

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import numpy as np
import matplotlib.pyplot as plt
```

```
# Choose dataset: "mnist" or "fashion"
dataset_choice = "mnist"

if dataset_choice == "mnist":
    (x_train, _), (x_test, _) = keras.datasets.mnist.load_data()
else:
    (x_train, _), (x_test, _) = keras.datasets.fashion_mnist.load_data()

# Normalize to [0,1]
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Flatten images (28x28 -> 784)
x_train = x_train.reshape(-1, 784)
x_test = x_test.reshape(-1, 784)

print("Training shape:", x_train.shape)
print("Testing shape:", x_test.shape)
```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>
11490434/11490434 ————— 1s 0us/step
 Training shape: (60000, 784)
 Testing shape: (10000, 784)

```
latent_dim = 2 # use 2 for latent visualization

inputs = keras.Input(shape=(784,))
h = layers.Dense(256, activation="relu")(inputs)
h = layers.Dense(128, activation="relu")(h)

z_mean = layers.Dense(latent_dim, name="z_mean")(h)
z_log_var = layers.Dense(latent_dim, name="z_log_var")(h)
```

```
def sampling(args):
    z_mean, z_log_var = args
    epsilon = tf.random.normal(shape=tf.shape(z_mean))
    return z_mean + tf.exp(0.5 * z_log_var) * epsilon

z = layers.Lambda(sampling, name="z")([z_mean, z_log_var])
```

```
encoder = keras.Model(inputs, [z_mean, z_log_var, z], name="encoder")
encoder.summary()
```

Model: "encoder"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 784)	0	-
dense (Dense)	(None, 256)	200,960	input_layer[0][0]
dense_1 (Dense)	(None, 128)	32,896	dense[0][0]
z_mean (Dense)	(None, 2)	258	dense_1[0][0]
z_log_var (Dense)	(None, 2)	258	dense_1[0][0]
z (Lambda)	(None, 2)	0	z_mean[0][0], z_log_var[0][0]

Total params: 234,372 (915.52 KB)
 Trainable params: 234,372 (915.52 KB)

```
latent_inputs = keras.Input(shape=(latent_dim,))
x = layers.Dense(128, activation="relu")(latent_inputs)
x = layers.Dense(256, activation="relu")(x)
outputs = layers.Dense(784, activation="sigmoid")(x)
```

```
decoder = keras.Model(latent_inputs, outputs, name="decoder")
decoder.summary()
```

Model: "decoder"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 2)	0
dense_2 (Dense)	(None, 128)	384
dense_3 (Dense)	(None, 256)	33,024
dense_4 (Dense)	(None, 784)	201,488

Total params: 234,896 (917.56 KB)

Trainable params: 234,896 (917.56 KB)

```
class VAE(keras.Model):
    def __init__(self, encoder, decoder):
        super(VAE, self).__init__()
        self.encoder = encoder
        self.decoder = decoder

    def call(self, inputs): # Added call method
        z_mean, z_log_var, z = self.encoder(inputs)
        reconstruction = self.decoder(z)
        return reconstruction

    def train_step(self, data):
        if isinstance(data, tuple):
            data = data[0]

        with tf.GradientTape() as tape:
            z_mean, z_log_var, z = self.encoder(data)
            reconstruction = self.decoder(z)

            # Reconstruction loss
            recon_loss = tf.reduce_mean(
                keras.losses.binary_crossentropy(data, reconstruction)
            )

            # KL divergence loss
            kl_loss = -0.5 * tf.reduce_mean(
                tf.reduce_sum(
                    1 + z_log_var - tf.square(z_mean) - tf.exp(z_log_var),
                    axis=1
                )
            )

            total_loss = recon_loss + kl_loss

        grads = tape.gradient(total_loss, self.trainable_weights)
        self.optimizer.apply_gradients(zip(grads, self.trainable_weights))

        return {
            "loss": total_loss,
            "reconstruction_loss": recon_loss,
            "kl_loss": kl_loss,
        }
```

```
vae = VAE(encoder, decoder)
vae.compile(optimizer=keras.optimizers.Adam(), loss=tf.keras.losses.MeanSquaredError()) # Added a dummy loss function
```

```
history = vae.fit(
    x_train,
    epochs=30,
    batch_size=128,
    validation_data=(x_test, x_test) # Changed None to x_test for validation targets
)
```

```
Epoch 2/30
469/469 — 1s 3ms/step - kl_loss: 2.3701e-07 - loss: 0.2631 - reconstruction_loss: 0.2631 - val_loss: 0.0676
Epoch 3/30
469/469 — 2s 3ms/step - kl_loss: 1.5043e-07 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
```

Epoch 5/30

