Exercise Sheet 7: Variational Autoencoders

```
import os
import random
import time
import matplotlib.pyplot as plt; plt.rcdefaults()
import numpy as np

# Import Pytorch, Sklearn
from sklearn.manifold import TSNE
import torch
import torch.nn as nn
from torch.nn import functional as F

# Load FashionMNIST dataset
from torchvision import datasets, transforms

# set figure size
plt.figure(figsize=(10, 5))

plt.rcParams['figure.dpi'] = 150
plt.rcParams['axes.titlesize'] = 8
plt.rcParams['axes.labelsize'] = 8
plt.rcParams['xtick.labelsize'] = 6
plt.rcParams['ytick.labelsize'] = 6
```

```
<Figure size 1000x500 with 0 Axes>
```

```
# set random seed
random.seed(42)
torch.manual_seed(42)

# Set the device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

########################
##### HOUSEKEEPING #####

# set hyperparameters
EPOCHS = 7
BATCH_SIZE = 128
LEARNING_RATE = 1e-3
WEIGHT_DECAY = 1e-5

# set directories
RESULTS_DIR = 'results/'
DATA_DIR = 'data/'
MODEL_DIR = 'models/'
```

```
########################
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# if don't exist, create directories
if not os.path.exists(RESULTS_DIR):
    os.makedirs(RESULTS_DIR)

if not os.path.exists(DATA_DIR):
    os.makedirs(DATA_DIR)

if not os.path.exists(MODEL_DIR):
    os.makedirs(MODEL_DIR)
```

```
Using device: cpu
```

```
import torch
import torch.nn as nn

class VAE(nn.Module):

    def __init__(self, num_channels=1, num_classes=10, latent_dim=2,
embed_dim=16):
        super(VAE, self).__init__()

        self.latent_dim = latent_dim
        self.embedding = nn.Embedding(num_embeddings=num_classes,
embedding_dim=embed_dim)

        # Encoder
        self.encoder = nn.ModuleList([
            nn.Conv2d(in_channels=num_channels, out_channels=8,
kernel_size=3, stride=2, padding=1),
            nn.Conv2d(in_channels=8, out_channels=16, kernel_size=3,
stride=2, padding=1),
            nn.Conv2d(in_channels=16, out_channels=32, kernel_size=3,
stride=2, padding=1),
        ])

        # Decoder
        self.decoder = nn.ModuleList([
            nn.Conv2d(in_channels=32, out_channels=16, kernel_size=3,
padding=1),
            nn.Conv2d(in_channels=16, out_channels=8, kernel_size=3),
            nn.Conv2d(in_channels=8, out_channels=num_channels,
kernel_size=3, padding=1),
        ])

        # Fully connected layers for learning representations
        self.fc_latent = nn.Linear(in_features=latent_dim + embed_dim,
out_features=512)
```

```
        self.fc_mean = nn.Linear(in_features=512 + embed_dim,
out_features=latent_dim)
        self.fc_var = nn.Linear(in_features=512 + embed_dim,
out_features=latent_dim)
        self.leaky_relu = nn.LeakyReLU()
        self.sigmoid = nn.Sigmoid()

    def forward(self, x, y):
        """
        Args:
            x (tensor): Image(s) of shape [B, C, H, W].
            y (tensor): Class label(s) of shape [B,].

        Returns:
            x_recon (tensor): Reconstructed image(s) of shape [B, C,
H, W].
            mean (tensor): Mean of shape [B, latent_dim].
            log_var (tensor): Log variance of shape [B, latent_dim].
        """
        mean, log_var = self.encode(x, y)
        # Reparameterization Trick
        eps = torch.randn(log_var.shape, device=log_var.device)
        z = mean + torch.exp(log_var * 0.5) * eps
        x_recon = self.decode(z, y)
        return x_recon, mean, log_var

    def encode(self, x, y):
        """
        Args:
            x (tensor): Image(s) of shape [B, C, H, W].
            y (tensor): Class label(s) of shape [B,].

        Returns:
            mean (tensor): Mean of shape [B, latent_dim].
            log_var (tensor): Log variance of shape [B, latent_dim].
        """
        for layer in self.encoder:
            x = layer(x)
            x = self.leaky_relu(x)
        x = torch.reshape(x, (x.shape[0], -1))
        class_embed = self.embedding(y)
        # Concat class information
        mean = self.fc_mean(torch.cat((x, class_embed), dim=1))
        log_var = self.fc_var(torch.cat((x, class_embed), dim=1))
        return mean, log_var

    def decode(self, z, y):
        """
        Args:
            z (tensor): Latent variable(s) of shape [B, latent_dim].
```

```python
            y (tensor): Class label(s) of shape [B,].

        Returns:
            x (tensor): Reconstructed image(s) of shape [B, C, H, W].
        """
        class_embed = self.embedding(y)
        # Concat class information
        x = self.fc_latent(torch.cat((z, class_embed), dim=1))
        x = torch.reshape(x, (-1, 32, 4, 4))
        for layer in self.decoder:
            x = nn.functional.interpolate(x, scale_factor=2,
mode='bilinear', align_corners=True)
            x = self.leaky_relu(x)
            x = layer(x)
        x = self.sigmoid(x)
        return x

    def sample(self, y, device):
        """
        Args:
            y (int): Class label.
            device (torch.device): Which device to use (cuda or cpu).

        Returns:
            (tensor): Image of shape [1, C, H, W].
        """
        z = torch.randn((1, self.latent_dim), device=device)
        return self.decode(z, torch.tensor([y], device=device))

    def sample_latent(self, x, y):
        """
        Args:
            x (tensor): Image(s) of shape [B, C, H, W].
            y (tensor): Class label(s) of shape [B,].

        Returns:
            z (tensor): Latent variable(s) of shape [B, latent_dim].
        """
        mean, log_var = self.encode(x, y)
        # Reparameterization Trick
        eps = torch.randn(log_var.shape, device=log_var.device)
        z = mean + torch.exp(log_var * 0.5) * eps
        return z
```

Task 1: Training a Variational Autoencoder on MNIST

```python
# Task 1.1 Download the MNIST dataset

# Define a transform to normalize the data
transform = transforms.Compose([transforms.ToTensor()])
```

```python
# Download and load the training dataset
trainset = datasets.MNIST(DATA_DIR, download=True, train=True,
transform=transform)
trainloader = torch.utils.data.DataLoader(trainset,
batch_size=BATCH_SIZE, shuffle=True)

# Download and load the test dataset
testset = datasets.MNIST(DATA_DIR, download=True, train=False,
transform=transform)
testloader = torch.utils.data.DataLoader(testset,
batch_size=BATCH_SIZE, shuffle=False)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-
ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-
images-idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-
images-idx3-ubyte.gz to data/MNIST/raw/train-images-idx3-ubyte.gz

100%|██████████| 9912422/9912422 [00:05<00:00, 1770704.65it/s]

Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-
ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-
labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-
labels-idx1-ubyte.gz to data/MNIST/raw/train-labels-idx1-ubyte.gz

100%|██████████| 28881/28881 [00:00<00:00, 237235.82it/s]

Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-
idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-
idx3-ubyte.gz to data/MNIST/raw/t10k-images-idx3-ubyte.gz

100%|██████████| 1648877/1648877 [00:00<00:00, 1957087.00it/s]
```

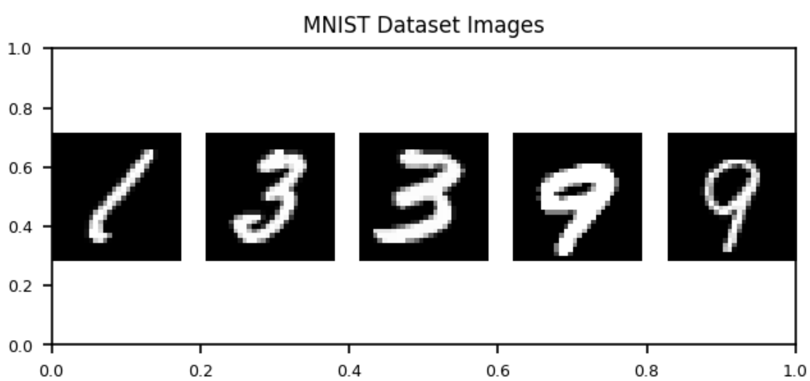
```
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-
idx1-ubyte.gz to data/MNIST/raw/t10k-labels-idx1-ubyte.gz

100%|██████████| 4542/4542 [00:00<00:00, 2137386.82it/s]

Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
```

```python
num_images = 5

# Plot the images from trainloader
plt.figure(figsize=(num_images, 2))
plt.title('MNIST Dataset Images')
# place it on GPU if available
dataiter = iter(trainloader)
for i in range(num_images):
    # Get the next batch of images
    images, _ = next(dataiter)

    # Plot the first image in the batch
    plt.subplot(1, num_images, i + 1)
    plt.imshow(images[0].numpy().squeeze(), cmap='gray')
    plt.axis('off')

plt.show()
plt.savefig(RESULTS_DIR + 'mnist_dataset_images.png')
```

