```python
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
import numpy as np

transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomCrop(32, padding=4),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])


train_dataset = torchvision.datasets.CIFAR10(root="./data",
train=True, transform=transform, download=True)
test_dataset = torchvision.datasets.CIFAR10(root="./data",
train=False, transform=transform, download=True)


batch_size = 128
train_loader = DataLoader(train_dataset, batch_size=batch_size,
shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size,
shuffle=False)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data\cifar-10-python.tar.gz

100%|██████████| 170M/170M [05:19<00:00, 534kB/s]

Extracting ./data\cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

```python
class VAE(nn.Module):
    def __init__(self, latent_dim=256):
        super(VAE, self).__init__()
        self.latent_dim = latent_dim

        # Encoder
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.Dropout(0.3),  # Regularization

            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(0.3),

            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.Dropout(0.3),
        )

        self.fc_mu = nn.Linear(128 * 4 * 4, latent_dim)
        self.fc_logvar = nn.Linear(128 * 4 * 4, latent_dim)


        self.decoder_input = nn.Linear(latent_dim, 128 * 4 * 4)
        self.decoder = nn.Sequential(
            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),

            nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),

            nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2,
padding=1),
            nn.Tanh()
        )

    def reparameterization(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def forward(self, x):
        x = self.encoder(x)
        x = x.view(x.size(0), -1)
        mu, logvar = self.fc_mu(x), self.fc_logvar(x)
        z = self.reparameterization(mu, logvar)
        x = self.decoder_input(z).view(x.size(0), 128, 4, 4)
        x = self.decoder(x)
        return x, mu, logvar

def vae_loss_function(recon_x, x, mu, logvar, beta=0.1):
    reconstruction_loss = F.mse_loss(recon_x, x, reduction="sum")
    kl_divergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) -
logvar.exp())
    return reconstruction_loss + beta * kl_divergence
```

```
vae = VAE(latent_dim=256).to(device)
optimizer = optim.Adam(vae.parameters(), lr=0.001, weight_decay=1e-4)

scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=10,
gamma=0.5)

num_epochs = 300

for epoch in range(num_epochs):
    total_loss = 0
    vae.train()

    for images, _ in train_loader:
        images = images.to(device)
        optimizer.zero_grad()
        outputs, mu, logvar = vae(images)
        loss = vae_loss_function(outputs, images, mu, logvar)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    scheduler.step()
    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {total_loss /
len(train_loader):.4f}")
```

