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Introduction to Deep Learning

Midterm project report on

Deep Convolutional GAN (DCGAN) for image super-resolution

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Introduction

1. Problem Definition

- Images with low resolution frequently lack detail and clarity, which makes them unsuitable for applications that demand high-quality visuals. Our goal is to enhance the resolution and quality of these images.

2. Objective

- We propose a Deep Convolutional Generative Adversarial Network (DCGAN) method to enhance the quality of low-light images. This system comprises two parts: the generative network and the discriminative network.
- The objective of the generative network is to enhance low-light images in order to enhance the quality of the images.

Background

1. Image Super-Resolution Overview

- Image Super-Resolution is a machine learning task aimed at enhancing the resolution of an image while preserving its content and details.
- This technique is applicable in various domains, including computer vision and medical imaging, resulting in a high-resolution version of the original image.

2. Generative Adversarial Networks (GANs)

- A Generative Adversarial Network (GAN) is a deep learning framework that involves two neural networks competing against each other to create realistic new data from a given training set.
- One network generates new data by taking an input data sample and modifying it as much as possible.
- The other network tries to predict whether the generated data output belongs in the original dataset, essentially determining if the data is real or fake.

3. Deep Convolutional GAN (DCGAN)

- Deep Convolutional GAN (DCGAN) is a specific implementation of GANs that utilizes deep convolutional networks in both the generator and discriminator.
- The generator takes a random noise vector as input and uses fractional-strided convolutions to upsample it into a high-resolution image, applying ReLU activations in all layers except the output, which uses Tanh activation.
- The discriminator, on the other hand, uses strided convolutions to downsample the input image, employing LeakyReLU activations throughout.

- Both components utilize batch normalization to stabilize training.
- Key modifications from standard GANs include the replacement of fully connected layers with convolutional layers, the use of batch normalization, and specific activation functions, all of which contribute to more stable training and higher quality image generation.

Dataset and preprocessing

1. Dataset

- In this project, we used the CelebA dataset, which is a large-scale face attributes dataset containing over 200.000 celebrity images with various facial expressions, backgrounds, and lighting conditions. CelebA is widely used for image generation tasks, making it an ideal choice for training a DCGAN model.
- Due to the time constraints, we selected only 4000 images from the dataset for training.

2. Preprocessing

- Before training the DCGAN model, the dataset underrwent several steps to ensure the compatibility with the architecture:
  - Resizing: All images were resize to 64x64 pixels, matching the input size expected by the model.
  - Normalization: Pixel values were normalized to the range [-1,1] by subtracting 0.5 and dividing by 0.5, which helps with stabilizing the training process in the generator and discriminator.
- PyTorch's Dataloader was utilized for efficient dataset loading, using 128 images per batch, enabling shuffling to ensure variety across batches during training, and emplyed 2 workers for loading and preprocessing.

DCGAN Model

1. Generator Architecture

- The Generator neural network is built using the nn.Sequential module, which defines the model as a sequence of layers consisting of transpose convolution layers, batch normalization layers, and ReLU activations.
- The first layer takes a random noise vector of size nz = 100 as the input and transforms it into a feature map of size (ngf*8)x4x4 using a transpose convolution operation.
- This architecture consists of 5 transposed convolutional layers that progressively upsample the input noise into an image, each layer increases the spatial dimensions while reducing the number of feature maps.
- The final layer produces a 3x64x64 mage

- The ReLU activation is applied after each transpose convolutional layer, except for the output layer, which uses a Tanh activation function to scale the pixel values to range of [-1, 1].
- The Batch normalization is applied after transpose convolutional layer to stabilize and accelerate training.

```
Generator(
  (main): Sequential(
    (0): ConvTranspose2d(100, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (4): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): ReLU(inplace=True)
    (6): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (7): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): ReLU(inplace=True)
    (9): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): ReLU(inplace=True)
    (12): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (13): Tanh()
  )
)
```

