In [1]:
```
import lucid
import lucid.nn as nn
import lucid.nn.functional as F
import lucid.optim as optim
import lucid.data as data
import lucid.datasets as datasets
import lucid.models as models

from tqdm import tqdm
import matplotlib.pyplot as plt
```

In [2]:
```
batch_size = 64
learning_rate = 1e-4
num_epochs = 50
latent_dim = 20

lucid.random.seed(42)
```

In [3]:
```
train_set = datasets.FashionMNIST(root="../../data/fashion_mnist", train=Tr
test_set = datasets.FashionMNIST(root="../../data/fashion_mnist",train=Fals
```

In [4]:
```
train_loader = data.DataLoader(train_set, batch_size=batch_size, shuffle=Tr
test_loader = data.DataLoader(test_set, batch_size=batch_size, shuffle=Fals
```

In [5]:
```
class VAE(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(784, 500)
        self.fc2_mean = nn.Linear(500, latent_dim)
        self.fc2_logvar = nn.Linear(500, latent_dim)
        self.fc3 = nn.Linear(latent_dim, 500)
        self.fc4 = nn.Linear(500, 784)

    def encode(self, x):
        h1 = F.relu(self.fc1(x))
        mean = self.fc2_mean(h1)
        logvar = self.fc2_logvar(h1).clip(-10.0, 10.0)
        return mean, logvar

    def reparameterize(self, mean, logvar):
        std = lucid.exp(0.5 * logvar)
        eps = lucid.random.randn(std.shape)
```

```
        return mean + eps * std

    def decode(self, z):
        h3 = F.relu(self.fc3(z))
        return F.sigmoid(self.fc4(h3))

    def forward(self, x):
        mean, logvar = self.encode(x)
        z = self.reparameterize(mean, logvar)
        return self.decode(z), mean, logvar
```

In [6]:

```
def loss_function(recon_x, x, mean, logvar):
    BCE = F.binary_cross_entropy(recon_x, x, reduction='sum')
    KLD = -0.5 * lucid.sum(1 + logvar - mean ** 2 - lucid.exp(logvar))
    return BCE + KLD
```

In [7]:

```
def normalize(x):
    norm = x.astype(lucid.Float) / 255.0
    return norm.reshape(-1, 784)
```

In [8]:

```
def train(model, train_loader, optimizer, num_epochs):
    losses = []
    model.train()
    for epoch in range(num_epochs):
        epoch_loss = 0
        progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_epoc
        for data, _ in progress_bar:
            optimizer.zero_grad()
            data = normalize(data)
            recon_batch, mean, logvar = model(data)

            loss = loss_function(recon_batch, data, mean, logvar)
            loss.backward()
            optimizer.step()

            batch_loss = loss.item()
            losses.append(batch_loss)
            epoch_loss += batch_loss
            progress_bar.set_postfix(loss=batch_loss)

    return losses
```

In [9]:

```
def test(model, test_loader):
    model.eval()
    test_loss = 0
    losses = []
    with lucid.no_grad():
        progress_bar = tqdm(test_loader, desc="Testing")
        for data, _ in progress_bar:
            recon_batch, mean, logvar = model(data)
            loss = loss_function(recon_batch, data, mean, logvar).eval()
            batch_loss = loss.item()

            test_loss += batch_loss
            losses.append(batch_loss)
            progress_bar.set_postfix(loss=batch_loss)
```

```python
    avg_loss = test_loss / len(test_loader)
    print(f"\nAverage Test Loss: {avg_loss:.4f}")
    return losses
```

In [10]:

```python
model = VAE()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

models.summarize(model, input_shape=(1, 784))
```

```
                                        Summary of VAE
============================================================================
====================
Layer                                    Input Shape          Output Shape
Parameter Size
============================================================================
====================
VAE                                      (1, 784)             None
815,824
├── Linear                               (1, 500)             (1, 784)
392,784
├── Linear                               (1, 20)              (1, 500)
10,500
├── Linear                               (1, 500)             (1, 20)
10,020
├── Linear                               (1, 500)             (1, 20)
10,020
├── Linear                               (1, 784)             (1, 500)
392,500
============================================================================
====================
Total Layers(Submodules): 5
Total Parameters: 815,824 (815.82K)
Total FLOPs: 827,276 (827.28K)
============================================================================
====================
```

In [11]:

