```python
# Import and creating some helper functions
import copy

import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt

from tensorflow.keras import layers
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model


def preprocess(array):
    """
    Normalizes the supplied array and reshapes it into the appropriate format.
    """

    array = array.astype("float32") / 255.0
    array = np.reshape(array, (len(array), 28, 28, 1))
    return array


def noise(array):
    """
    Adds random noise to each image in the supplied array.
    """

    noise_factor = 0.4
    noisy_array = array + noise_factor * np.random.normal(
        loc=0.0, scale=1.0, size=array.shape
    )

    return np.clip(noisy_array, 0.0, 1.0)


def occlude(array):
    """
    Adds occlusion to an image.
    """
    new_array = copy.deepcopy(array)

    for k in range(len(new_array)):
        x = np.random.randint(0, 25)
        new_array[k, x: x + 2, :] = 1.0

    return new_array


def display(array1, array2):
    """
    Displays ten random images from each one of the supplied arrays.
    """

    n = 10

    indices = np.random.randint(len(array1), size=n)
    images1 = array1[indices, :]
    images2 = array2[indices, :]

    plt.figure(figsize=(20, 4))
    for i, (image1, image2) in enumerate(zip(images1, images2)):
        ax = plt.subplot(2, n, i + 1)
        plt.imshow(image1.reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

        ax = plt.subplot(2, n, i + 1 + n)
        plt.imshow(image2.reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

    plt.show()
```

```
tf.config.list_logical_devices("GPU")
```

```
[LogicalDevice(name='/device:GPU:0', device_type='GPU')]
```

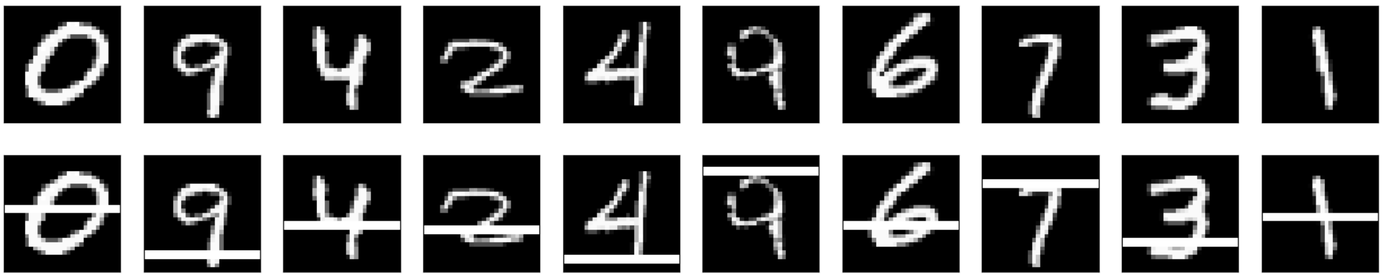
```
# Since we only need images from the dataset to encode and decode, we
# won't use the labels.
(train_data, train_labels), (test_data, test_labels) = mnist.load_data()

# Normalize and reshape the data
train_data = preprocess(train_data)
test_data = preprocess(test_data)

# Create a copy of the data with added noise
noisy_train_data = occlude(train_data)
noisy_test_data = occlude(test_data)

# Display the train data and a version of it with added noise
display(train_data, noisy_train_data)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```



```
# Our input shape is 28 x 28 x 1
input = layers.Input(shape=(28, 28, 1))

# The Encoder Model
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(input)
x = layers.MaxPooling2D((2, 2), padding="same")(x)
x = layers.Conv2D(32, (3, 3), activation="relu", padding="same")(x)
x = layers.MaxPooling2D((2, 2), padding="same")(x)

# The Decoder Model
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="same")(x)
x = layers.Conv2DTranspose(32, (3, 3), strides=2, activation="relu", padding="same")(x)
x = layers.Conv2D(1, (3, 3), activation="sigmoid", padding="same")(x)

# Autoencoder - Note it is the entire concatenation of the encoder and decoder
autoencoder = Model(input, x)

autoencoder.compile(optimizer="adam", loss="binary_crossentropy")
autoencoder.summary()
```