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```

```
# Task 1.1 Write pytorch code for loss function (BCE + KL Divergence)
#          L(x(i),θ,φ) = −Ez ~qφ(z|x(i))[log pθ(x(i)|z)] + DKL(qφ(z|
x(i)) ‖pθ(z))

def loss_function(x, x_recon, mean, log_var, KL_weight=1e-3):
    """
    Args:
        x (tensor): Image(s) of shape [B, C, H, W].
        x_recon (tensor): Reconstructed image(s) of shape [B, C, H,
W].
        mean (tensor): Mean of shape [B, latent_dim].
        log_var (tensor): Log variance of shape [B, latent_dim].

    Returns:
        loss (tensor): Loss value.
    """
    # Ensure the input and output are of the same shape
    assert x.shape == x_recon.shape, "x and x_recon must have the same
shape"

    # BCE Loss -- reconstruction loss
    BCE_loss = nn.functional.binary_cross_entropy(x_recon, x,
reduction='sum')
    # KL Divergence -- regularization loss
    KL_loss = -0.5 * torch.sum(1 + log_var - mean.pow(2) -
log_var.exp())
    # Total loss -- balance between the two (lower KL weight for
better reconstruction)
    return BCE_loss + (KL_weight * KL_loss)

def reconstruction_loss_function(x, x_recon):
    """
    Args:
        x (tensor): Image(s) of shape [B, C, H, W].
        x_recon (tensor): Reconstructed image(s) of shape [B, C, H,
W].
        mean (tensor): Mean of shape [B, latent_dim].
        log_var (tensor): Log variance of shape [B, latent_dim].

    Returns:
        loss (tensor): Loss value.
    """
    # Ensure the input and output are of the same shape
    assert x.shape == x_recon.shape, "x and x_recon must have the same
shape"

    # BCE Loss -- reconstruction loss
    BCE_loss = nn.functional.binary_cross_entropy(x_recon, x,
reduction='sum')
    return BCE_loss
```

```
# Task 1.1 Write pytorch code for loss function (BCE + KL Divergence)
#          L(x(i),θ,φ) = −Ez ~qφ(z|x(i))[log pθ(x(i)|z)] + DKL(qφ(z|
x(i)) ‖pθ(z))

def regularization_loss_function(mean, log_var):
    """
    Args:
        x (tensor): Image(s) of shape [B, C, H, W].
        x_recon (tensor): Reconstructed image(s) of shape [B, C, H,
W].
        mean (tensor): Mean of shape [B, latent_dim].
        log_var (tensor): Log variance of shape [B, latent_dim].

    Returns:
        loss (tensor): Loss value.
    """
    KL_loss = -0.5 * torch.sum(1 + log_var - mean.pow(2) -
log_var.exp())
    return KL_loss

# Task 1.2 Implement the VAE model
vae = VAE(latent_dim=2).to(device)

# Implement the ADAM optimizer
optimizer = torch.optim.Adam(vae.parameters(), lr=LEARNING_RATE,
weight_decay=WEIGHT_DECAY)

def train(model, optimizer, epochs, trainloader, device,
loss_type='total_loss'):
    """
    Train VAE model and plot sample image per class after each epoch.

    Args:
        model (nn.Module): VAE model.
        optimizer (torch.optim): Optimizer.
        epochs (int): Number of epochs.
        trainloader (DataLoader): Training data loader.
        device (torch.device): Which device to use (cuda or cpu).

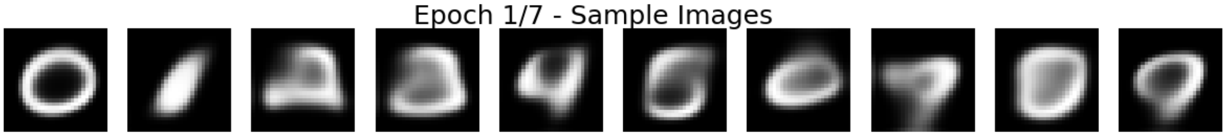
    Returns:
        None
    """
    training_losses = []

    model.train()
    for epoch in range(epochs):
        train_loss = 0
        for i, (images, labels) in enumerate(trainloader):
            x = images.to(device)
            y = labels.to(device)
```

```python
            # Forward pass
            optimizer.zero_grad()
            x_recon, mean, log_var = model(x, y)

            # Select the loss function
            if loss_type == 'total_loss':
                loss = loss_function(x, x_recon, mean, log_var)
            elif loss_type == 'reconstruction_loss':
                loss = reconstruction_loss_function(x, x_recon)
            elif loss_type == 'regularization_loss':
                loss = regularization_loss_function(mean, log_var)
            else:
                raise ValueError("Invalid loss type. Choose from
['total_loss', 'reconstruction_loss', 'regularization_loss']")

            # Backward pass
            loss.backward()
            optimizer.step()

            train_loss += loss.item()

        # Save the training loss
        training_losses.append(train_loss / len(trainloader.dataset))

        # Print the stats
        print(f'Epoch {epoch + 1}/{epochs}, Training Loss: {train_loss
/ len(trainloader.dataset):.6f}')

        # Plot sample image per class
        sample_images = []
        for i in range(10):
            sample_images.append(model.sample(i,
device).cpu().detach().numpy())

        plt.figure(figsize=(10, 1))
        plt.suptitle(f'Epoch {epoch + 1}/{epochs} - Sample Images')
        for i in range(10):
            plt.subplot(1, 10, i + 1)
            plt.imshow(sample_images[i].squeeze(), cmap='gray')
            plt.axis('off')
        plt.show()
        plt.savefig(RESULTS_DIR + f'sample_images_epoch_{epoch +
1}.png')

    return training_losses

# train the VAE model
training_losses = train(vae, optimizer, EPOCHS, trainloader, device)
```

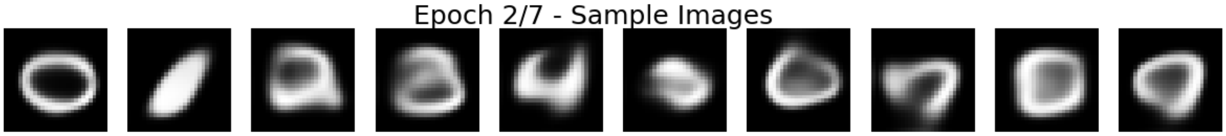
```
Epoch 1/7, Training Loss: 194.003004
```

Epoch 1/7 - Sample Images



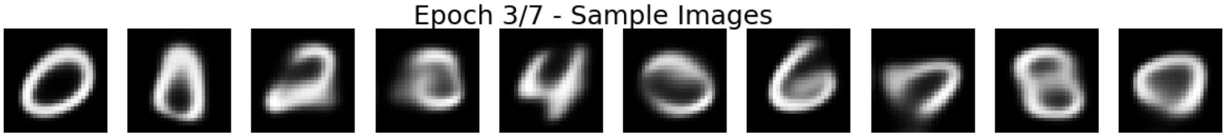
```
Epoch 2/7, Training Loss: 138.144506

<Figure size 960x720 with 0 Axes>
```

Epoch 2/7 - Sample Images



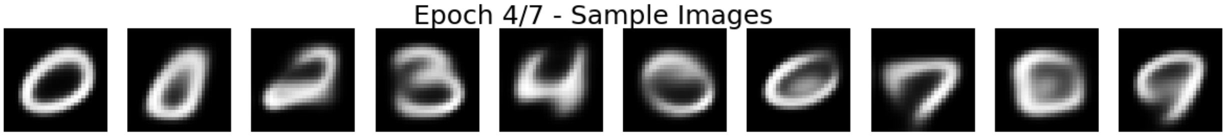
```
Epoch 3/7, Training Loss: 134.567883

<Figure size 960x720 with 0 Axes>
```

Epoch 3/7 - Sample Images



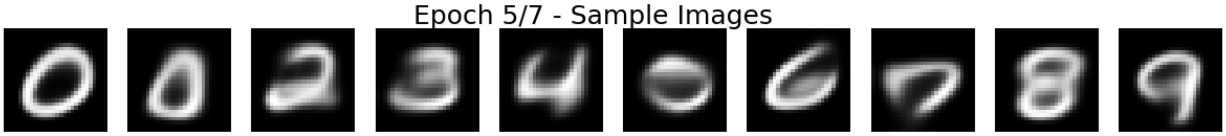
```
Epoch 4/7, Training Loss: 132.909833

<Figure size 960x720 with 0 Axes>
```