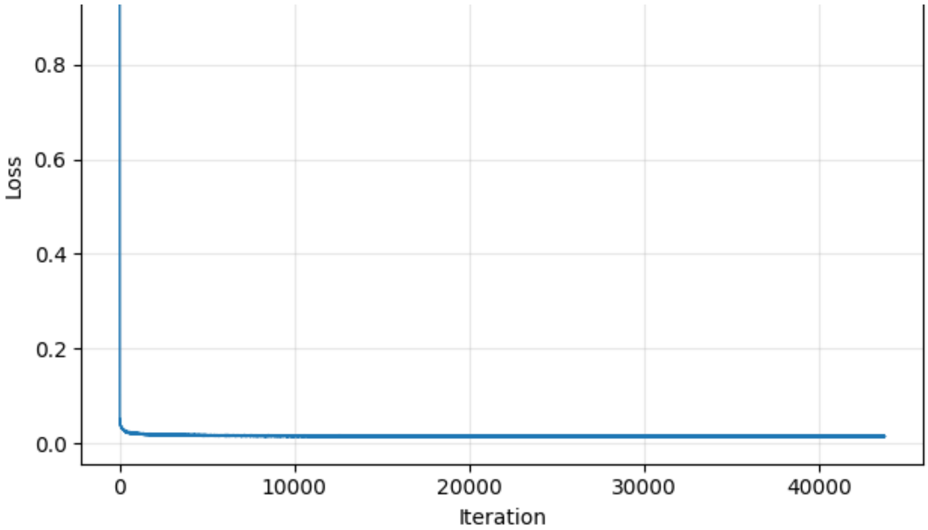
```python
train_losses = train(model, train_loader, optimizer, num_epochs)
```

```
Epoch 1/50: 100%|██████████| 875/875 [00:23<00:00, 37.79it/s, loss=2.21e+4]
Epoch 2/50: 100%|██████████| 875/875 [00:20<00:00, 42.21it/s, loss=1.89e+4]
Epoch 3/50: 100%|██████████| 875/875 [00:20<00:00, 43.10it/s, loss=1.82e+4]
Epoch 4/50: 100%|██████████| 875/875 [00:18<00:00, 46.77it/s, loss=1.84e+4]
Epoch 5/50: 100%|██████████| 875/875 [00:19<00:00, 45.99it/s, loss=1.77e+4]
Epoch 6/50: 100%|██████████| 875/875 [00:18<00:00, 46.57it/s, loss=1.82e+4]
Epoch 7/50: 100%|██████████| 875/875 [00:18<00:00, 47.87it/s, loss=1.77e+4]
Epoch 8/50: 100%|██████████| 875/875 [00:18<00:00, 46.08it/s, loss=1.74e+4]
Epoch 9/50: 100%|██████████| 875/875 [00:19<00:00, 46.01it/s, loss=1.82e+4]
Epoch 10/50: 100%|██████████| 875/875 [00:16<00:00, 51.68it/s, loss=1.74e+
4]
Epoch 11/50: 100%|██████████| 875/875 [00:17<00:00, 50.44it/s, loss=1.62e+
4]
Epoch 12/50: 100%|██████████| 875/875 [00:17<00:00, 49.76it/s, loss=1.64e+
4]
Epoch 13/50: 100%|██████████| 875/875 [00:18<00:00, 46.08it/s, loss=1.79e+
4]
Epoch 14/50: 100%|██████████| 875/875 [00:17<00:00, 50.43it/s, loss=1.7e+4]
Epoch 15/50: 100%|██████████| 875/875 [00:17<00:00, 49.97it/s, loss=1.61e+
4]
Epoch 16/50: 100%|██████████| 875/875 [00:18<00:00, 47.95it/s, loss=1.66e+
4]
Epoch 17/50: 100%|██████████| 875/875 [00:17<00:00, 50.57it/s, loss=1.52e+
4]
Epoch 18/50: 100%|██████████| 875/875 [00:17<00:00, 51.19it/s, loss=1.56e+
4]
Epoch 19/50: 100%|██████████| 875/875 [00:17<00:00, 50.17it/s, loss=1.61e+
4]
```

```
Epoch 20/50: 100%|██████████| 875/875 [00:19<00:00, 44.73it/s, loss=1.56e+
4]
Epoch 21/50: 100%|██████████| 875/875 [00:17<00:00, 49.68it/s, loss=1.75e+
4]
Epoch 22/50: 100%|██████████| 875/875 [00:17<00:00, 49.49it/s, loss=1.51e+
4]
Epoch 23/50: 100%|██████████| 875/875 [00:17<00:00, 49.01it/s, loss=1.54e+
4]
Epoch 24/50: 100%|██████████| 875/875 [00:17<00:00, 49.42it/s, loss=1.63e+
4]
Epoch 25/50: 100%|██████████| 875/875 [00:18<00:00, 47.33it/s, loss=1.51e+
4]
Epoch 26/50: 100%|██████████| 875/875 [00:18<00:00, 46.12it/s, loss=1.66e+
4]
Epoch 27/50: 100%|██████████| 875/875 [00:18<00:00, 48.07it/s, loss=1.53e+
4]
Epoch 28/50: 100%|██████████| 875/875 [00:19<00:00, 45.95it/s, loss=1.58e+
4]
Epoch 29/50: 100%|██████████| 875/875 [00:19<00:00, 45.19it/s, loss=1.62e+
4]
Epoch 30/50: 100%|██████████| 875/875 [00:17<00:00, 50.84it/s, loss=1.65e+
4]
Epoch 31/50: 100%|██████████| 875/875 [00:17<00:00, 49.56it/s, loss=1.55e+
4]
Epoch 32/50: 100%|██████████| 875/875 [00:17<00:00, 49.30it/s, loss=1.57e+
4]
Epoch 33/50: 100%|██████████| 875/875 [00:18<00:00, 47.83it/s, loss=1.66e+
4]
Epoch 34/50: 100%|██████████| 875/875 [00:19<00:00, 45.97it/s, loss=1.51e+
4]
Epoch 35/50: 100%|██████████| 875/875 [00:19<00:00, 45.73it/s, loss=1.64e+
4]
Epoch 36/50: 100%|██████████| 875/875 [00:17<00:00, 48.95it/s, loss=1.58e+
4]
Epoch 37/50: 100%|██████████| 875/875 [00:17<00:00, 49.94it/s, loss=1.61e+
4]
Epoch 38/50: 100%|██████████| 875/875 [00:17<00:00, 50.32it/s, loss=1.57e+
4]
Epoch 39/50: 100%|██████████| 875/875 [00:18<00:00, 47.74it/s, loss=1.51e+
4]
Epoch 40/50: 100%|██████████| 875/875 [00:19<00:00, 45.81it/s, loss=1.61e+
4]
Epoch 41/50: 100%|██████████| 875/875 [00:18<00:00, 46.21it/s, loss=1.48e+
4]
Epoch 42/50: 100%|██████████| 875/875 [00:19<00:00, 46.00it/s, loss=1.59e+
4]
Epoch 43/50: 100%|██████████| 875/875 [00:17<00:00, 49.93it/s, loss=1.57e+
4]
Epoch 44/50: 100%|██████████| 875/875 [00:19<00:00, 45.65it/s, loss=1.63e+
4]
Epoch 45/50: 100%|██████████| 875/875 [00:17<00:00, 49.52it/s, loss=1.58e+
4]
Epoch 46/50: 100%|██████████| 875/875 [00:18<00:00, 47.46it/s, loss=1.5e+4]
Epoch 47/50: 100%|██████████| 875/875 [00:17<00:00, 50.76it/s, loss=1.63e+
4]
Epoch 48/50: 100%|██████████| 875/875 [00:17<00:00, 49.97it/s, loss=1.58e+
4]
Epoch 49/50: 100%|██████████| 875/875 [00:18<00:00, 47.41it/s, loss=1.66e+
4]
Epoch 50/50: 100%|██████████| 875/875 [00:17<00:00, 50.13it/s, loss=1.57e+
4]
```