```
Model: "functional"
```

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 28, 28, 1)	0
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 32)	0
conv2d_transpose (Conv2DTranspose)	(None, 14, 14, 32)	9,248
conv2d_transpose_1 (Conv2DTranspose)	(None, 28, 28, 32)	9,248
conv2d_2 (Conv2D)	(None, 28, 28, 1)	289

Total params: 28,353 (110.75 KB)

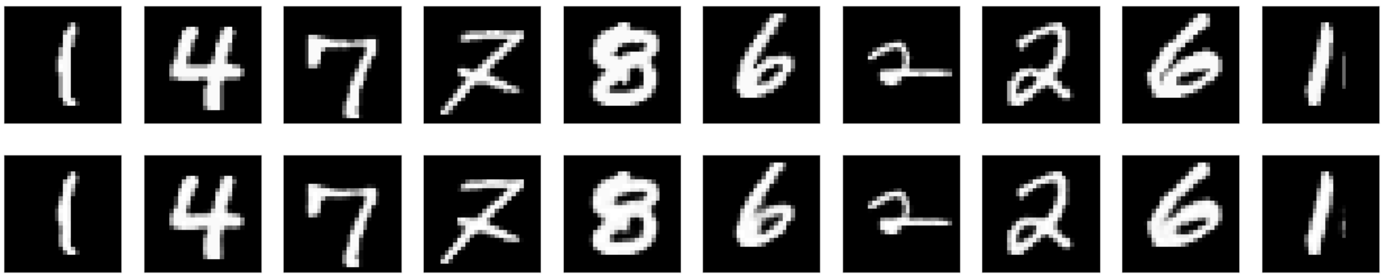
```
with tf.device("/device:GPU:0"):
  autoencoder.fit(
      x=train_data,
      y=train_data,
      epochs=50,
      batch_size=128,
      shuffle=True,
      validation_data=(test_data, test_data),
  )
```

```
Epoch 22/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0637 - val_loss: 0.0632
Epoch 23/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0636 - val_loss: 0.0631
Epoch 24/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0635 - val_loss: 0.0631
Epoch 25/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0634 - val_loss: 0.0630
```

```
Epoch 47/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - loss: 0.0627 - val_loss: 0.0623
Epoch 48/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0627 - val_loss: 0.0623
Epoch 49/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0627 - val_loss: 0.0622
Epoch 50/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0625 - val_loss: 0.0622
```

