```python
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
import pandas as pd

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

```
device(type='cuda')
```

```python
transform = transforms.Compose([
    transforms.ToTensor()
])

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

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

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

```
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```

```python
latent_dim = 128

class Decoder(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(latent_dim, 512)
        self.fc2 = nn.Linear(512, 32*32*3)

    def forward(self, z):
        z = torch.relu(self.fc1(z))
        x = torch.sigmoid(self.fc2(z))
        return x.view(-1, 3, 32, 32)
```

****AUTOENCODER (WITHOUT KL DIVERGENCE)****

```python
class AE_Encoder(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(32*32*3, 512)
        self.fc2 = nn.Linear(512, latent_dim)
    def forward(self, x):
        x = x.view(-1, 32*32*3)
        x = torch.relu(self.fc1(x))
        return self.fc2(x)

class Autoencoder(nn.Module):
    def __init__(self):
        super().__init__()
        self.encoder = AE_Encoder()
        self.decoder = Decoder()

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

ae = Autoencoder().to(device)
criterion = nn.MSELoss()
optimizer = optim.Adam(ae.parameters(), lr=1e-3)

epochs = 10

for epoch in range(epochs):
    ae.train()
    total_loss = 0

    for x, _ in train_loader:
        x = x.to(device)
        optimizer.zero_grad()

        x_recon = ae(x)
        loss = criterion(x_recon, x)

        loss.backward()
        optimizer.step()
        total_loss += loss.item()

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

```
AE Epoch [1/10] Loss: 0.0266
AE Epoch [2/10] Loss: 0.0156
AE Epoch [3/10] Loss: 0.0133
AE Epoch [4/10] Loss: 0.0120
AE Epoch [5/10] Loss: 0.0110
AE Epoch [6/10] Loss: 0.0104
AE Epoch [7/10] Loss: 0.0098
AE Epoch [8/10] Loss: 0.0107
AE Epoch [9/10] Loss: 0.0110
AE Epoch [10/10] Loss: 0.0093
```

****VARIATIONAL AUTOENCODER (WITH KL DIVERGENCE)****

```python
class VAE_Encoder(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(32*32*3, 512)
        self.fc_mu = nn.Linear(512, latent_dim)
        self.fc_logvar = nn.Linear(512, latent_dim)

    def forward(self, x):
        x = x.view(-1, 32*32*3)
        x = torch.relu(self.fc1(x))
        return self.fc_mu(x), self.fc_logvar(x)

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

class VAE(nn.Module):
    def __init__(self):
        super().__init__()
        self.encoder = VAE_Encoder()
        self.decoder = Decoder()

    def forward(self, x):
        mu, logvar = self.encoder(x)
        z = reparameterize(mu, logvar)
        x_recon = self.decoder(z)
        return x_recon, mu, logvar

def vae_loss(x_recon, x, mu, logvar):
    recon_loss = nn.MSELoss()(x_recon, x)
    kl_loss = -0.5 * torch.mean(
        1 + logvar - mu.pow(2) - logvar.exp()
    )
    return recon_loss + kl_loss

vae = VAE().to(device)
optimizer = optim.Adam(vae.parameters(), lr=1e-3)

epochs = 15

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

    for x, _ in train_loader:
        x = x.to(device)
        optimizer.zero_grad()

        x_recon, mu, logvar = vae(x)
        loss = vae_loss(x_recon, x, mu, logvar)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    print(f"VAE Epoch [{epoch+1}/{epochs}] Loss:
{total_loss/len(train_loader):.4f}")
```

```
VAE Epoch [1/15] Loss: 0.0637
VAE Epoch [2/15] Loss: 0.0623
VAE Epoch [3/15] Loss: 0.0622
VAE Epoch [4/15] Loss: 0.0622
VAE Epoch [5/15] Loss: 0.0621
VAE Epoch [6/15] Loss: 0.0621
VAE Epoch [7/15] Loss: 0.0621
VAE Epoch [8/15] Loss: 0.0621
VAE Epoch [9/15] Loss: 0.0621
VAE Epoch [10/15] Loss: 0.0621
VAE Epoch [11/15] Loss: 0.0621
VAE Epoch [12/15] Loss: 0.0621
VAE Epoch [13/15] Loss: 0.0621
VAE Epoch [14/15] Loss: 0.0621
VAE Epoch [15/15] Loss: 0.0621
```

```
def show_images(original, reconstructed, title):
    original = original.cpu()[:8]
    reconstructed = reconstructed.cpu()[:8]

    plt.figure(figsize=(12,4))
    for i in range(8):
        plt.subplot(2,8,i+1)
        plt.imshow(original[i].permute(1,2,0))
        plt.axis("off")

        plt.subplot(2,8,i+9)
        plt.imshow(reconstructed[i].permute(1,2,0))
        plt.axis("off")

    plt.suptitle(title)
    plt.show()

def reconstruction_accuracy(model, loader, is_vae=False):
    model.eval()
    total_loss = 0
    criterion = nn.MSELoss()

    with torch.no_grad():
        for x, _ in loader:
            x = x.to(device)

            if is_vae:
                x_recon, _, _ = model(x)
            else:
                x_recon = model(x)

            loss = criterion(x_recon, x)
            total_loss += loss.item()

    avg_loss = total_loss / len(loader)
    accuracy = (1 - avg_loss) * 100
    return avg_loss, accuracy
```