In [12]:

```
plt.plot(train_losses, lw=1, label="Recon + KL-Div")
plt.xlabel("Iteration")
plt.ylabel("Loss")
plt.title("VAE FashionMNIST Training Loss")
plt.grid(alpha=0.3)
plt.legend()
plt.tight_layout()
```



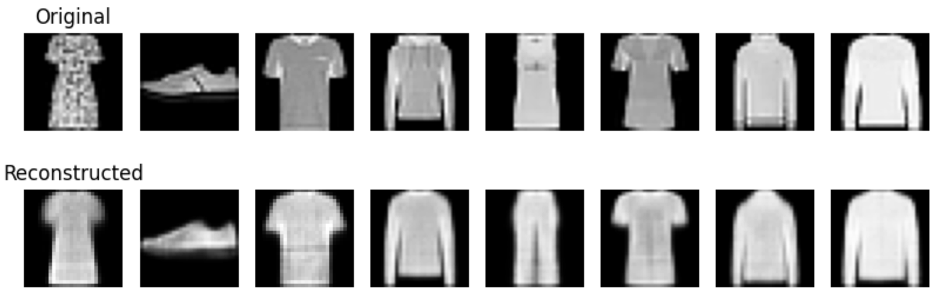
In [13]:

```
model.eval()
data_batch, _ = next(iter(test_loader))
data_batch = normalize(data_batch)
recon_batch, _, _ = model(data_batch[:8])

import matplotlib.pyplot as plt

fig, axes = plt.subplots(2, 8, figsize=(8, 3))
for i in range(8):
    axes[0, i].imshow(data_batch[i].reshape(28, 28).data, cmap='gray')
    axes[1, i].imshow(recon_batch[i].reshape(28, 28).data, cmap='gray')
    axes[0, i].axis('off')
    axes[1, i].axis('off')

axes[0, 0].set_title("Original")
axes[1, 0].set_title("Reconstructed")
plt.tight_layout()
```



In [14]:

```
z = lucid.random.randn(25, 20)
samples = model.decode(z)

fig, axes = plt.subplots(5, 5, figsize=(5, 5))
for i, ax in enumerate(axes.flat):
    ax.imshow(samples[i].reshape(28, 28).data, cmap='gray')
```

```
    ax.imshow(samples[i].reshape(28, 28).data, cmap="gray")
    ax.axis("off")

plt.suptitle("Samples from Latent Space")
plt.tight_layout()
```