2. Discriminator Architecture

- The Discriminator neural network is also built using nn.Sequential, similar to the generator, but with a different architecture. It consists of convolution layers, batch normalization layers, and LeakyReLU activations to classify the input image as real or fake.
- The Discriminator takes a 3x64x64 image as input, representing either a real image from the dataset or a generated image from the generator.
- This architecture has total of 5 convolutional layers to progressively downsample the input image, reducing its spatial dimensions while increasing the number of feature maps.
- The final layer reduces the feature map to a 1x1x1 scalar output, which represents a single value or probability. By using Sigmoid activation, it convert the scalar value into a probability between 0 and 1
- The LeakyReLU activation function is used throughout the network. It allows a small gradient when the input is negative, preventing the dying ReLU problem and helping the discriminator better differentiate between real and fake images.

```
Discriminator(
  (main): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): LeakyReLU(negative_slope=0.2, inplace=True)
    (2): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (4): LeakyReLU(negative_slope=0.2, inplace=True)
    (5): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (7): LeakyReLU(negative_slope=0.2, inplace=True)
    (8): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (9): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (10): LeakyReLU(negative_slope=0.2, inplace=True)
    (11): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (12): Sigmoid()
  )
)
```

3. Hyperparameters

- Learning rate: 0.0002
- Batch size: 128
- Latent vector (z) Size: 100
- Optimizer: Adam optimizer with B1 = 0.5 and B2 = 0.999

4. Training setup

- Number of training: For this project, we trained total of 15 times, each time 10 epochs.
- Hardware: In this project, we used Google Colab GPU for the training and using Pytorch's GPU support for faster calculation.
- Loss function: Binary Cross Entropy Loss (BCE Loss) was used for both generator and discriminator.

5. Training Procedure

a) Initialize model:

- The generator and discriminator were initialized before training.
- Both model's weight of convolutional layer were initialized using a normal distribution with mean 0 and standard deviation 0.02. This type of initialization ensures that the weights are set to small random values, which is important for stabilizing the training process in deep neural networks.
- For the weight of normalization layer, it were initialized with normal distribution with mean 1 and standard deviation 0.02.

b) Load data: The CelebA dataset was preprocessed, and the DataLoader was used to load mini batches of images for each epoch.

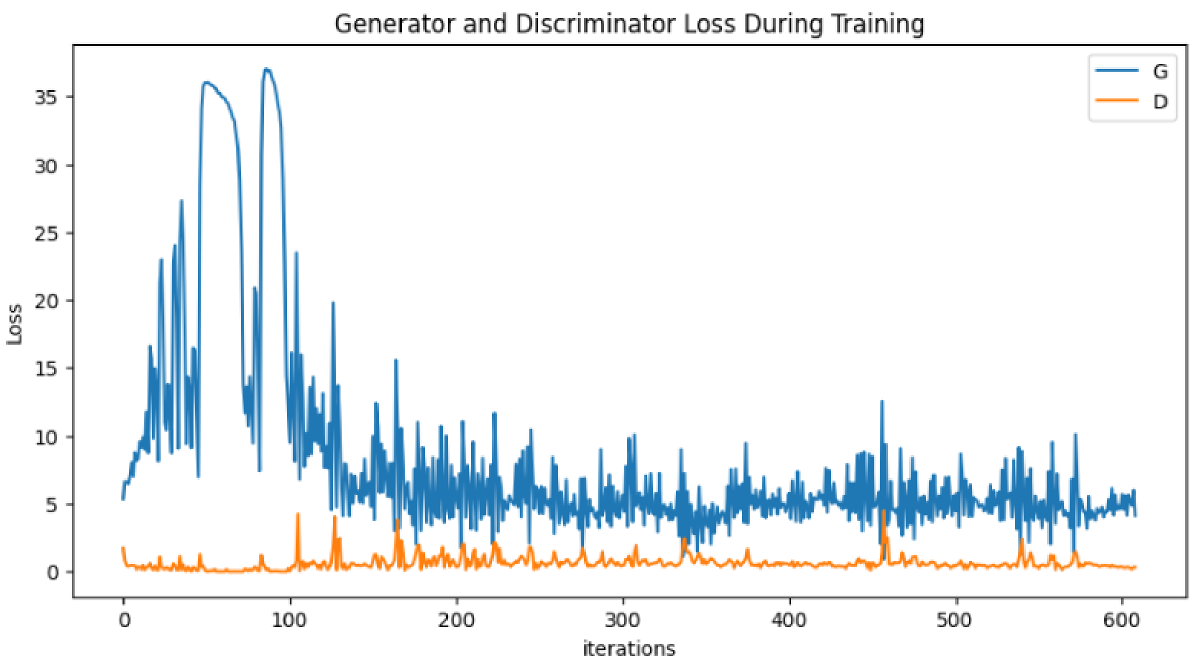
c) Training loop:

- Train the discriminator
  - A batch of real images from the dataset was put into the discriminator, and the discriminator’s real loss was computed
  - A batch of fake images was generated by feeding random noise into the generator, and the discriminator’s fake loss was computed.
  - The discriminator’s total loss was calculated, and backpropagation was performed to update its weights

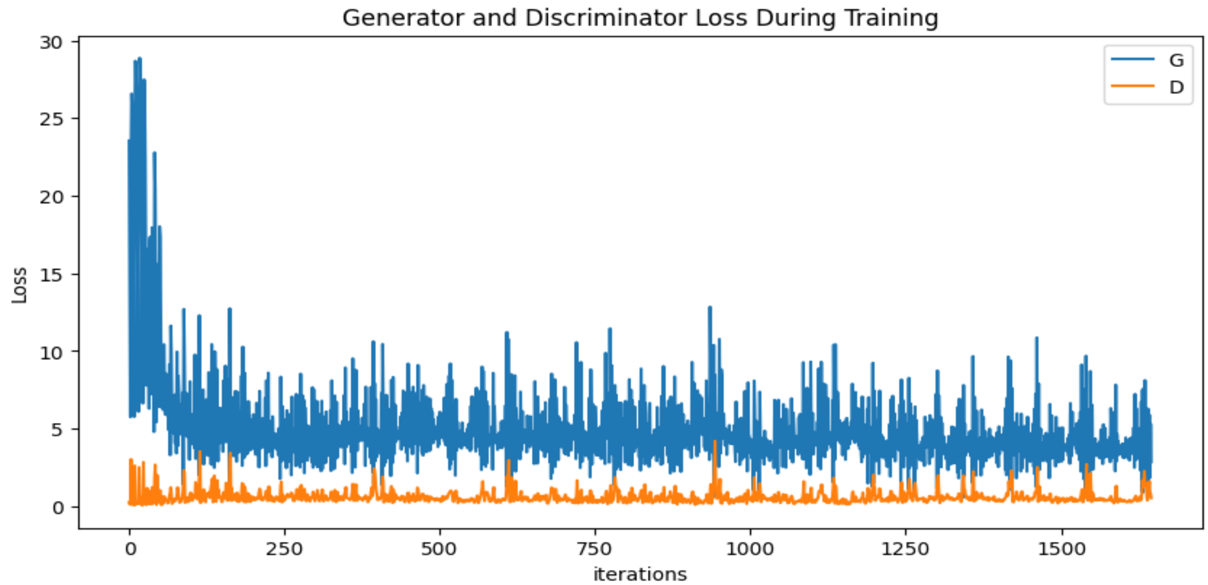
- Train the generator
  - A new batch of fake images was generated
  - These fake images were passed through the discriminator again, and the generator’s loss was computed based on how well it fooled the discriminator.
  - Backpropagation was performed to update the generator’s weights, with the goal of improving its ability to generate realistic images.