```
Epoch [1/300], Loss: 41056.5003
Epoch [2/300], Loss: 23134.0243
Epoch [3/300], Loss: 20244.6839
Epoch [4/300], Loss: 18828.0475
Epoch [5/300], Loss: 17890.2783
Epoch [6/300], Loss: 17168.6471
Epoch [7/300], Loss: 16745.5004
Epoch [8/300], Loss: 16362.5803
Epoch [9/300], Loss: 16143.9096
Epoch [10/300], Loss: 15819.3558
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Epoch [296/300], Loss: 13430.4897
Epoch [297/300], Loss: 13427.7705
Epoch [298/300], Loss: 13441.2670
Epoch [299/300], Loss: 13436.5345
Epoch [300/300], Loss: 13412.4288
```
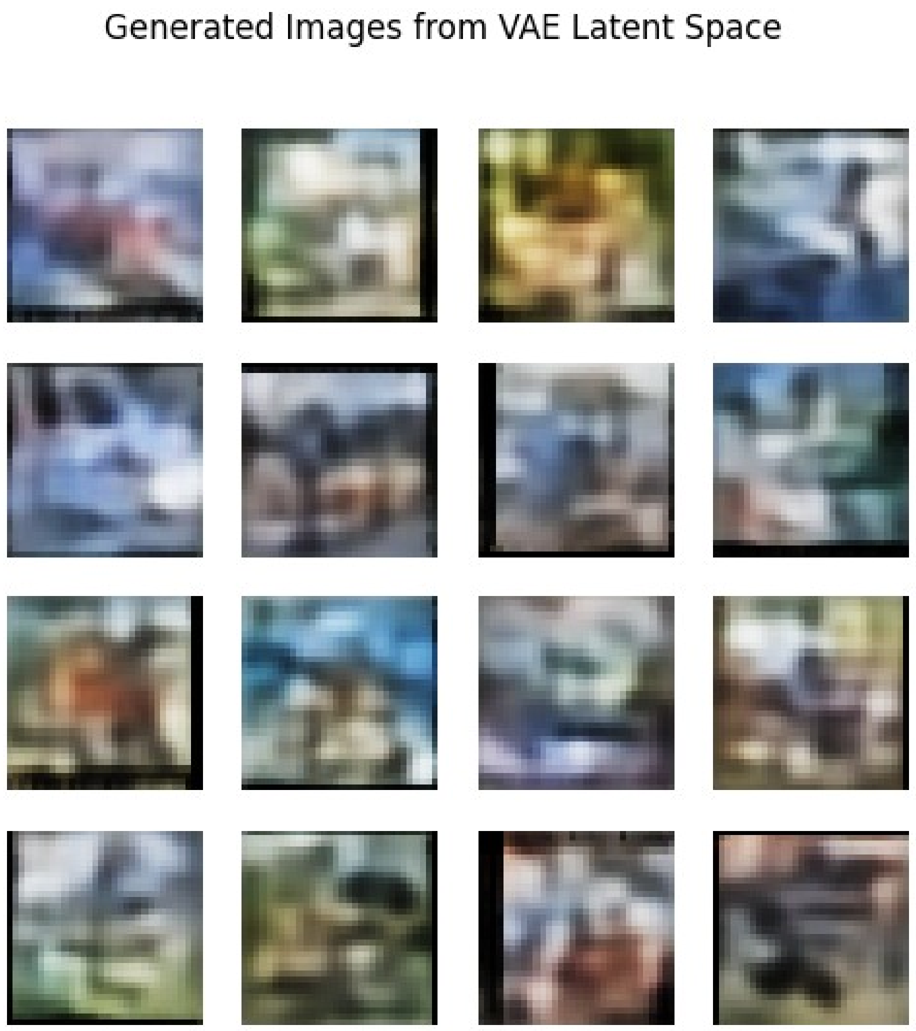

```
vae.eval()
with torch.no_grad():
    z = torch.randn(16, 256).to(device)
    generated_images = vae.decoder(vae.decoder_input(z).view(16, 128,
4, 4)).cpu()

# Plot generated images
fig, axes = plt.subplots(4, 4, figsize=(6, 6))
for i, ax in enumerate(axes.flat):
    ax.imshow(generated_images[i].permute(1, 2, 0).numpy() * 0.5 +
0.5)
    ax.axis("off")

plt.suptitle("Generated Images from VAE Latent Space")
plt.show()
```



```
torch.save(vae.state_dict(), "vae_cifar10.pth")
print("□ VAE model saved!")
```

```
□ VAE model saved!
```

```
test_images, _ = next(iter(test_loader))
test_images = test_images.to(device)


vae.eval()
with torch.no_grad():
    reconstructed_images, _, _ = vae(test_images)

loss = F.mse_loss(reconstructed_images, test_images).item()
print(f"□ VAE Reconstruction Loss: {loss:.4f}")
```

```
□ VAE Reconstruction Loss: 0.0207
```

```python
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision
from torch.utils.data import DataLoader


class Autoencoder(nn.Module):
    def __init__(self, latent_dim=100):
        super(Autoencoder, self).__init__()

        # Encoder
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=4, stride=2, padding=1),
            nn.ReLU(),
            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=1),
            nn.ReLU(),
            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),
            nn.ReLU(),
            nn.Flatten(),
            nn.Linear(128 * 4 * 4, latent_dim)
        )


        self.decoder = nn.Sequential(
            nn.Linear(latent_dim, 128 * 4 * 4),
            nn.ReLU(),
            nn.Unflatten(1, (128, 4, 4)),
            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2,
padding=1),
            nn.ReLU(),
            nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2,
padding=1),
            nn.ReLU(),
            nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2,
padding=1),
            nn.Sigmoid()

    def forward(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded


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


transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = torchvision.datasets.CIFAR10(root="./data",
train=True, transform=transform, download=True)
train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)


ae_model = Autoencoder(latent_dim=100).to(device)
criterion = nn.MSELoss()
optimizer = optim.Adam(ae_model.parameters(), lr=0.001)


num_epochs = 50
for epoch in range(num_epochs):
    total_loss = 0
    for images, _ in train_loader:
        images = images.to(device)
        optimizer.zero_grad()
        outputs = ae_model(images)
        loss = criterion(outputs, images)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    print(f"Epoch [{epoch+1}/{num_epochs}], AE Loss: {total_loss /
len(train_loader):.4f}")


torch.save(ae_model.state_dict(), "autoencoder_cifar10.pth")
print("� Autoencoder training completed!")
```

