Project Proposal - ECE 176

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Abstract

This project focuses on the reimplementation of a traditional Generative Adversarial Network (GAN) (Goodfellow et al., 2014) from scratch. The aim is to understand the fundamental working principles of GANs and explore potential improvements of the generator in training stability and image quality. This proposal outlines the motivation, tentative methodology, and planned experiments for the GAN reimplementation.

1 Problem Definition

Generative Adversarial Networks (GANs) have demonstrated significant success in generating high-quality synthetic images. However, training GANs is unstable. The goal of this project is to thoroughly reimplement a baseline GAN and investigate strategies to improve its training dynamics and performance. The key challenges include:

- Stabilizing the adversarial training process.
- Ensuring diverse and high-quality image generation.
- Experimenting with modifications to the generator and discriminator architectures.

2 Tentative Method

To reimplement and analyze GAN training, we plan the following steps:

2.1 Baseline GAN Implementation

- Implement a standard GAN
- Train using standard adversarial loss with the original Goodfellow approach.
- Use CelebA dataset for evaluation.

2.2 Training Stability Improvements

- Experiment with different normalization techniques like batch normalization and spectral normalization.
- Investigate alternative loss functions.
- Implement learning rate scheduling and adaptive optimizers (e.g., Adam)

2.3 Regularization and Architectural Enhancements

- Apply feature matching to stabilize gradients.
- Explore progressive growing of GANs for high-resolution generation.
- Add the feedback loop that can affect the training of the generator.

3 Experiments

3.1 Datasets

We plan to evaluate the GAN reimplementation on:

- **CelebA**: Facial image dataset

3.2 Experimental Setup

1. **Baseline Training:** Train the reimplemented GAN using standard techniques and compare performance.
2. **Evaluation Metrics:** Fr’echet Inception Distance (FID) for realism.
3. **Ablation Study:** Analyze the effect of normalization, different loss functions, and regularization techniques.

References

1. Ian Goodfellow et al., "Generative Adversarial Networks," NeurIPS, 2014.