Epoch 4/7 - Sample Images



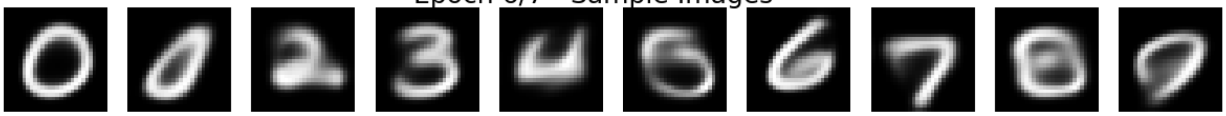
```
Epoch 5/7, Training Loss: 131.950459

<Figure size 960x720 with 0 Axes>
```

Epoch 5/7 - Sample Images



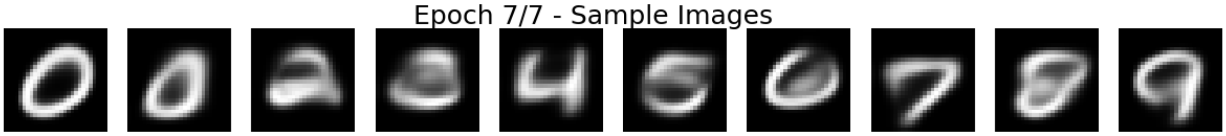
```
Epoch 6/7, Training Loss: 131.232240

<Figure size 960x720 with 0 Axes>
```

Epoch 6/7 - Sample Images

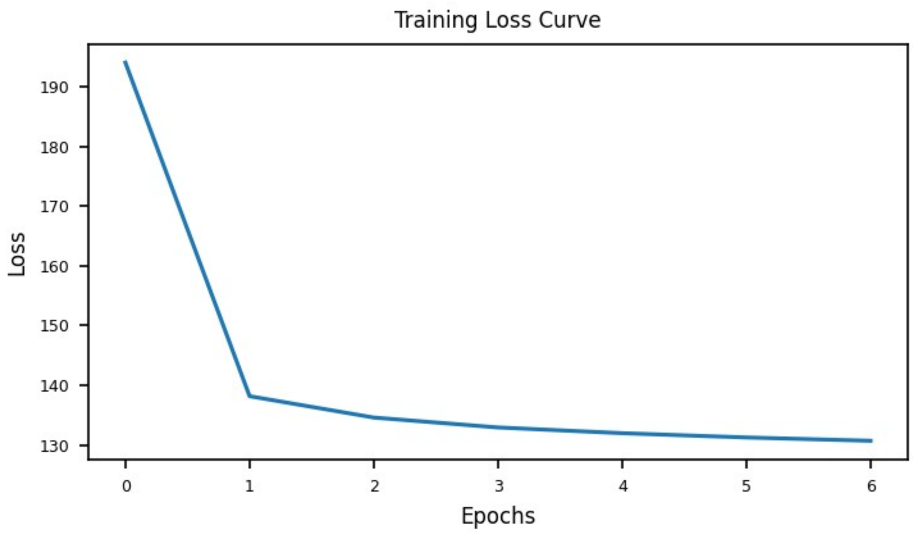


```
Epoch 7/7, Training Loss: 130.682452

<Figure size 960x720 with 0 Axes>
```

Epoch 7/7 - Sample Images



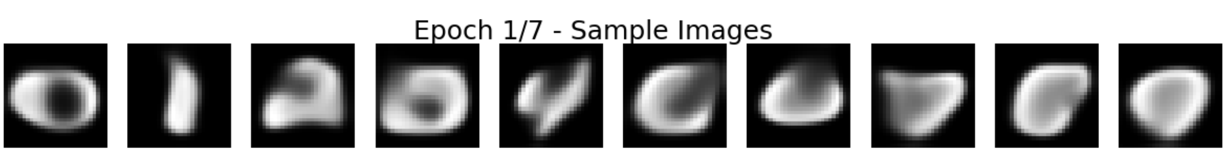
```
<Figure size 960x720 with 0 Axes>

# Task 1.3 Plot the training curve (loss) of the VAE model with epochs
on x-axis and loss on y-axis

def plot_loss_curve(training_losses, figsize=(5, 3),
file_name='training_loss_curve'):
    """ Plot the training loss curve."""
    plt.figure(figsize=figsize)
    plt.plot(training_losses)
    plt.title('Training Loss Curve')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.tight_layout()
    plt.show()
    plt.savefig(RESULTS_DIR + file_name + '.png')

# Plot the training curve
plot_loss_curve(training_losses, figsize=(5, 3),
file_name='vae_training_loss_curve')
```



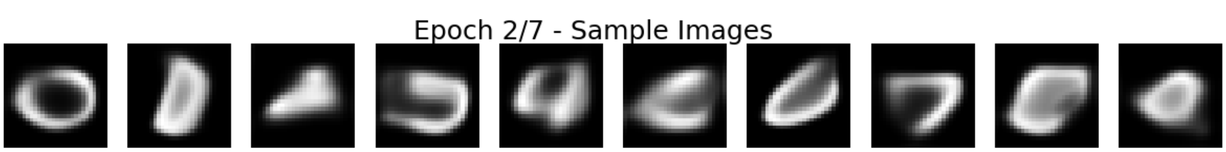

```
<Figure size 960x720 with 0 Axes>
```

Task 2: Visualize the latent space

```
# Task 2.1 train VAE again using only reconstruction loss
vae_rec = VAE(latent_dim=2).to(device)

# Implement the ADAM optimizer
optimizer = torch.optim.Adam(vae_rec.parameters(), lr=LEARNING_RATE,
weight_decay=WEIGHT_DECAY)

# train the VAE model with only reconstruction loss
training_losses = train(vae_rec, optimizer, EPOCHS, trainloader,
device, loss_type='reconstruction_loss')

Epoch 1/7, Training Loss: 186.668833
```

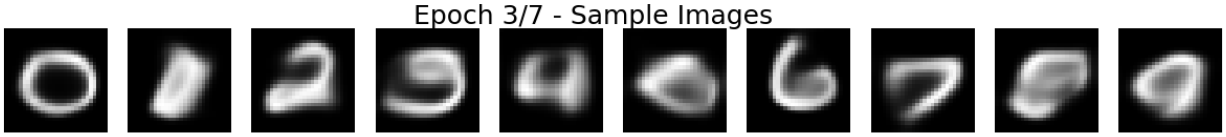



```
Epoch 2/7, Training Loss: 138.399085

<Figure size 960x720 with 0 Axes>
```



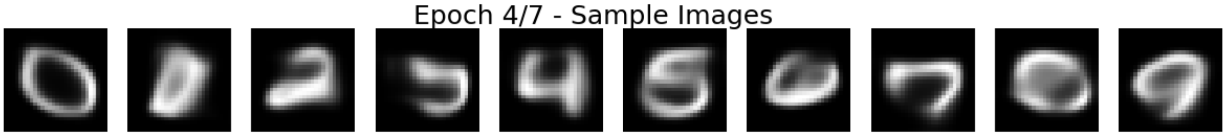
```
Epoch 3/7, Training Loss: 134.174906

<Figure size 960x720 with 0 Axes>
```

Epoch 3/7 - Sample Images



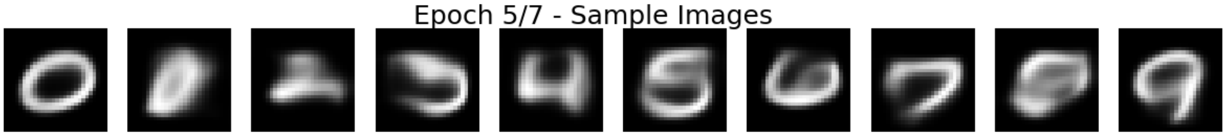
```
Epoch 4/7, Training Loss: 132.291108

<Figure size 960x720 with 0 Axes>
```

Epoch 4/7 - Sample Images



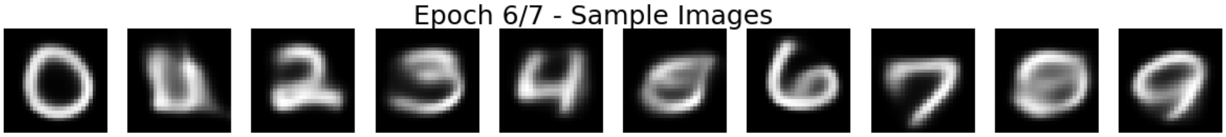
```
Epoch 5/7, Training Loss: 131.302706

<Figure size 960x720 with 0 Axes>
```