```
Files already downloaded and verified
Epoch [1/50], AE Loss: 0.2609
Epoch [2/50], AE Loss: 0.2560
Epoch [3/50], AE Loss: 0.2560
Epoch [4/50], AE Loss: 0.2560
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Epoch [10/50], AE Loss: 0.2560
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Epoch [38/50], AE Loss: 0.2560
Epoch [39/50], AE Loss: 0.2560
Epoch [40/50], AE Loss: 0.2560
Epoch [41/50], AE Loss: 0.2560
Epoch [42/50], AE Loss: 0.2560
Epoch [43/50], AE Loss: 0.2560
Epoch [44/50], AE Loss: 0.2560
Epoch [45/50], AE Loss: 0.2560
Epoch [46/50], AE Loss: 0.2560
Epoch [47/50], AE Loss: 0.2560
Epoch [48/50], AE Loss: 0.2560
Epoch [49/50], AE Loss: 0.2560
Epoch [50/50], AE Loss: 0.2560
□ Autoencoder training completed!
```

```python
torch.save(ae_model.state_dict(), "autoencoder_cifar10.pth")
print("□ Autoencoder model weights saved successfully!")
```

```
□ Autoencoder model weights saved successfully!
```

```python
ae_model = Autoencoder(latent_dim=100).to(device)


ae_model.load_state_dict(torch.load("autoencoder_cifar10.pth"))


ae_model.eval()
print("□ Autoencoder model loaded successfully!")
```

```
□ Autoencoder model loaded successfully!
```

```
C:\Users\CSIR_prosthetic\AppData\Local\Temp\
ipykernel_16016\3136093701.py:5: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  ae_model.load_state_dict(torch.load("autoencoder_cifar10.pth"))
```

```
import torch


ae_model.load_state_dict(torch.load("autoencoder_cifar10.pth"))
ae_model.eval()


vae.load_state_dict(torch.load("vae_cifar10.pth"))
vae.eval()

print("□ Both AE and VAE models loaded successfully!")
```

```
□ Both AE and VAE models loaded successfully!
```

```
C:\Users\CSIR_prosthetic\AppData\Local\Temp\
ipykernel_16016\1444863018.py:4: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  ae_model.load_state_dict(torch.load("autoencoder_cifar10.pth"))
C:\Users\CSIR_prosthetic\AppData\Local\Temp\
ipykernel_16016\1444863018.py:8: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  vae.load_state_dict(torch.load("vae_cifar10.pth"))
```

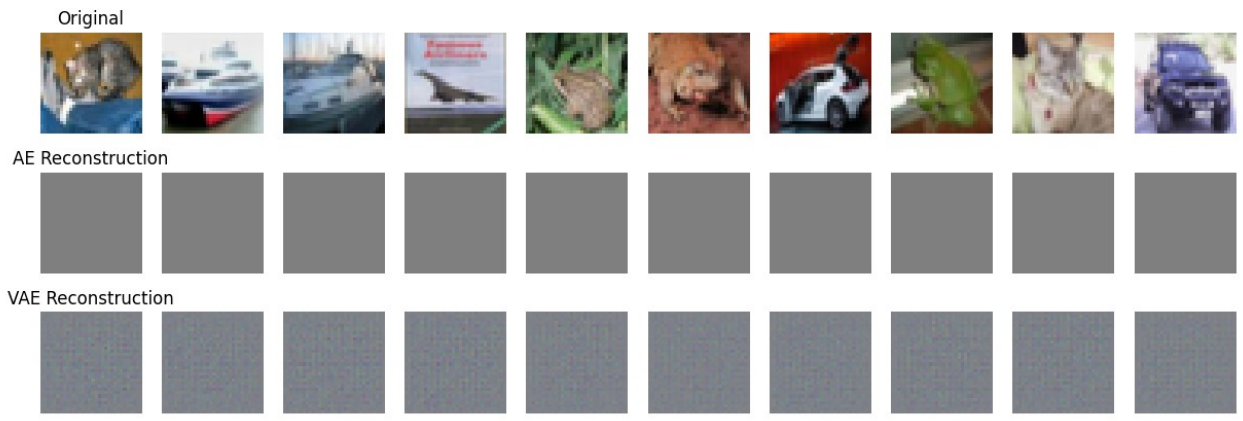
```
import torchvision.transforms as transforms
import torchvision
from torch.utils.data import DataLoader


transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])


test_dataset = torchvision.datasets.CIFAR10(root="./data",
train=False, transform=transform, download=True)
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)

print("□ Test dataset loaded!")
```

```
Files already downloaded and verified
□ Test dataset loaded!
```

```
import torch.nn.functional as F
import matplotlib.pyplot as plt

# Get a batch of test images
test_images, _ = next(iter(test_loader))
test_images = test_images.to(device)

# Compute reconstructions
with torch.no_grad():
    ae_reconstructed = ae_model(test_images).cpu()
    vae_reconstructed, _, _ = vae(test_images)

ae_loss = F.mse_loss(ae_reconstructed.to(device), test_images).item()
vae_loss = F.mse_loss(vae_reconstructed, test_images).item()
```

```
print(f"□ Autoencoder Reconstruction Loss: {ae_loss:.4f}")
print(f"□ Variational Autoencoder Reconstruction Loss:
{vae_loss:.4f}")


fig, axes = plt.subplots(3, 10, figsize=(15, 5))

for i in range(10):

    axes[0, i].imshow(test_images[i].cpu().permute(1, 2, 0) * 0.5 +
0.5)
    axes[0, i].axis("off")


    axes[1, i].imshow(ae_reconstructed[i].cpu().permute(1, 2,
0).numpy() * 0.5 + 0.5)
    axes[1, i].axis("off")


    axes[2, i].imshow(vae_reconstructed[i].cpu().permute(1, 2,
0).numpy() * 0.5 + 0.5)
    axes[2, i].axis("off")

axes[0, 0].set_title("Original", fontsize=12)
axes[1, 0].set_title("AE Reconstruction", fontsize=12)
axes[2, 0].set_title("VAE Reconstruction", fontsize=12)
plt.show()
```

```
□ Autoencoder Reconstruction Loss: 0.2658
□ Variational Autoencoder Reconstruction Loss: 0.2752
```



VAE Without Regularization

```
transform = transforms.Compose([
    transforms.ToTensor(),
```

```python
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = torchvision.datasets.CIFAR10(root="./data",
train=True, transform=transform, download=True)
train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data\cifar-10-python.tar.gz

100%|██████████| 170M/170M [00:18<00:00, 9.33MB/s]

Extracting ./data\cifar-10-python.tar.gz to ./data
```

```python
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision
from torch.utils.data import DataLoader
import torch.nn.functional as F
import matplotlib.pyplot as plt


class VAE_NoReg(nn.Module):
    def __init__(self, latent_dim=256):
        super(VAE_NoReg, self).__init__()
        self.latent_dim = latent_dim


        self.encoder = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),

            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),

            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
        )


        self.fc_mu = nn.Linear(128 * 4 * 4, latent_dim)
        self.fc_logvar = nn.Linear(128 * 4 * 4, latent_dim)


        self.decoder_input = nn.Linear(latent_dim, 128 * 4 * 4)
        self.decoder = nn.Sequential(
            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),

            nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),

            nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2,
padding=1),
            nn.Tanh()
        )

    def reparameterization(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def forward(self, x):
        x = self.encoder(x)
        x = x.view(x.size(0), -1)
        mu, logvar = self.fc_mu(x), self.fc_logvar(x)
        z = self.reparameterization(mu, logvar)
        x = self.decoder_input(z).view(x.size(0), 128, 4, 4)
        x = self.decoder(x)
        return x, mu, logvar

