EX 8 IMAGE GENERATION USING VARIATIONAL AUTOENCODER (VAE)

Problem Statement:

Implement a Variational Autoencoder (VAE) to generate new images from a given dataset. Train the model to learn the latent representation of images and generate new samples from the learned distribution.

Suggested Dataset: CelebA Dataset

Objectives:

- 1. Understand the concept of generative models using latent space representations.
- 2. Implement encoder-decoder architecture with reparameterization.
- 3. Train a VAE on CelebA and generate new human face images.
- 4. Visualize generated samples from the latent space.

Scope:

VAEs are probabilistic generative models capable of learning latent representations and generating realistic samples. This experiment explores the VAE pipeline—encoding, sampling via reparameterization, and decoding—to generate new samples that resemble the training distribution.

Tools and Libraries Used:

- 1. Python 3.x
- 2. PyTorch
- 3. torchvision
- 4. matplotlib
- 5. CelebA Dataset

Implementation Steps:

Step 1: Import Required Libraries

import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, Subset
import matplotlib.pyplot as plt

Step 2: Configure Parameters and Load Dataset

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```
device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
image size = 64
batch size = 128
latent dim = 100
num_epochs = 5
learning rate = 1e-3
transform = transforms.Compose([
  transforms.CenterCrop(178),
  transforms.Resize(image size),
  transforms.ToTensor(),
  transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
1)
dataset = datasets.CelebA(root='data', split='train', download=True, transform=transform)
dataset = Subset(dataset, range(500)) # Limit to 500 samples for speed
dataloader = DataLoader(dataset, batch size=batch size, shuffle=True)
Step 3: Define Encoder Network
class Encoder(nn.Module):
  def __init__(self, latent_dim):
    super(Encoder, self).__init__()
    self.conv = nn.Sequential(
      nn.Conv2d(3, 64, 4, 2, 1), nn.ReLU(),
      nn.Conv2d(64, 128, 4, 2, 1), nn.BatchNorm2d(128), nn.ReLU(),
      nn.Conv2d(128, 256, 4, 2, 1), nn.BatchNorm2d(256), nn.ReLU(),
      nn.Conv2d(256, 512, 4, 2, 1), nn.BatchNorm2d(512), nn.ReLU()
    self.fc_mu = nn.Linear(512*4*4, latent_dim)
    self.fc_logvar = nn.Linear(512*4*4, latent_dim)
  def forward(self, x):
    x = self.conv(x)
    x = x.view(x.size(o), -1)
    return self.fc_mu(x), self.fc_logvar(x)
Step 4: Define Decoder Network
class Decoder(nn.Module):
  def init (self, latent dim):
    super(Decoder, self).__init__()
    self.fc = nn.Linear(latent_dim, 512*4*4)
    self.deconv = nn.Sequential(
      nn.ConvTranspose2d(512, 256, 4, 2, 1), nn.BatchNorm2d(256), nn.ReLU(),
      nn.ConvTranspose2d(256, 128, 4, 2, 1), nn.BatchNorm2d(128), nn.ReLU(),
      nn.ConvTranspose2d(128, 64, 4, 2, 1), nn.BatchNorm2d(64), nn.ReLU(),
      nn.ConvTranspose2d(64, 3, 4, 2, 1), nn.Tanh()
```

```
)
  def forward(self, z):
    x = self.fc(z)
    x = x.view(x.size(0), 512, 4, 4)
    return self.deconv(x)
Step 5: Define the VAE Model
class VAE(nn.Module):
  def <u>init</u> (self, latent_dim):
    super(VAE, self).__init__()
    self.encoder = Encoder(latent dim)
    self.decoder = Decoder(latent_dim)
  def reparameterize(self, mu, logvar):
    std = torch.exp(0.5 * logvar)
    eps = torch.randn_like(std)
    return mu + eps * std
  def forward(self, x):
    mu, logvar = self.encoder(x)
    z = self.reparameterize(mu, logvar)
    return self.decoder(z), mu, logvar
Step 6: Define Loss Function
def vae_loss(recon_x, x, mu, logvar):
  recon_loss = F.mse_loss(recon_x, x, reduction='sum')
  kl_div = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
 return recon loss + kl div
Step 7: Train the Model and Generate Images
model = VAE(latent_dim).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr=learning rate)
for epoch in range(num_epochs):
  model.train()
  total loss = 0
  for images, _ in dataloader:
    images = images.to(device)
    recon, mu, logvar = model(images)
    loss = vae loss(recon, images, mu, logvar)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
    total loss += loss.item()
```

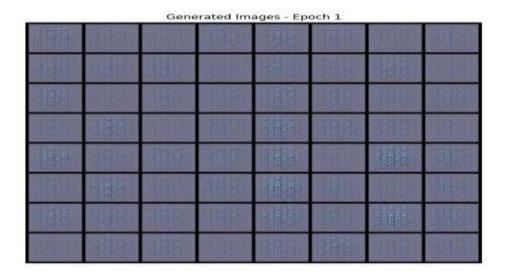
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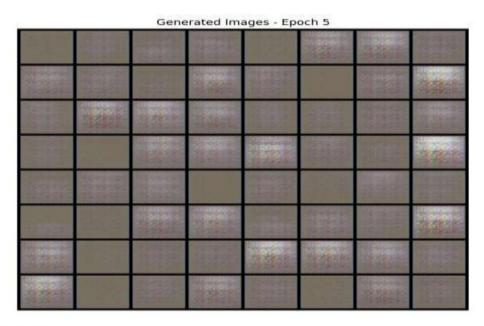
```
print(f"Epoch [{epoch+1}/{num_epochs}],
{total_loss/len(dataloader.dataset):.4f}")

# Generate and visualize samples
model.eval()
with torch.no_grad():
    z = torch.randn(64, latent_dim).to(device)
    sample_images = model.decoder(z).cpu() * 0.5 + 0.5 # De-normalize
    grid = torchvision.utils.make_grid(sample_images, nrow=8)
    plt.imshow(grid.permute(1, 2, 0))
    plt.axis('off')
    plt.title(f"Generated Faces - Epoch {epoch+1}")
    plt.show()
```

Loss:

Output:





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