Epoch 5/7 - Sample Images



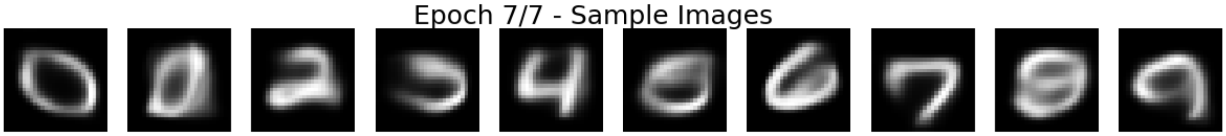
```
Epoch 6/7, Training Loss: 130.609699

<Figure size 960x720 with 0 Axes>
```

Epoch 6/7 - Sample Images



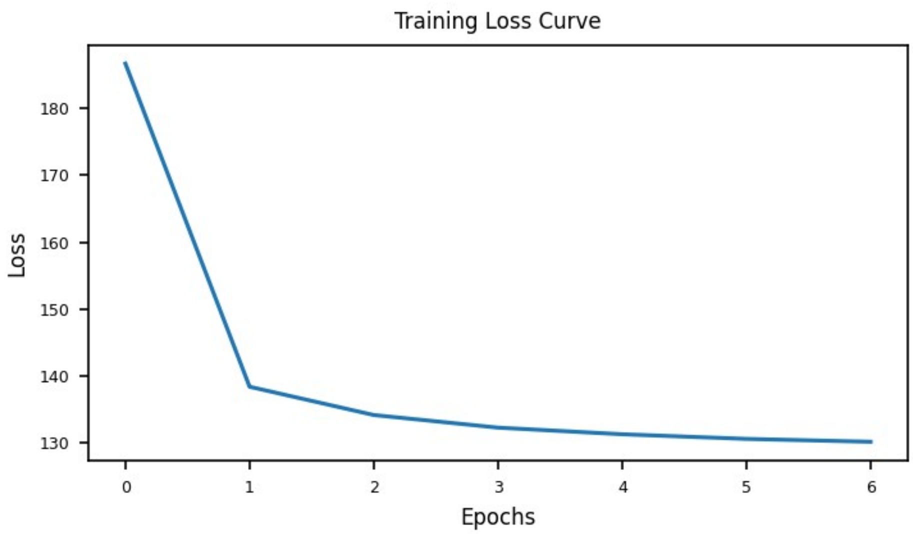
```
Epoch 7/7, Training Loss: 130.181550

<Figure size 960x720 with 0 Axes>
```

Epoch 7/7 - Sample Images



```
<Figure size 960x720 with 0 Axes>
```

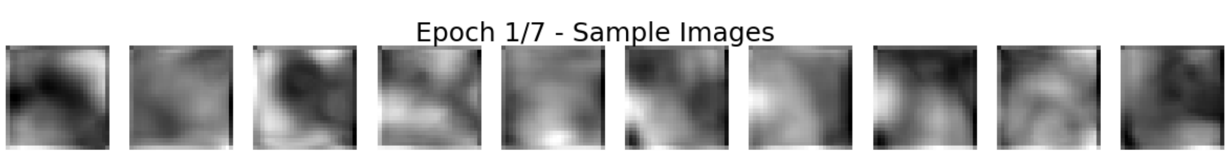
```python
# Plot the training curve
plot_loss_curve(training_losses, figsize=(5, 3),
file_name='vae_rec_training_loss_curve')
```




```
<Figure size 960x720 with 0 Axes>
```

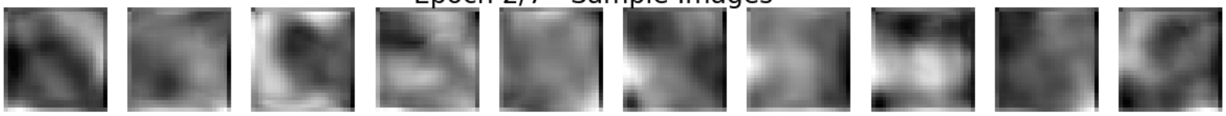
```python
# Task 2.2 train VAE again using only regularization loss
vae_reg = VAE(latent_dim=2).to(device)

# Implement the ADAM optimizer
optimizer = torch.optim.Adam(vae_reg.parameters(), lr=LEARNING_RATE,
weight_decay=WEIGHT_DECAY)

# Train the model
training_losses = train(vae_reg, optimizer, EPOCHS, trainloader,
device, loss_type='regularization_loss')
```

```
Epoch 1/7, Training Loss: 0.000381
```



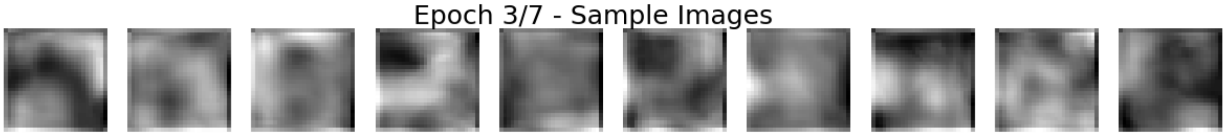

```
Epoch 2/7, Training Loss: 0.000001

<Figure size 960x720 with 0 Axes>
```

Epoch 2/7 - Sample Images



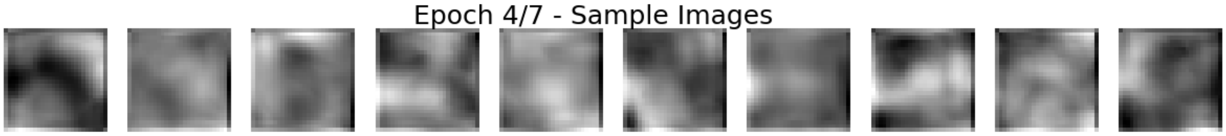
```
Epoch 3/7, Training Loss: 0.000000

<Figure size 960x720 with 0 Axes>
```

Epoch 3/7 - Sample Images



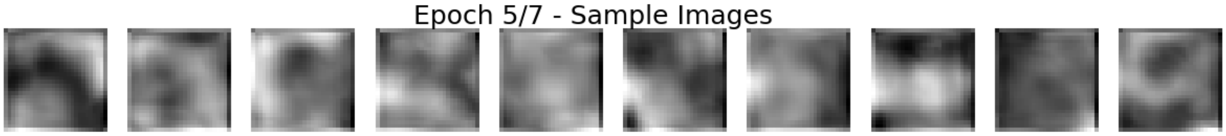
```
Epoch 4/7, Training Loss: 0.000000

<Figure size 960x720 with 0 Axes>
```

Epoch 4/7 - Sample Images



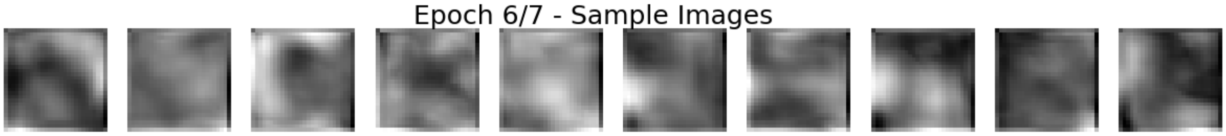
```
Epoch 5/7, Training Loss: 0.000000

<Figure size 960x720 with 0 Axes>
```

Epoch 5/7 - Sample Images



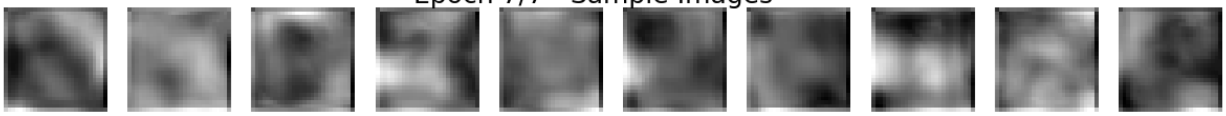
```
Epoch 6/7, Training Loss: 0.000000

<Figure size 960x720 with 0 Axes>
```

Epoch 6/7 - Sample Images



```
Epoch 7/7, Training Loss: 0.000000

<Figure size 960x720 with 0 Axes>
```

Epoch 7/7 - Sample Images



```
<Figure size 960x720 with 0 Axes>
```

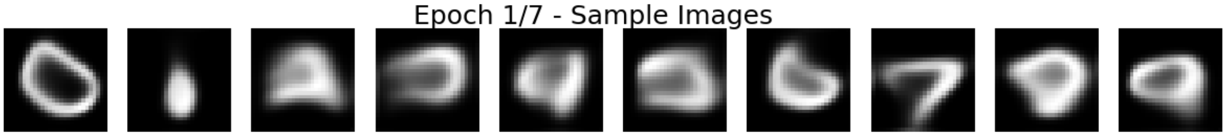
```python
# Plot the training curve
plot_loss_curve(training_losses, figsize=(5, 3),
file_name='vae_reg_training_loss_curve')
```


```
<Figure size 960x720 with 0 Axes>
```

```python
# Task 2.3 train VAE again using both reconstruction and
regularization loss
vae_t = VAE(latent_dim=2).to(device)


# Implement the ADAM optimizer
optimizer = torch.optim.Adam(vae_t.parameters(), lr=LEARNING_RATE,
weight_decay=WEIGHT_DECAY)

# Train the model
training_losses = train(vae_t, optimizer, EPOCHS, trainloader, device)
```