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


transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = torchvision.datasets.CIFAR10(root="./data",
train=True, transform=transform, download=True)
train_loader = DataLoader(train_dataset, batch_size=128, shuffle=True)


vae_noreg = VAE_NoReg(latent_dim=256).to(device)


optimizer_noreg = optim.Adam(vae_noreg.parameters(), lr=0.001)


scheduler_noreg = optim.lr_scheduler.StepLR(optimizer_noreg,
step_size=10, gamma=0.5)


def vae_loss_function(recon_x, x, mu, logvar, beta=0.1):
    reconstruction_loss = F.mse_loss(recon_x, x, reduction="sum")  #
MSE loss
    kl_divergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) -
logvar.exp())
    return reconstruction_loss + beta * kl_divergence


num_epochs = 50

for epoch in range(num_epochs):
    total_loss = 0
    vae_noreg.train()

    for images, _ in train_loader:
        images = images.to(device)
        optimizer_noreg.zero_grad()
        outputs, mu, logvar = vae_noreg(images)
        loss = vae_loss_function(outputs, images, mu, logvar)
        loss.backward()
        optimizer_noreg.step()
        total_loss += loss.item()

    scheduler_noreg.step()
    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {total_loss /
len(train_loader):.4f}")


torch.save(vae_noreg.state_dict(), "vae_noreg_cifar10.pth")
print("□ VAE Without Regularization training completed!")
```

```
Files already downloaded and verified
Epoch [1/50], Loss: 31211.1843
Epoch [2/50], Loss: 17457.9144
Epoch [3/50], Loss: 14738.9099
Epoch [4/50], Loss: 13450.2570
Epoch [5/50], Loss: 12701.9288
Epoch [6/50], Loss: 12173.6998
Epoch [7/50], Loss: 11763.4107
Epoch [8/50], Loss: 11497.8540
Epoch [9/50], Loss: 11283.7870
Epoch [10/50], Loss: 11027.9619
Epoch [11/50], Loss: 10573.3972
Epoch [12/50], Loss: 10472.9955
Epoch [13/50], Loss: 10445.9973
Epoch [14/50], Loss: 10357.2275
Epoch [15/50], Loss: 10244.6717
Epoch [16/50], Loss: 10198.1254
Epoch [17/50], Loss: 10146.5468
Epoch [18/50], Loss: 10088.9099
Epoch [19/50], Loss: 10048.2824
Epoch [20/50], Loss: 9970.0887
Epoch [21/50], Loss: 9818.2931
Epoch [22/50], Loss: 9763.9938
Epoch [23/50], Loss: 9753.7868
Epoch [24/50], Loss: 9736.8847
Epoch [25/50], Loss: 9719.2252
Epoch [26/50], Loss: 9690.5807
Epoch [27/50], Loss: 9657.5045
Epoch [28/50], Loss: 9666.0228
Epoch [29/50], Loss: 9629.4477
Epoch [30/50], Loss: 9623.6919
Epoch [31/50], Loss: 9519.7519
Epoch [32/50], Loss: 9496.3041
Epoch [33/50], Loss: 9488.5218
Epoch [34/50], Loss: 9475.4387
Epoch [35/50], Loss: 9472.3994
Epoch [36/50], Loss: 9457.6601
Epoch [37/50], Loss: 9453.8410
Epoch [38/50], Loss: 9445.1707
Epoch [39/50], Loss: 9430.7967
Epoch [40/50], Loss: 9439.0696
Epoch [41/50], Loss: 9380.0093
Epoch [42/50], Loss: 9357.0304
Epoch [43/50], Loss: 9369.4039
Epoch [44/50], Loss: 9360.2726
Epoch [45/50], Loss: 9352.8620
Epoch [46/50], Loss: 9341.1434
Epoch [47/50], Loss: 9364.0040
Epoch [48/50], Loss: 9349.8577
Epoch [49/50], Loss: 9343.4700
Epoch [50/50], Loss: 9340.7514
□ VAE Without Regularization training completed!
```

```python
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision
from torch.utils.data import DataLoader
import torch.nn.functional as F
import matplotlib.pyplot as plt

# Define VAE Model with Regularization
class VAE(nn.Module):
    def __init__(self, latent_dim=256):
        super(VAE, self).__init__()
        self.latent_dim = latent_dim

        # Encoder
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.Dropout(0.3),  # Regularization

            nn.Conv2d(32, 64, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(0.3),

            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(),
            nn.Dropout(0.3),
        )

