Generative Models: Generative Adversarial Networks (GANs)

Overview

Generative Adversarial Networks (GANs) are a class of generative models that consist of two neural networks: a **Generator** and a **Discriminator**. These networks compete against each other in a game-theoretic setup, where:

- **Generator**: Learns to generate fake data resembling real data.
- **Discriminator**: Learns to distinguish between real and fake data.

Key Features of Vanilla GAN:

- **Generator**: Takes random noise (latent vector) as input and generates synthetic data (e.g., images).
- **Discriminator**: Takes data as input and outputs a probability indicating whether the data is real or fake.
- **Adversarial Process**: The generator tries to fool the discriminator, while the discriminator tries to detect fake data. This competition drives both networks to improve over time.

Why Use Vanilla GAN?

- **Data Generation**: GANs are widely used for generating realistic images, audio, video, and text.
- **Image Synthesis**: They have applications in generating new images from random noise, style transfer, image super-resolution, and more.
- **Training Stability**: Although GANs are powerful, they can be difficult to train due to mode collapse and vanishing gradients, but various modifications (e.g., Wasserstein GAN) can help address these issues.

Prerequisites

- **Python 3.x**: Ensure Python 3.x is installed.

- **PyTorch**: Install PyTorch for building and training GANs.

  ```
  pip install torch torchvision
  ```

Code Description

1. Generator Network

```
class VanillaGenerator(nn.Module):
    def __init__(self, z_dim, img_dim):
        super(VanillaGenerator, self).__init__()
        self.fc = nn.Sequential(
            nn.Linear(z_dim, 128),
            nn.ReLU(True),
            nn.Linear(128, img_dim),
            nn.Tanh()
        )

    def forward(self, z):
```

```
        return self.fc(z)
```

Explanation:

- **Linear Layers**: The generator consists of fully connected (FC) layers. The input `z` is a random noise vector of dimensionality `z_dim`. The network outputs an image of dimensionality `img_dim` (in this case, 784, which corresponds to a flattened 28x28 image).
- **Activation Functions**:
  - ReLU is used for the hidden layer to introduce non-linearity.
  - Tanh is used for the output layer to scale the generated image values between -1 and 1.

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2. Discriminator Network

```
class VanillaDiscriminator(nn.Module):
    def __init__(self, img_dim):
        super(VanillaDiscriminator, self).__init__()
        self.fc = nn.Sequential(
            nn.Linear(img_dim, 128),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(128, 1),
            nn.Sigmoid()
        )

    def forward(self, img):
        return self.fc(img)
```

Explanation:

- **Linear Layers**: The discriminator also consists of fully connected layers. It takes an image as input and outputs a probability score indicating whether the input is real or fake.
- **Activation Functions**:
  - LeakyReLU is used to avoid dying ReLU issues, allowing a small, non-zero gradient for negative input values.
  - Sigmoid is used at the output layer to produce a probability value between 0 and 1.

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3. Initialization of Hyperparameters

```
 z_dim = 100  # Dimensionality of the input noise vector
img_dim = 784  # Example: Flattened 28x28 image size (MNIST dataset)
generator = VanillaGenerator(z_dim, img_dim)
discriminator = VanillaDiscriminator(img_dim)
```

Explanation:

- **z_dim**: The size of the random noise vector that serves as input to the generator.
- **img_dim**: The size of the output image (784 corresponds to a flattened 28x28 image, as in the MNIST dataset).
- **Generator and Discriminator**: Instances of the generator and discriminator networks are created.

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4. Optimizer Setup

```
 # Example of initializing optimizers
lr = 0.0002
beta1 = 0.5
optimizer_g = optim.Adam(generator.parameters(), lr=lr, betas=(beta1, 0.999))
```

```
optimizer_d = optim.Adam(discriminator.parameters(), lr=lr, betas=(beta1, 0.999))
```

Explanation:

- **Learning Rate and Beta**: The Adam optimizer is used for both networks with a learning rate of 0.0002 and `beta1=0.5` for the momentum term.
- **Separate Optimizers**: Different optimizers are used for the generator and discriminator.

Expected Outputs

1. **Generated Data**: The generator will output synthetic images from random noise vectors.
2. **Discriminator Output**: The discriminator will classify whether the images are real (from the training set) or fake (generated by the generator).
3. **Training Process**: During training, both networks will improve iteratively as the generator becomes better at fooling the discriminator and the discriminator becomes better at distinguishing real from fake data.

Use Cases

- **Image Generation**: GANs can be used to generate realistic images, such as creating artwork, fashion items, or even human faces.
- **Super-Resolution**: GANs can generate high-resolution images from low-resolution inputs.
- **Data Augmentation**: GANs can be used to generate additional training data for machine learning models.

Future Enhancements

1. **Improved Architectures**: Explore more advanced GAN architectures such as DCGAN, WGAN, and StyleGAN for better performance.
2. **Training Techniques**: Experiment with different loss functions, such as Wasserstein loss, to stabilize training.
3. **Conditional GANs**: Use conditional GANs to generate data conditioned on specific inputs, such as class labels or other attributes.

References

- Goodfellow, I., et al. (2014). Generative Adversarial Nets. *NIPS 2014*. Link
- PyTorch Documentation for GANs: Link