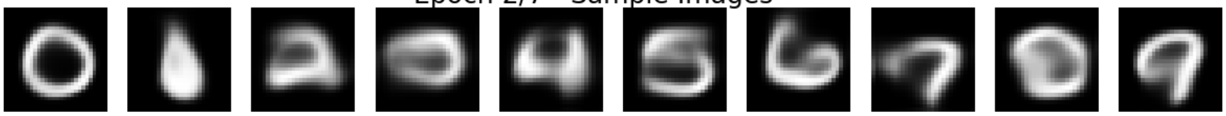
```
Epoch 1/7, Training Loss: 195.791238
```

Epoch 1/7 - Sample Images



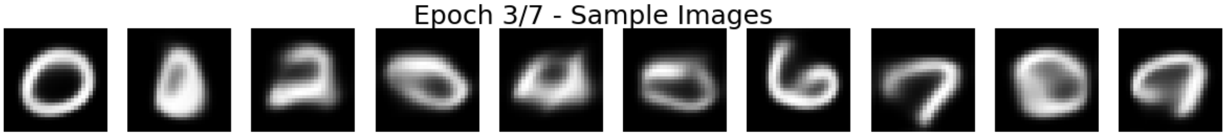
```
Epoch 2/7, Training Loss: 137.516372

<Figure size 960x720 with 0 Axes>
```

Epoch 2/7 - Sample Images



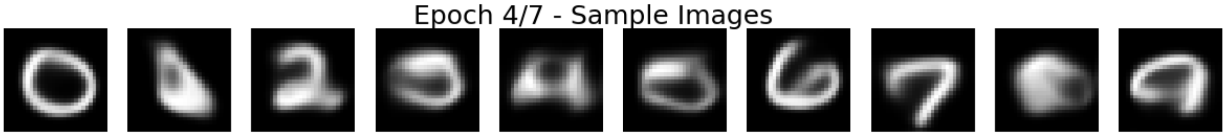
```
Epoch 3/7, Training Loss: 133.515400

<Figure size 960x720 with 0 Axes>
```

Epoch 3/7 - Sample Images



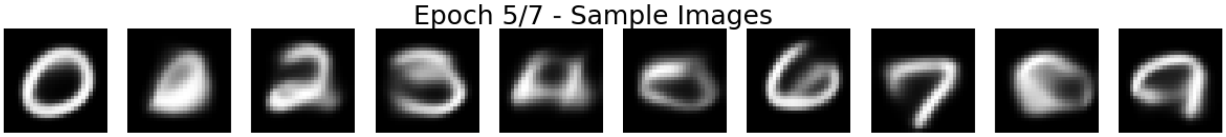
```
Epoch 4/7, Training Loss: 131.846455

<Figure size 960x720 with 0 Axes>
```

Epoch 4/7 - Sample Images



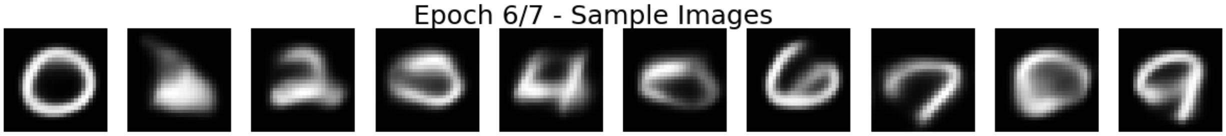
```
Epoch 5/7, Training Loss: 130.893433

<Figure size 960x720 with 0 Axes>
```

Epoch 5/7 - Sample Images



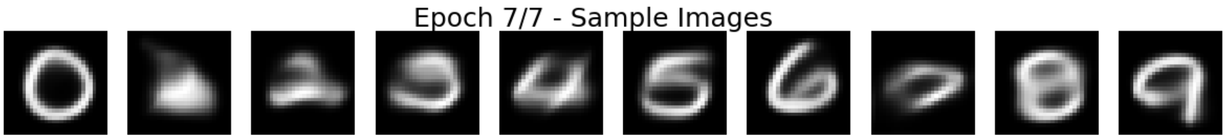
```
Epoch 6/7, Training Loss: 130.347532

<Figure size 960x720 with 0 Axes>
```

Epoch 6/7 - Sample Images

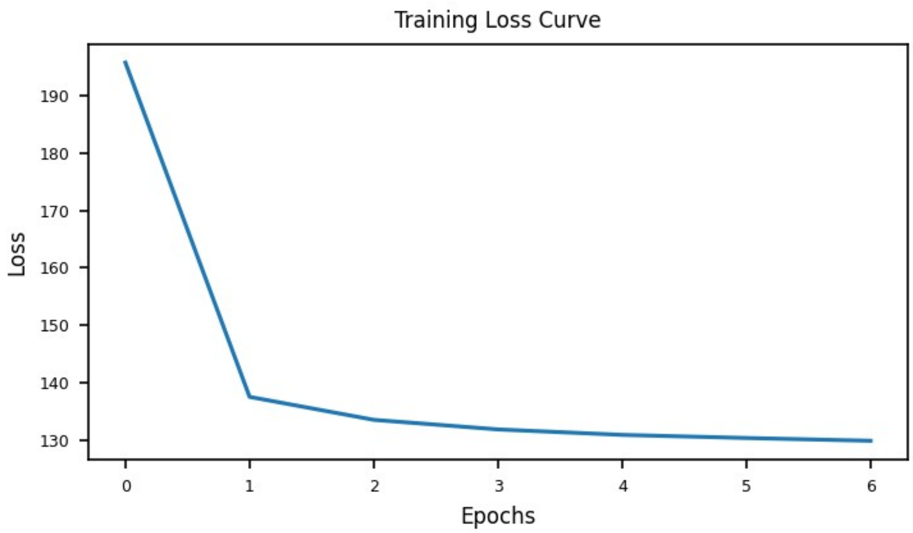


```
Epoch 7/7, Training Loss: 129.867220
```

```
<Figure size 960x720 with 0 Axes>
```

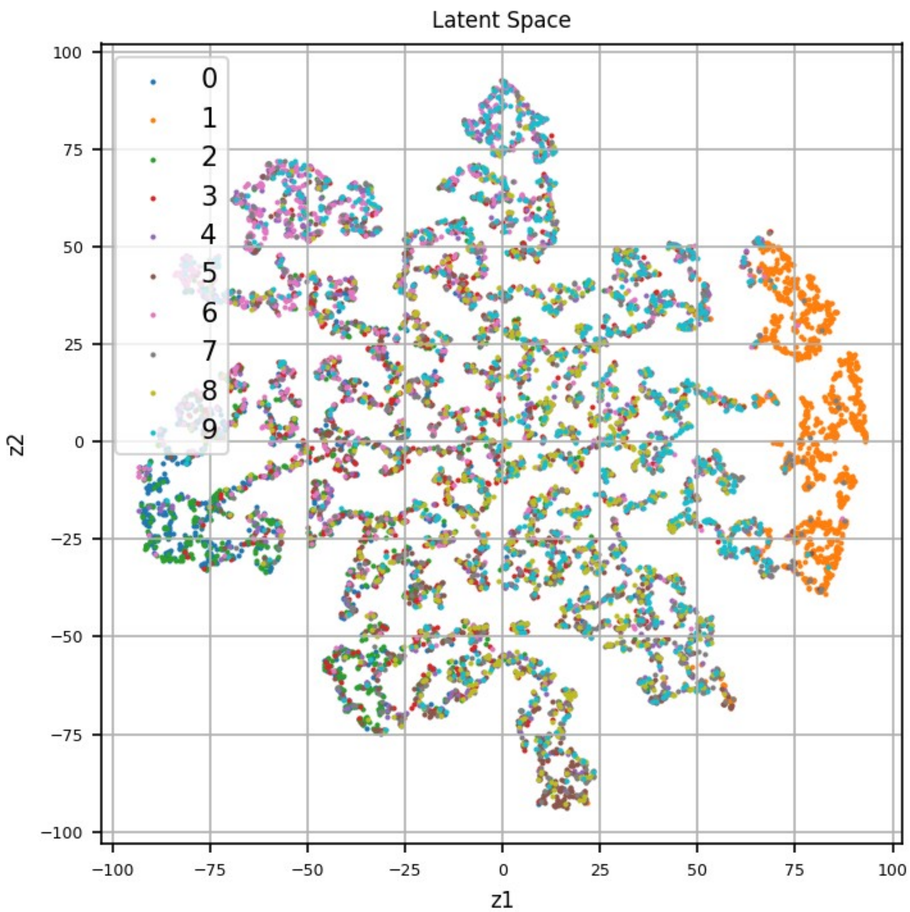



```
<Figure size 960x720 with 0 Axes>

plot_loss_curve(training_losses, figsize=(5, 3),
file_name='vae_total_training_loss_curve')
```