        # Latent space
        self.fc_mu = nn.Linear(128 * 4 * 4, latent_dim)
        self.fc_logvar = nn.Linear(128 * 4 * 4, latent_dim)

        # Decoder
        self.decoder_input = nn.Linear(latent_dim, 128 * 4 * 4)
        self.decoder = nn.Sequential(
            nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(),

            nn.ConvTranspose2d(64, 32, kernel_size=4, stride=2,
padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),

            nn.ConvTranspose2d(32, 3, kernel_size=4, stride=2,
padding=1),
            nn.Tanh()  # Outputs [-1,1] to match input normalization
        )

    def reparameterization(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std  # Reparameterization trick

    def forward(self, x):
        x = self.encoder(x)
        x = x.view(x.size(0), -1)
        mu, logvar = self.fc_mu(x), self.fc_logvar(x)
        z = self.reparameterization(mu, logvar)
        x = self.decoder_input(z).view(x.size(0), 128, 4, 4)
        x = self.decoder(x)
        return x, mu, logvar

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

# Initialize VAE
vae = VAE(latent_dim=256).to(device)

# Define optimizer with weight decay (L2 regularization)
optimizer = optim.Adam(vae.parameters(), lr=0.001, weight_decay=1e-4)

scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=10,
gamma=0.5)

# Define VAE Loss Function
def vae_loss_function(recon_x, x, mu, logvar, beta=0.1):
    reconstruction_loss = F.mse_loss(recon_x, x, reduction="sum")  #
MSE loss
    kl_divergence = -0.5 * torch.sum(1 + logvar - mu.pow(2) -
logvar.exp())
    return reconstruction_loss + beta * kl_divergence

num_epochs = 50

for epoch in range(num_epochs):
    total_loss = 0
    vae.train()

    for images, _ in train_loader:
        images = images.to(device)
        optimizer.zero_grad()
        outputs, mu, logvar = vae(images)
        loss = vae_loss_function(outputs, images, mu, logvar)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    scheduler.step()
    print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {total_loss /
len(train_loader):.4f}")

torch.save(vae.state_dict(), "vae_cifar10.pth")
print("� VAE with Regularization training completed & saved!")
```

```
Epoch [1/50], Loss: 36622.1502
Epoch [2/50], Loss: 22355.5351
Epoch [3/50], Loss: 19684.5893
Epoch [4/50], Loss: 18240.7286
Epoch [5/50], Loss: 17484.1456
Epoch [6/50], Loss: 16873.3327
Epoch [7/50], Loss: 16453.1217
Epoch [8/50], Loss: 16107.1204
Epoch [9/50], Loss: 15873.8878
Epoch [10/50], Loss: 15616.4633
Epoch [11/50], Loss: 15129.2866
Epoch [12/50], Loss: 15004.5605
Epoch [13/50], Loss: 14946.0318
Epoch [14/50], Loss: 14873.9146
Epoch [15/50], Loss: 14793.3773
Epoch [16/50], Loss: 14714.7136
Epoch [17/50], Loss: 14673.6771
Epoch [18/50], Loss: 14634.6020
Epoch [19/50], Loss: 14562.6632
Epoch [20/50], Loss: 14548.8211
Epoch [21/50], Loss: 14280.1390
Epoch [22/50], Loss: 14253.6773
Epoch [23/50], Loss: 14219.1534
Epoch [24/50], Loss: 14209.1928
Epoch [25/50], Loss: 14160.7959
Epoch [26/50], Loss: 14159.2915
Epoch [27/50], Loss: 14147.2288
Epoch [28/50], Loss: 14106.4327
Epoch [29/50], Loss: 14080.5106
Epoch [30/50], Loss: 14090.6420
Epoch [31/50], Loss: 13965.3719
Epoch [32/50], Loss: 13947.2107
Epoch [33/50], Loss: 13910.9031
Epoch [34/50], Loss: 13928.2878
Epoch [35/50], Loss: 13933.1986
Epoch [36/50], Loss: 13898.3767
Epoch [37/50], Loss: 13884.4297
Epoch [38/50], Loss: 13886.3403
Epoch [39/50], Loss: 13878.5189
Epoch [40/50], Loss: 13876.2656
Epoch [41/50], Loss: 13805.0497
Epoch [42/50], Loss: 13822.1130
Epoch [43/50], Loss: 13770.3236
Epoch [44/50], Loss: 13773.6785
Epoch [45/50], Loss: 13777.5534
Epoch [46/50], Loss: 13771.4209
Epoch [47/50], Loss: 13766.8313
Epoch [48/50], Loss: 13759.1609
Epoch [49/50], Loss: 13763.7416
Epoch [50/50], Loss: 13754.3169
□ VAE with Regularization training completed & saved!
```