****BEFORE KL DIVERGENCE****

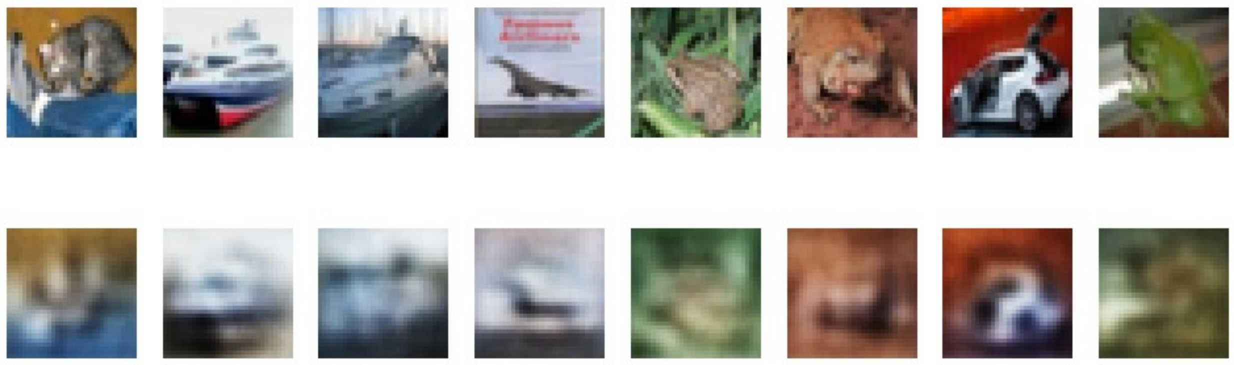
```
x, _ = next(iter(test_loader))
x = x.to(device)

with torch.no_grad():
    x_recon = ae(x)

show_images(x, x_recon, "Before KL Divergence (Autoencoder)")

loss_before, acc_before = reconstruction_accuracy(ae, test_loader)
print("Before KL:")
print("Loss:", loss_before)
print("Accuracy:", acc_before)
```

Before KL Divergence (Autoencoder)



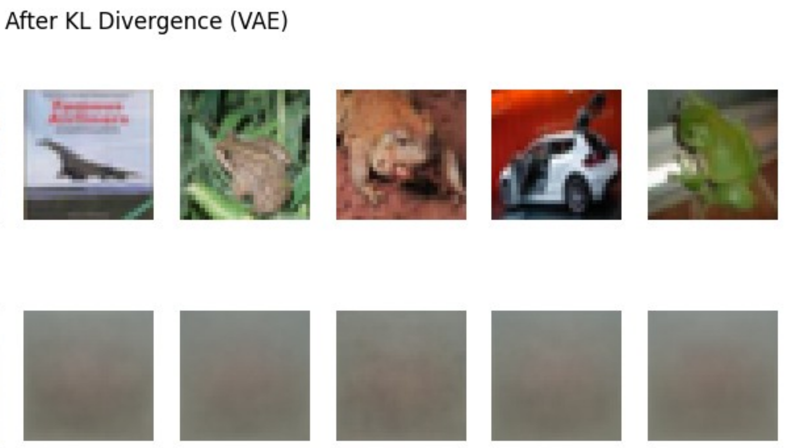
```
Before KL:
Loss: 0.009040074399377726
Accuracy: 99.09599256006223
```

****After KL Divergence****

```
with torch.no_grad():
    x_recon, _, _ = vae(x)
```

```
show_images(x, x_recon, "After KL Divergence (VAE)")

loss_after, acc_after = reconstruction_accuracy(vae, test_loader,
True)
print("After KL:")
print("Loss:", loss_after)
print("Accuracy:", acc_after)
```



```
After KL:
Loss: 0.0619609412041646
Accuracy: 93.80390587958354

results = pd.DataFrame({
    "Model": ["Without KL (AE)", "With KL (VAE)"],
    "Reconstruction Loss": [loss_before, loss_after],
    "Reconstruction Accuracy (%)": [acc_before, acc_after]
})

results

              Model  Reconstruction Loss  Reconstruction Accuracy (%)
0  Without KL (AE)             0.009040                    99.095993
1    With KL (VAE)             0.061961                    93.803906
```