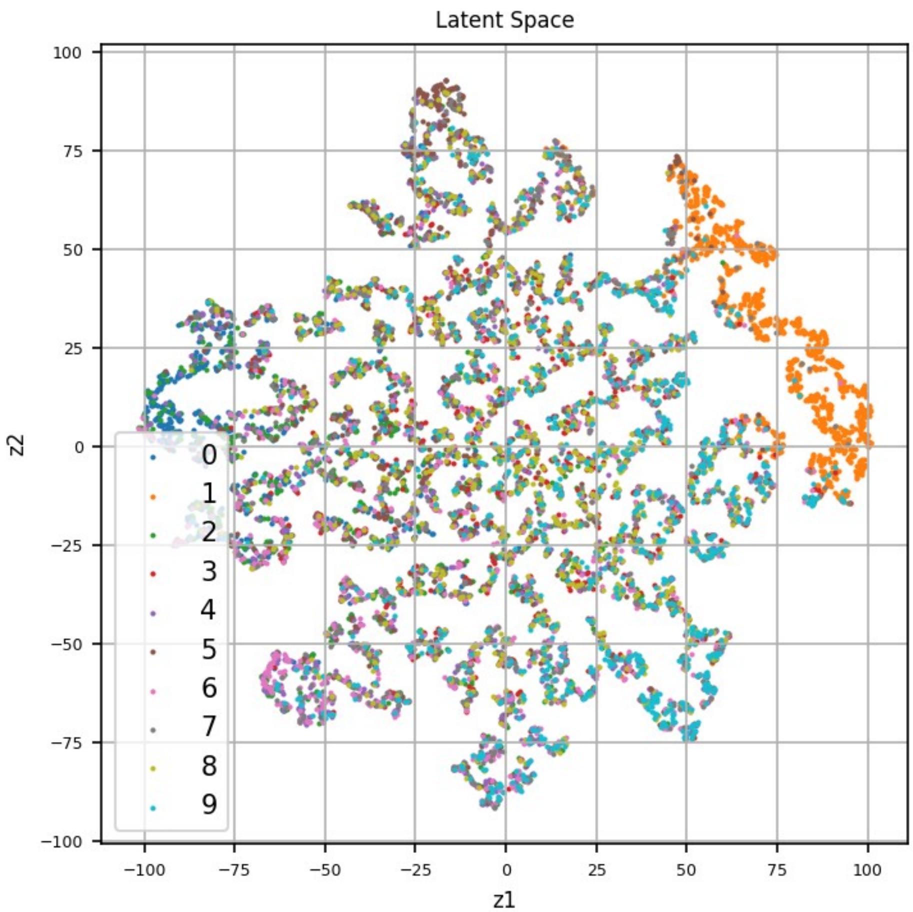



```
<Figure size 960x720 with 0 Axes>

def plot_latent_space(vae, dataloader, n=1000, figsize=5,
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu'),
file_name='vae_latent_space'):
    """ Posterior sampling based on a given MNIST test image. Extract
the latent space and plot it using t-SNE.

    Args:
        vae (nn.Module): VAE model.
        dataloader (DataLoader): Dataloader to use for sampling from
the true data distribution.
        n (int): Number of samples to plot.
        figsize (int): Size of the figure.
        method (str): Method to use for projecting the latent space to
2D. Should be 'TSNE'.
        device (torch.device): Device to use for tensor operations.

    Returns:
```

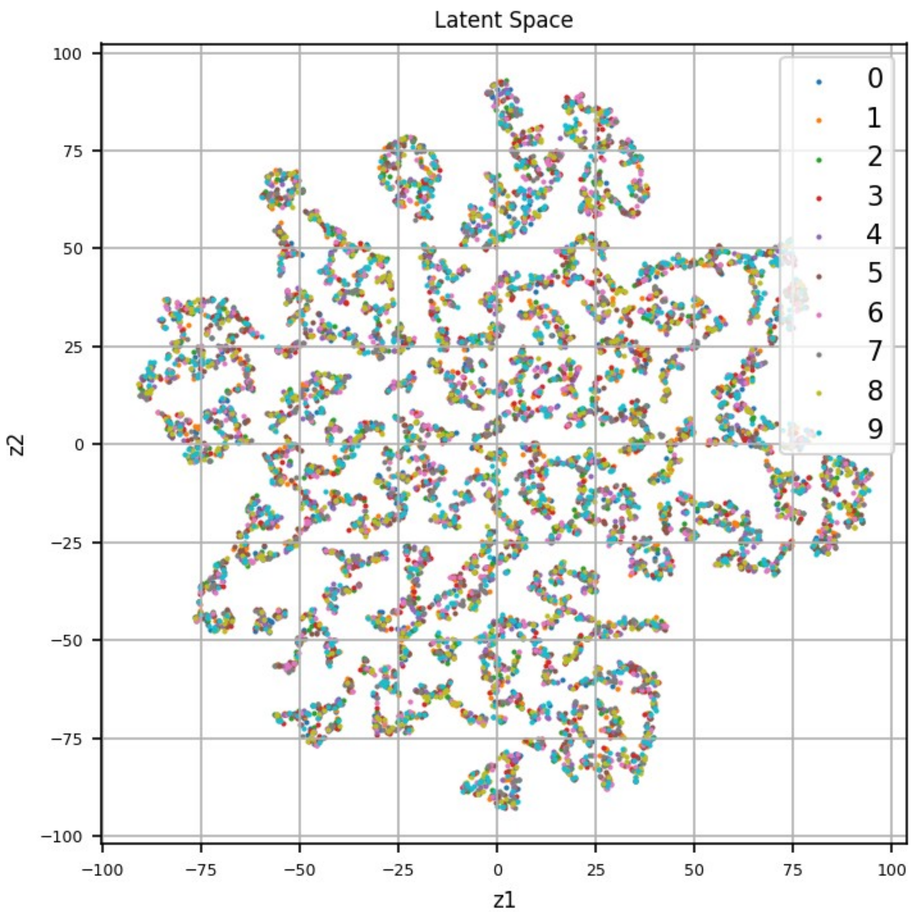
```
        None
    """
    vae.eval()

    # Sample a large number of points from the true data distribution
and encode to obtain latent space samples
    latents = []
    labels = []
    with torch.no_grad():
        for i, (data, label) in enumerate(dataloader):
            if len(latents) >= n:
                break
            data = data.to(device)
            label = label.to(device)
            latent = vae.sample_latent(data, label)
            latents.append(latent)
            labels.append(label)
        latents = torch.cat(latents, dim=0)
        labels = torch.cat(labels, dim=0)

    # Project the latent space to 2D using t-SNE
    tsne = TSNE(n_components=2, random_state=42)
    latents_2d = tsne.fit_transform(latents.cpu().numpy())

    # Plot the latent space
    plt.figure(figsize=(figsize, figsize))
    plt.xlabel('z1')
    plt.ylabel('z2')
    plt.title('Latent Space')
    for i in range(10):
        plt.scatter(latents_2d[labels == i, 0], latents_2d[labels ==
i, 1], label=str(i), s=1)
    plt.legend()
    plt.grid()
    plt.tight_layout()
    plt.show()

# Visualize the latent space
plot_latent_space(vae, testloader, n=1000, figsize=5, device=device,
file_name='vae_latent_space')
```