```python
import torch

# Load VAE with Regularization
vae_with_reg = VAE(latent_dim=256).to(device)
vae_with_reg.load_state_dict(torch.load("vae_cifar10.pth"))
vae_with_reg.eval()

# Load VAE without Regularization
vae_noreg = VAE_NoReg(latent_dim=256).to(device)
vae_noreg.load_state_dict(torch.load("vae_noreg_cifar10.pth"))
vae_noreg.eval()

print("▯ Both VAE models (with and without regularization) loaded
successfully!")
```

```
▯ Both VAE models (with and without regularization) loaded
successfully!

C:\Users\CSIR_prosthetic\AppData\Local\Temp\
ipykernel_21772\2812163446.py:5: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
related to this experimental feature.
  vae_with_reg.load_state_dict(torch.load("vae_cifar10.pth"))
C:\Users\CSIR_prosthetic\AppData\Local\Temp\
ipykernel_21772\2812163446.py:10: FutureWarning: You are using
`torch.load` with `weights_only=False` (the current default value),
which uses the default pickle module implicitly. It is possible to
construct malicious pickle data which will execute arbitrary code
during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-
models for more details). In a future release, the default value for
`weights_only` will be flipped to `True`. This limits the functions
that could be executed during unpickling. Arbitrary objects will no
longer be allowed to be loaded via this mode unless they are
explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control
of the loaded file. Please open an issue on GitHub for any issues
```

```
related to this experimental feature.
  vae_noreg.load_state_dict(torch.load("vae_noreg_cifar10.pth"))
```

```
import torchvision.transforms as transforms
import torchvision
from torch.utils.data import DataLoader

# Define transform
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# Load CIFAR-10 test dataset
test_dataset = torchvision.datasets.CIFAR10(root="./data",
train=False, transform=transform, download=True)
test_loader = DataLoader(test_dataset, batch_size=128, shuffle=False)

print("□ Test dataset loaded!")
```

```
Files already downloaded and verified
□ Test dataset loaded!
```

```
import torch.nn.functional as F
import matplotlib.pyplot as plt

# Get a batch of test images
test_images, _ = next(iter(test_loader))
test_images = test_images.to(device)

# Compute reconstructions
with torch.no_grad():
    vae_reg_reconstructed, _, _ = vae_with_reg(test_images)
    vae_noreg_reconstructed, _, _ = vae_noreg(test_images)

# Compute MSE Loss for both models
vae_reg_loss = F.mse_loss(vae_reg_reconstructed, test_images).item()
vae_noreg_loss = F.mse_loss(vae_noreg_reconstructed,
test_images).item()

print(f"□ VAE with Regularization Loss: {vae_reg_loss:.4f}")
print(f"□ VAE without Regularization Loss: {vae_noreg_loss:.4f}")
```

```
□ VAE with Regularization Loss: 0.0220
□ VAE without Regularization Loss: 0.0150
```

```
# Plot Original vs. Reconstructed Images
fig, axes = plt.subplots(3, 10, figsize=(15, 5))

for i in range(10):
    # Original images
    axes[0, i].imshow(test_images[i].cpu().permute(1, 2, 0) * 0.5 +
0.5)
    axes[0, i].axis("off")

    # VAE without Regularization
    axes[1, i].imshow(vae_noreg_reconstructed[i].cpu().permute(1, 2,
0) * 0.5 + 0.5)
    axes[1, i].axis("off")

    # VAE with Regularization
    axes[2, i].imshow(vae_reg_reconstructed[i].cpu().permute(1, 2, 0)
* 0.5 + 0.5)
    axes[2, i].axis("off")

axes[0, 0].set_title("Original")
axes[1, 0].set_title("VAE No Reg")
axes[2, 0].set_title("VAE With Reg")
plt.show()
```