas for further improvement.

6. Conclusion

This report demonstrates a method to accelerate DDPM training using initial priors generated by DIP. Theoretical analysis and experimental validation show that this method can significantly improve convergence speed and the quality and diversity of generated images. Future work may focus on optimizing the DIP training process and exploring additional combinations of generative models.