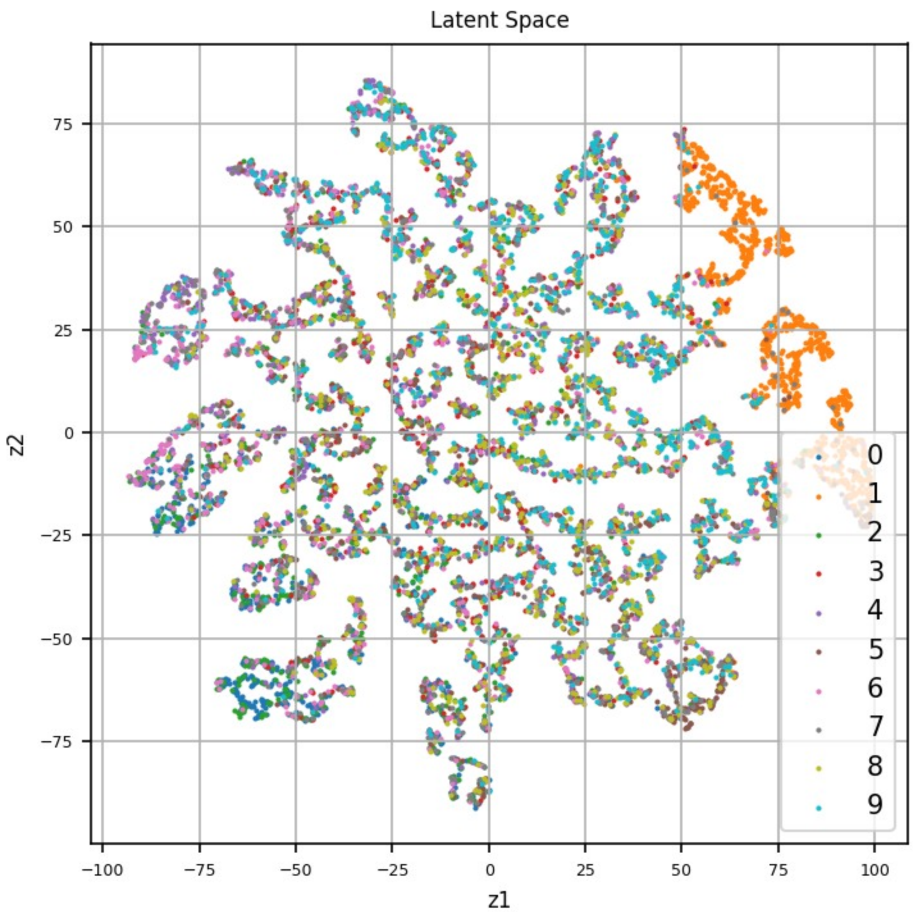

```
# Visualize the latent space for all three models -- reconstruction loss only
plot_latent_space(vae_rec, testloader, n=1000, figsize=5,
device=device, file_name='vae_rec_latent_space')
```




```
# Visualize the latent space for all three models -- regularization
loss only
plot_latent_space(vae_reg, testloader, n=1000, figsize=5,
device=device, file_name='vae_reg_latent_space')
```

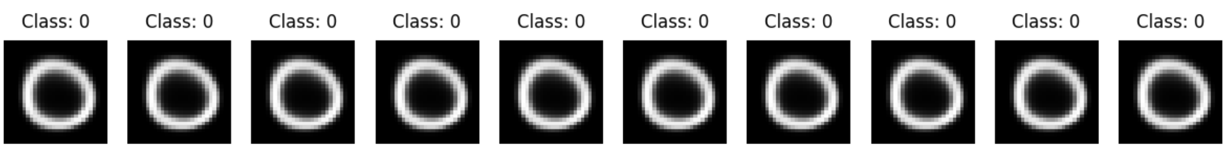



```python
# Visualize the latent space -- total loss
plot_latent_space(vae_t, testloader, n=1000, figsize=5, device=device,
file_name='vae_t_latent_space')
```

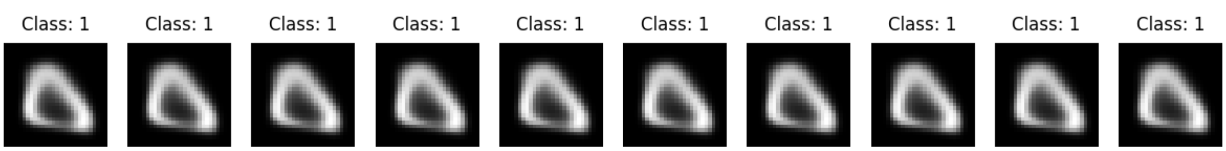



```python
# Plot a grid of samples produced by fixing one latent variable and
varying the other

def plot_latent_traversal(vae, device, n=10):
    """ Plot a grid of samples produced by fixing one latent variable
and varying the other.

    Args:
        vae (nn.Module): VAE model.
        device (torch.device): Device to use for tensor operations.
        n (int): Number of samples to plot.

    Returns:
        None
    """
    vae.eval()

    # Sample a latent variable based on a standard normal distribution
    z = torch.randn((1, vae.latent_dim), device=device)
    z = z.repeat(n, 1)
```

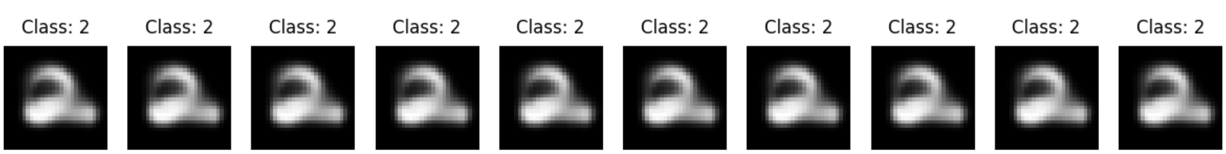
```python
    # Plot 10x10 grid of samples
    for i in range(0, n):
        # Select fixed label
        y = torch.tensor([i] * n, device=device)

        # Decode the latent variable
        with torch.no_grad():
            samples = vae.decode(z, y)

        # Plot the samples
        plt.figure(figsize=(n, 1))
        for i in range(n):
            plt.subplot(1, n, i + 1)
            plt.imshow(samples[i].squeeze().cpu().numpy(),
cmap='gray')
            plt.axis('off')
            # add class label
            plt.title(f'Class: {y[i].item()}')
        plt.show()
        plt.savefig(RESULTS_DIR + f'vae_latent_traversal_{i}.png')

# Plot the latent traversal
plot_latent_traversal(vae, device, n=10)
```



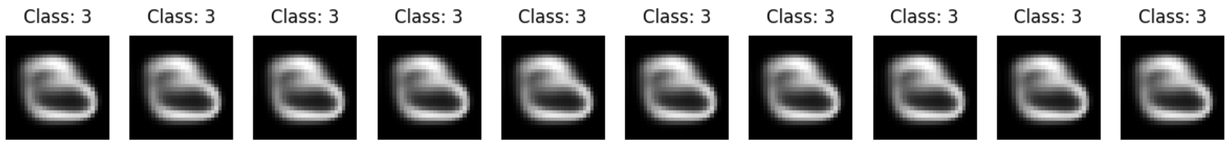

```
<Figure size 960x720 with 0 Axes>
```



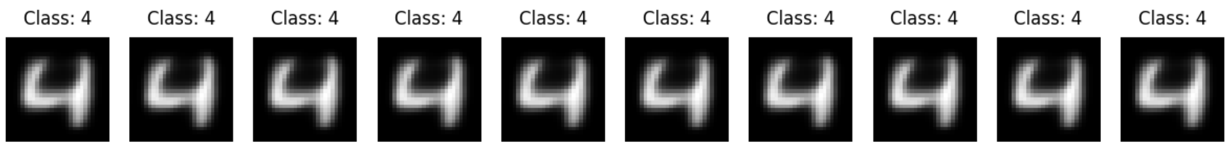

```
<Figure size 960x720 with 0 Axes>
```



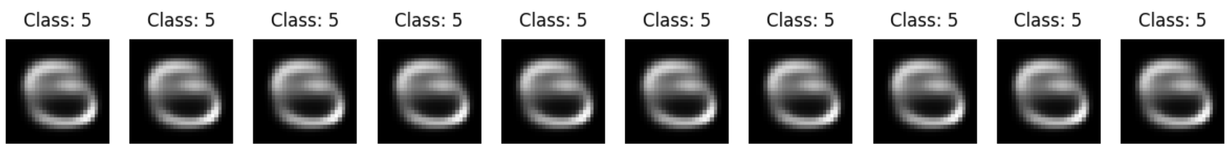

```
<Figure size 960x720 with 0 Axes>
```