```
predictions = autoencoder.predict(test_data)
display(test_data, predictions)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



```
# Extracting the encoder part of the autoencoder
encoder = Model(inputs=autoencoder.input, outputs=autoencoder.layers[4].output)
encoder.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 28, 28, 1)	0
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 32)	0

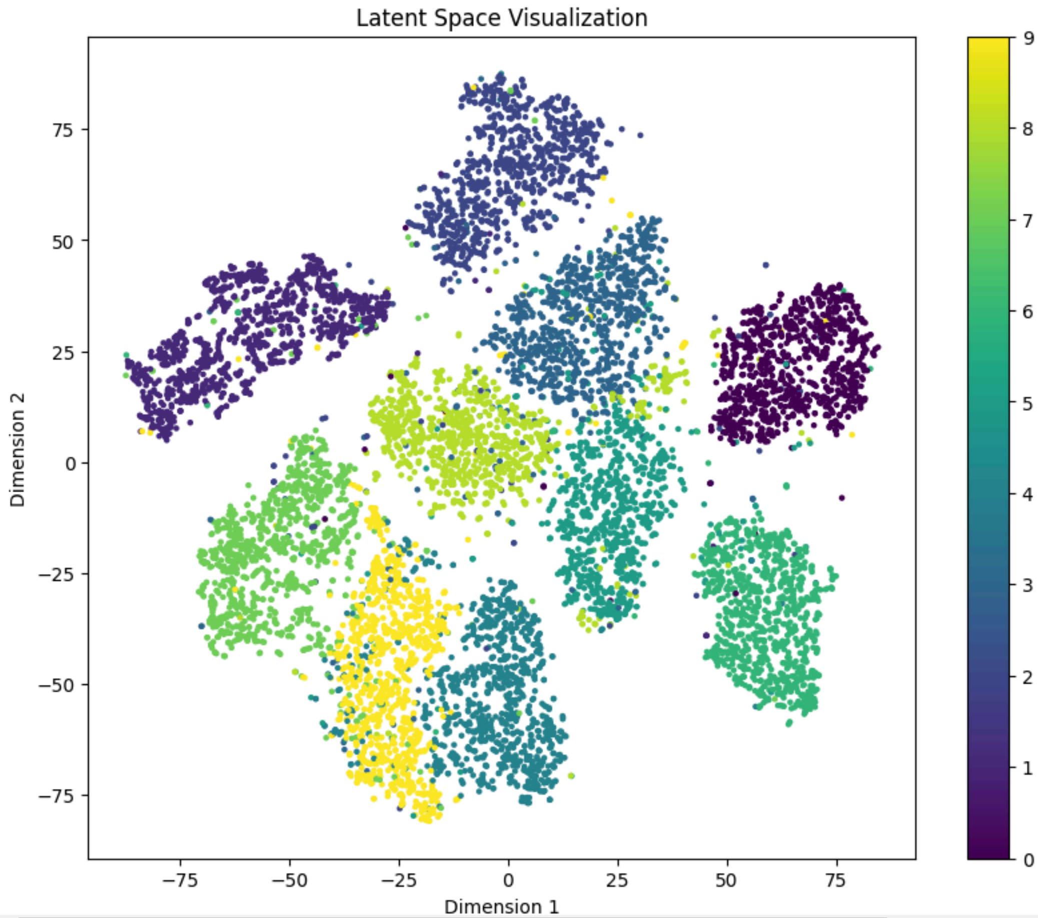
Total params: 9,568 (37.38 KB)

```
# Use the encoder to generate latent space representations
latent_train = encoder.predict(train_data)
latent_test = encoder.predict(test_data)
print(latent_test.shape)
```

```
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
(10000, 7, 7, 32)
```

```
from sklearn.manifold import TSNE

# Reduce the dimensionality of the latent space to 2D using t-SNE
latent_2d = TSNE(n_components=2, random_state=42).fit_transform(latent_test.reshape(len(latent_test), -1))
#colors = np.random.rand(latent_2d.shape[0])
# Plot the 2D latent space
plt.figure(figsize=(10, 8))
plt.scatter(latent_2d[:, 0], latent_2d[:, 1],  c=test_labels,cmap='viridis',  s=5)
plt.colorbar()
plt.title("Latent Space Visualization")
plt.xlabel("Dimension 1")
plt.ylabel("Dimension 2")
plt.show()
```




```
autoencoder.fit(
    x=noisy_train_data,
    y=train_data,
    epochs=50,
    batch_size=128,
    shuffle=True,
    validation_data=(noisy_test_data, test_data),
)
```

```
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0668 - val_loss: 0.0664
Epoch 39/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 0.0668 - val_loss: 0.0663
Epoch 40/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0669 - val_loss: 0.0663
Epoch 41/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0670 - val_loss: 0.0664
Epoch 42/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0667 - val_loss: 0.0664
Epoch 43/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0669 - val_loss: 0.0663
Epoch 44/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 0.0668 - val_loss: 0.0662
Epoch 45/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0667 - val_loss: 0.0664
Epoch 46/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0668 - val_loss: 0.0663
Epoch 47/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0668 - val_loss: 0.0663
Epoch 48/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.0666 - val_loss: 0.0664
Epoch 49/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.0666 - val_loss: 0.0662
Epoch 50/50
469/469 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - loss: 0.0667 - val_loss: 0.0662
<keras.src.callbacks.history.History at 0x7f9742cfe710>
```

```
predictions = autoencoder.predict(noisy_test_data)
display(noisy_test_data, predictions)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```