



Superior Note Books

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Index

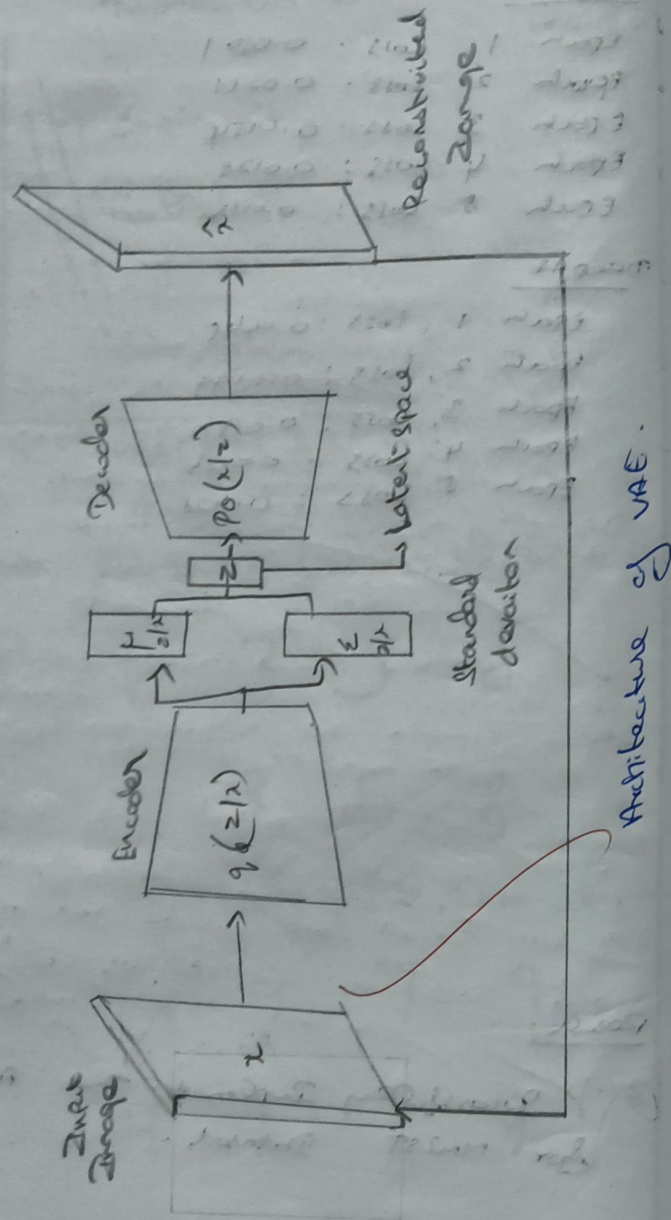
Name : Vishva S

Subject : DL

Std. : Sec. : Roll No.

School :

No.	Date	Title	Marks	Signature
1	24/7/25	Exploring the DL platforms.		Signature
2	31/7/25	Implement a classifier using open source dataset		
3	7/8/25	Study the classifier with respect to statistical parameters.		Signature
4	14/8/25	Build a simple feed forward neural network to recognize handwritten characters.		Signature 22/8/25
5	22/8/25	Study of Activation functions & their role.		Signature 9/9/25
6	9/9/25	Implement Gradient Descent & Backpropagation in Deep neural network		Signature 16/9/25
7	16/9/25	Build a CNN model to classify cat & dog image.		Signature 23/9/25
8	30/9/25	Build a RNN network.		Signature 30/9
9	9/10/25	Experiment using LSTM		Signature 11/10/25
10	9/10/25	Autoencoder		Signature
11	9/10/25	Variational Autoencoder		Signature
12	17/10/25	Deep convolutional GAN		Signature



Architecture of VAE.

9/10/20

Lab 11: Experiments using Variational Autoencoder (VAE)

Aim:

To implement a Variational Autoencoder to learn probabilistic latent representations of input image and generate new images from the learned latent space.

Objectives

- 1) To understand the difference between Autoencoders & Variational Autoencoders.
- 2) To apply probabilistic encoding using mean & variance.
- 3) To generate new images by sampling from the latent space.
- 4) To visualize the learned latent distribution & reconstructed images.

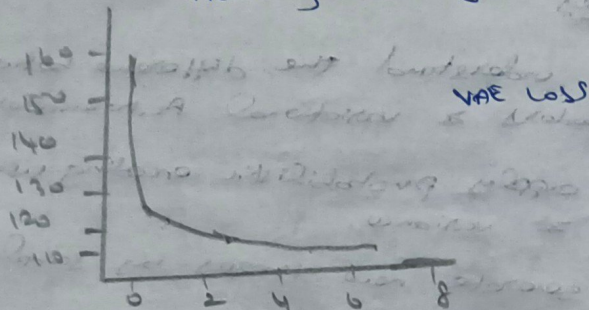
Observation

- The VAE extends the Autoencoder by introducing probabilistic latent variables.
- It learns a distribution rather than a fixed encoding, allowing sampling & generation of new data.
- The model is trained using a reconstruction loss and a KL divergence loss to balance accuracy & latent regularization.
- The generated samples resemble hand-written digits, showing that the model learned the data distribution.

Output.

Epoch 1, Loss: 164.378
Epoch 2, Loss: 121.282
Epoch 3, Loss: 114.511
Epoch 4, Loss: 111.603
Epoch 5, Loss: 109.8942
Epoch 6, Loss: 108.6767
Epoch 7, Loss: 107.8209
Epoch 8, Loss: 107.1627
Epoch 9, Loss: 106.6916
Epoch 10, Loss: 106.2222

Training Loss of VAE



Top: original Images / Bottom: VAE Reconstructed

0 2 6 4 0 9 8 5

0 2 6 4 0 9 8 5

Generated Digits from Random Latent Space

2 2 8 3 4 8 8

5 3 1

Pseudocode.