```

469/469 ————— 2s 3ms/step - kl_loss: 9.1528e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 6/30
469/469 ————— 2s 4ms/step - kl_loss: 6.9928e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 7/30
469/469 ————— 2s 3ms/step - kl_loss: 3.1418e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 8/30
469/469 ————— 2s 3ms/step - kl_loss: 4.0811e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 9/30
469/469 ————— 1s 3ms/step - kl_loss: 2.8286e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 10/30
469/469 ————— 2s 3ms/step - kl_loss: 2.4580e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 11/30
469/469 ————— 2s 3ms/step - kl_loss: 2.4709e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 12/30
469/469 ————— 2s 3ms/step - kl_loss: 2.7518e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 13/30
469/469 ————— 2s 4ms/step - kl_loss: 3.4669e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 14/30
469/469 ————— 2s 4ms/step - kl_loss: 3.5548e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 15/30
469/469 ————— 2s 3ms/step - kl_loss: 3.0239e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 16/30
469/469 ————— 2s 3ms/step - kl_loss: 3.1643e-08 - loss: 0.2630 - reconstruction_loss: 0.2630 - val_loss: 0.0675
Epoch 17/30
469/469 ————— 2s 3ms/step - kl_loss: 2.9542e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 18/30
469/469 ————— 2s 3ms/step - kl_loss: 2.3755e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 19/30
469/469 ————— 2s 3ms/step - kl_loss: 2.8768e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 20/30
469/469 ————— 2s 3ms/step - kl_loss: 2.7833e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 21/30
469/469 ————— 2s 4ms/step - kl_loss: 2.8125e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 22/30
469/469 ————— 2s 4ms/step - kl_loss: 1.9442e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 23/30
469/469 ————— 2s 3ms/step - kl_loss: 2.2122e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 24/30
469/469 ————— 2s 5ms/step - kl_loss: 2.2760e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 25/30
469/469 ————— 2s 3ms/step - kl_loss: 1.8928e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 26/30
469/469 ————— 2s 3ms/step - kl_loss: 2.1393e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 27/30
469/469 ————— 2s 3ms/step - kl_loss: 1.6838e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 28/30
469/469 ————— 2s 4ms/step - kl_loss: 2.0139e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 29/30
469/469 ————— 2s 4ms/step - kl_loss: 1.6624e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675
Epoch 30/30
469/469 ————— 1s 3ms/step - kl_loss: 1.5291e-08 - loss: 0.2629 - reconstruction_loss: 0.2629 - val_loss: 0.0675

```

```

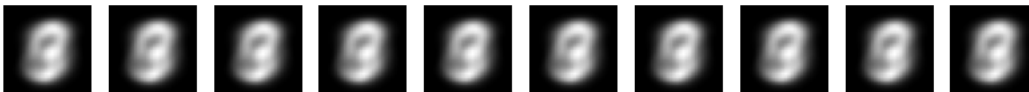
def plot_generated_images(decoder, n=10):
    z_random = np.random.normal(size=(n, latent_dim))
    generated = decoder.predict(z_random)

    plt.figure(figsize=(10, 2))
    for i in range(n):
        plt.subplot(1, n, i + 1)
        plt.imshow(generated[i].reshape(28, 28), cmap="gray")
        plt.axis("off")
    plt.show()

plot_generated_images(decoder)

```

1/1 ————— 0s 449ms/step



```

z_mean, _, z = encoder.predict(x_test[:10])
reconstructed = decoder.predict(z)

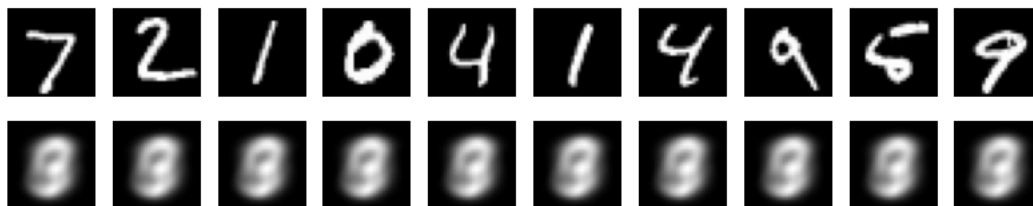
plt.figure(figsize=(10, 2))
for i in range(10):
    plt.subplot(2, 10, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap="gray")
    plt.axis("off")

```

```
plt.subplot(2, 10, i + 11)
plt.imshow(reconstructed[i].reshape(28, 28), cmap="gray")
plt.axis("off")
```

```
plt.show()
```

1/1 ————— 1s 1s/step
1/1 ————— 0s 51ms/step



```
z_mean, _, _ = encoder.predict(x_test)
```

```
plt.figure(figsize=(6, 6))
plt.scatter(z_mean[:, 0], z_mean[:, 1], s=2)
plt.xlabel("Latent Dimension 1")
plt.ylabel("Latent Dimension 2")
plt.title("Latent Space Representation")
plt.show()
```

313/313 ————— 3s 4ms/step