Experimented Results

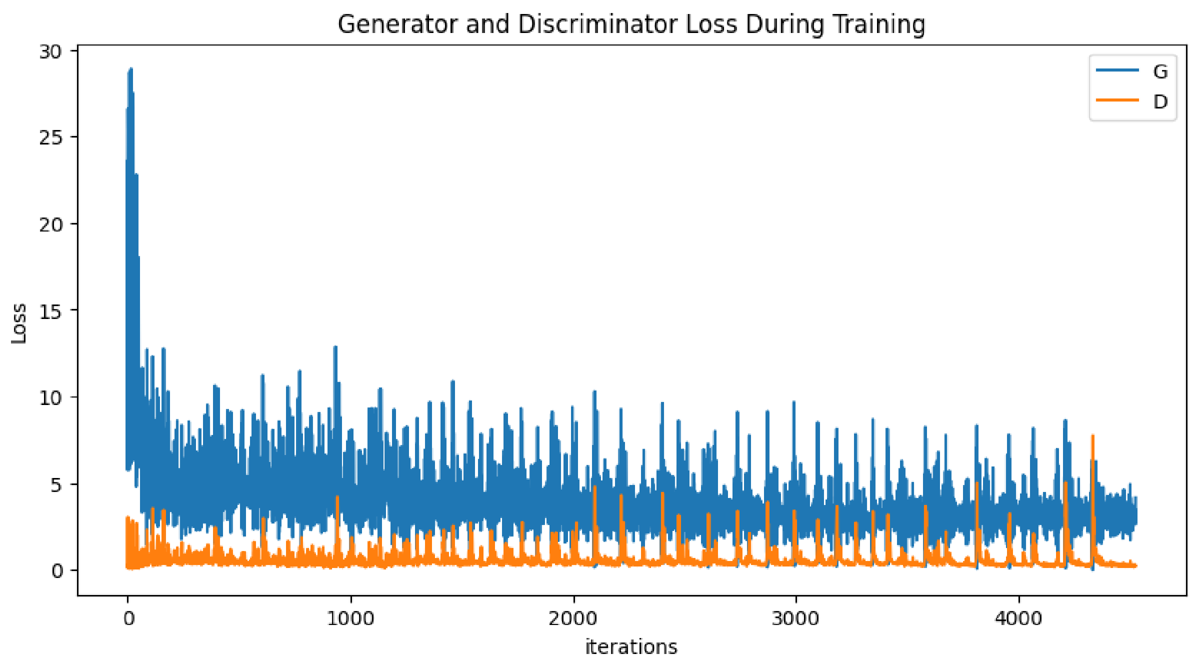
- Iteration of training versus loss
  - After the first 10 epochs:



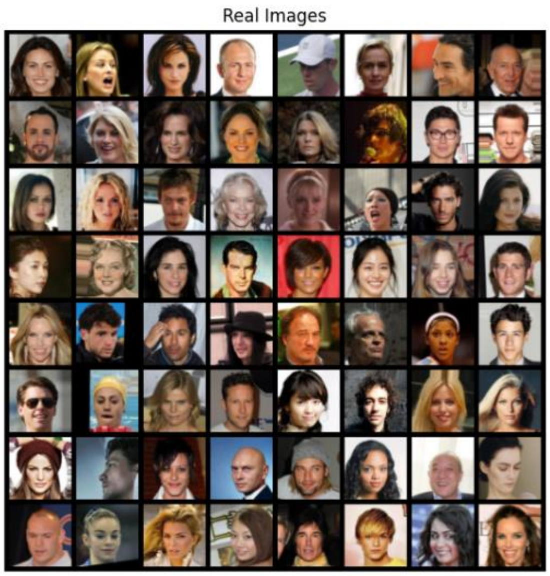
  - After 50 epochs:



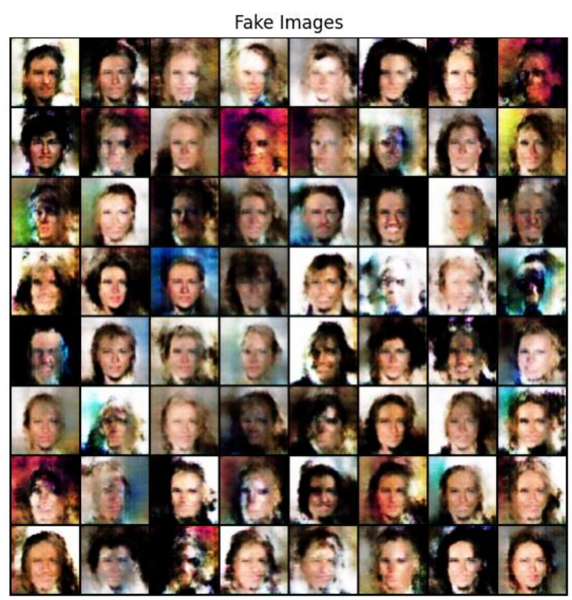
- After 150 epochs:



- Real images and fake images
    - After the first 10 epochs:



- After 50 epochs:



- After 150 epochs:

1. Discussion

- The trends observed from the loss chart show that the training is converging, with the generator improving its performance over time. The discriminator's loss remains low and stable, showing that the discriminator has adapted to the generator's output, indicating that it is still learning to keep pace.

2. Future Work

- Increase Dataset Diversity
- Modify the model to take different dataset
- Increase epoch to see better score
- Improve the Generator and Discriminator neural network
- Apply these GAN hacks to see the difference

References

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