BEGIN

St-1: Import Libraries

St-2: Load & normalize MNIST dataset

St-3: Define encoder

- Input: 784-dimensional image

- Dense hidden layers

- output: mean (μ) and log variance (σ^2)

St-4: Sample latent vector $z = \mu + \sigma \epsilon$

St-5: Define decoder

Input: z

- Dense layers to reconstruct 784-dimensional output

St-6: Define loss function

- Reconstruction loss + KL divergence

St-7: Train VAE using training data

St-8: Generate new images by sampling from latent space

St-9: Visualize reconstructed and generated images

END.

Result:

Successfully Implemented the VAE for MNIST dataset.


```
!pip install torch torchvision matplotlib
```

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```

```
# vae_mnist.py
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
```

```

1 import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt

# ---- Device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# ---- Load MNIST dataset
tf = transforms.Compose([transforms.ToTensor()])
train_data = datasets.MNIST(root='data', train=True, transform=tf, download=True)
train_loader = DataLoader(train_data, batch_size=128, shuffle=True)

# ---- Variational Autoencoder
class VAE(nn.Module):
    def __init__(self):
        super(VAE, self).__init__()
        self.fc1 = nn.Linear(784, 400)
        self.fc_mu = nn.Linear(400, 20) # Mean of latent vector
        self.fc_logvar = nn.Linear(400, 20) # Log variance of latent vector
        self.fc2 = nn.Linear(20, 400)
        self.fc3 = nn.Linear(400, 784)
        self.relu = nn.ReLU()
        self.sigmoid = nn.Sigmoid()

    def encode(self, x):
        h1 = self.relu(self.fc1(x))
        mu = self.fc_mu(h1)
        logvar = self.fc_logvar(h1)
        return mu, logvar

    def reparameterize(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std # z = μ + σ * ε

    def decode(self, z):
        h2 = self.relu(self.fc2(z))
        return self.sigmoid(self.fc3(h2))

    def forward(self, x):
        x = x.view(-1, 784)
        mu, logvar = self.encode(x)

```



```
# ---- Loss Function (Reconstruction + KL Divergence)
def vae_loss(recon_x, x, mu, logvar):
    BCE = nn.functional.binary_cross_entropy(recon_x, x.view(-1, 784), reduction='sum')
    # KL Divergence: how latent distribution differs from standard normal
    KLD = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
    return BCE + KLD

# ---- Model, Optimizer
model = VAE().to(device)
optimizer = optim.Adam(model.parameters(), lr=1e-3)

# ---- Training
epochs = 10
train_losses = []

for epoch in range(1, epochs + 1):
    model.train()
    total_loss = 0
    for imgs, _ in train_loader:
        imgs = imgs.to(device)
        optimizer.zero_grad()
        recon, mu, logvar = model(imgs)
        loss = vae_loss(recon, imgs, mu, logvar)
        loss.backward()
        total_loss += loss.item()
        optimizer.step()

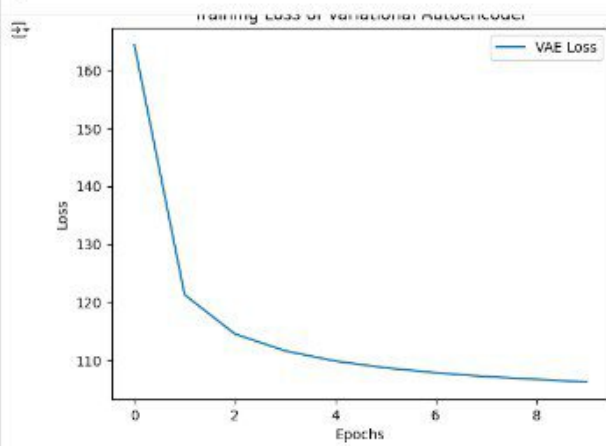
    avg_loss = total_loss / len(train_loader.dataset)
    train_losses.append(avg_loss)
    print(f"Epoch [{epoch}/{epochs}] Loss: {avg_loss:.4f}")

# ---- Plot Training Loss
plt.plot(train_losses, label="VAE Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Training Loss of Variational Autoencoder")
plt.legend()
plt.show()

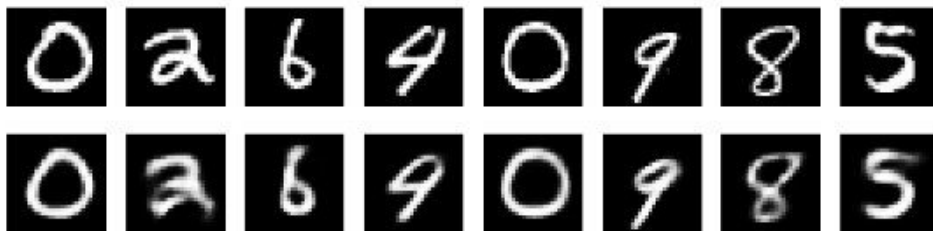
# ---- Reconstruction Visualization
model.eval()
imgs, _ = next(iter(train_loader))
imgs = imgs[:8].to(device)
with torch.no_grad():
    recons, _ = model(imgs)
```



```
plt.show()
```



Top: Original Images | Bottom: VAE Reconstructions



Generated Digits from Random Latent Space