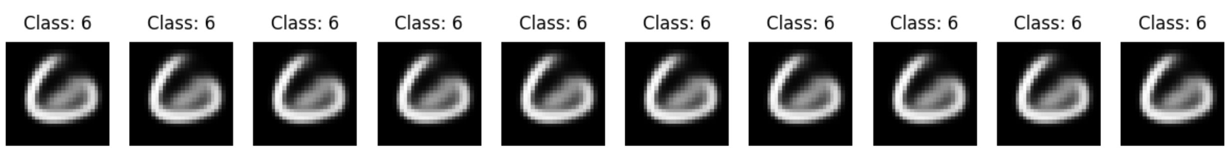
<Figure size 960x720 with 0 Axes>



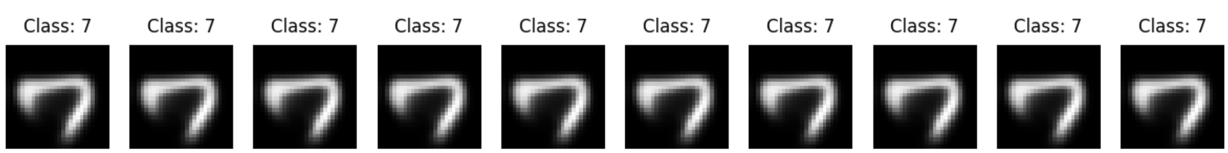
<Figure size 960x720 with 0 Axes>



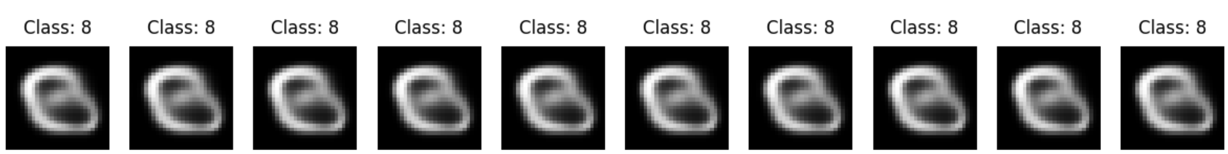
<Figure size 960x720 with 0 Axes>



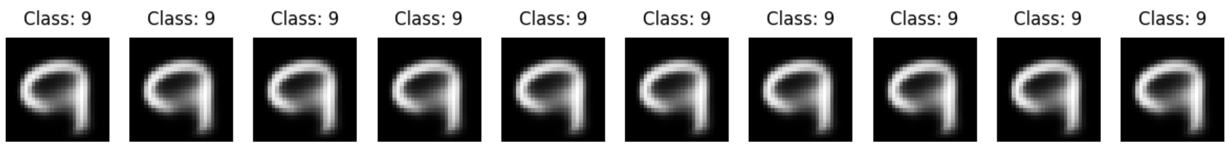
<Figure size 960x720 with 0 Axes>



<Figure size 960x720 with 0 Axes>



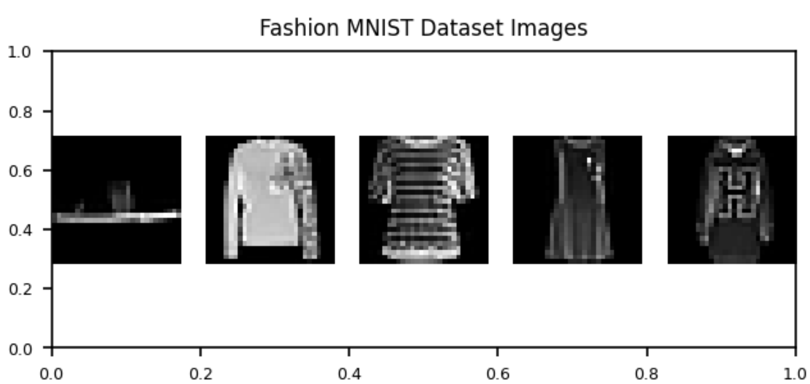
<Figure size 960x720 with 0 Axes>




```
<Figure size 960x720 with 0 Axes>
```

Task 3: Anomaly Detection using a Variational Autoencder

```python
# Task 3.1: Download the Fashion MINST dataset
transform = transforms.Compose([transforms.ToTensor()])

fashion_trainset = datasets.FashionMNIST(DATA_DIR, download=True,
train=True, transform=transform)
fashion_trainloader = torch.utils.data.DataLoader(fashion_trainset,
batch_size=BATCH_SIZE, shuffle=True)

fashion_testset = datasets.FashionMNIST(DATA_DIR, download=True,
train=False, transform=transform)
fashion_testloader = torch.utils.data.DataLoader(fashion_testset,
batch_size=BATCH_SIZE, shuffle=False)

# Plot 5 sample images from trainloader
plt.figure(figsize=(num_images, 2))
plt.title('Fashion MNIST Dataset Images')

dataiter = iter(fashion_trainloader)
for i in range(num_images):
    images, _ = next(dataiter)

    plt.subplot(1, num_images, i + 1)
    plt.imshow(images[0].numpy().squeeze(), cmap='gray')
    plt.axis('off')
```




```python
def compare_reconstruction_loss(vae, fashion_testloader,
mnist_testloader, device, file_name='reconstruction_loss_comparison'):
```

```
    """ Anomaly detection identifies data points that deviate 
significantly from the norm
        Compare the reconstruction loss between MNIST and Fashion 
MNIST datasets.

    Args:
        vae (nn.Module): VAE model.
        trainloader (DataLoader): Training data loader.
        testloader (DataLoader): Test data loader.
        device (torch.device): Which device to use (cuda or cpu).

    Returns:
        None
    """
    vae.eval()
    imgs_mnist = []
    imgs_fashion = []
    rec_loss_mnist = []
    rec_loss_fashion = []

    # Compute the reconstruction loss for MNIST dataset
    for i, (images, labels) in enumerate(mnist_testloader):
        images = images.to(device)
        labels = labels.to(device)
        x_recon, mean, log_var = vae(images, labels)
        loss = reconstruction_loss(images, x_recon)
        rec_loss_mnist.append(loss.item())
        imgs_mnist.append(images.cpu().detach().numpy())

    # Compute the reconstruction loss for Fashion MNIST dataset
    for i, (images, labels) in enumerate(fashion_testloader):
        images = images.to(device)
        labels = labels.to(device)
        x_recon, mean, log_var = vae(images, labels)
        loss = reconstruction_loss(images, x_recon)
        rec_loss_fashion.append(loss.item())
        imgs_fashion.append(images.cpu().detach().numpy())

    # Plot 10 sample MNIST images and their corresponding 
reconstruction loss values
    fig, axs = plt.subplots(2, figsize=(10, 5))
    fig.suptitle('MNIST Dataset Images and Reconstruction Loss')

    # Bar chart of reconstruction loss
    axs[0].bar(range(1, 11), rec_loss_mnist[:10])
    axs[0].set_xlabel('Image Index')
    axs[0].set_ylabel('Reconstruction Loss')
    axs[0].set_xticks(range(1, 11))
    # set range for y-axis
    axs[0].set_ylim([0, 120000])
```

```
    # Plot a line on top of the bar chart in red connecting each chart
element
    axs[0].plot(range(1, 11), rec_loss_mnist[:10], color='red',
linewidth=2)

    # MNIST images and their corresponding reconstruction loss values
    for i in range(10):
        ax = plt.subplot(1, 10, i + 1) # create a subplot for each
image
        ax.imshow(imgs_mnist[i][0].squeeze(), cmap='gray')
        ax.text(0.5, -0.1, f'Rec. Loss: {rec_loss_mnist[i]:.2f}',
ha='center', fontsize=4, color='w', transform=ax.transAxes) # display
the reconstruction loss value below the image
        ax.axis('off')

    plt.savefig(f'results/{file_name}_mnist.png')
    plt.show()

    # Plot 10 sample Fashion MNIST images and their corresponding
reconstruction loss values
    fig, axs = plt.subplots(2, figsize=(10, 5))
    fig.suptitle('Fashion MNIST Dataset Images and Reconstruction
Loss')

    # Bar chart of reconstruction loss
    axs[0].bar(range(1, 11), rec_loss_fashion[:10])
    axs[0].set_xlabel('Image Index')
    axs[0].set_ylabel('Reconstruction Loss')
    axs[0].set_xticks(range(1, 11))
    # set range for y-axis
    axs[0].set_ylim([0, 120000])

    # Plot a line on top of the bar chart in red connecting each chart
element
    axs[0].plot(range(1, 11), rec_loss_fashion[:10], color='red',
linewidth=2)

    # Fashion MNIST images and their corresponding reconstruction loss
values
    for i in range(10):
        ax = plt.subplot(1, 10, i + 1) # create a subplot for each
image
        ax.imshow(imgs_fashion[i][0].squeeze(), cmap='gray')
        ax.text(0.5, -0.1, f'Rec. Loss: {rec_loss_fashion[i]:.2f}',
ha='center', fontsize=4, color='w', transform=ax.transAxes)
        ax.axis('off')

    plt.savefig(f'results/{file_name}_fashion_mnist.png')
    plt.show()
```

```
# Compare the reconstruction loss between MNIST and Fashion MNIST
datasets
# Use samples from MNIST handwritten digit dataset and the MNIST.
fashion dataset to showcase the difference in reconstruction loss.
Plot 10 samples of each dataset and their corresponding reconstruction
loss.
compare_reconstruction_loss(vae, fashion_testloader, testloader,
device, file_name='reconstruction_loss_comparison')
```