Ungraded Lab: Convolutional Autoencoders

In this lab, you will use convolution layers to build your autoencoder. This usually leads to better results than dense networks and you will see it in action with the Fashion MNIST dataset.

Imports

```
try:
  # %tensorflow_version only exists in Colab.
  %tensorflow_version 2.x
except Exception:
  pass

import tensorflow as tf
import tensorflow_datasets as tfds

import numpy as np
import matplotlib.pyplot as plt
```

```
Colab only includes TensorFlow 2.x; %tensorflow_version has no effect.
```

Prepare the Dataset

As before, you will load the train and test sets from TFDS. Notice that we don't flatten the image this time. That's because we will be using convolutional layers later that can deal with 2D images.

```
def map_image(image, label):
  '''Normalizes the image. Returns image as input and label.'''
  image = tf.cast(image, dtype=tf.float32)
  image = image / 255.0

  return image, image
```

```
BATCH_SIZE = 128
SHUFFLE_BUFFER_SIZE = 1024

train_dataset = tfds.load('fashion_mnist', as_supervised=True, split="train")
train_dataset = train_dataset.map(map_image)
train_dataset = train_dataset.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE).repeat()

test_dataset = tfds.load('fashion_mnist', as_supervised=True, split="test")
test_dataset = test_dataset.map(map_image)
test_dataset = test_dataset.batch(BATCH_SIZE).repeat()
```

```
Downloading and preparing dataset 29.45 MiB (download: 29.45 MiB, generated: 36.42 MiB, total: 65.87 Mi
```

Dl Completed...: 100% 4/4 [00:04<00:00, 1.16s/ url]

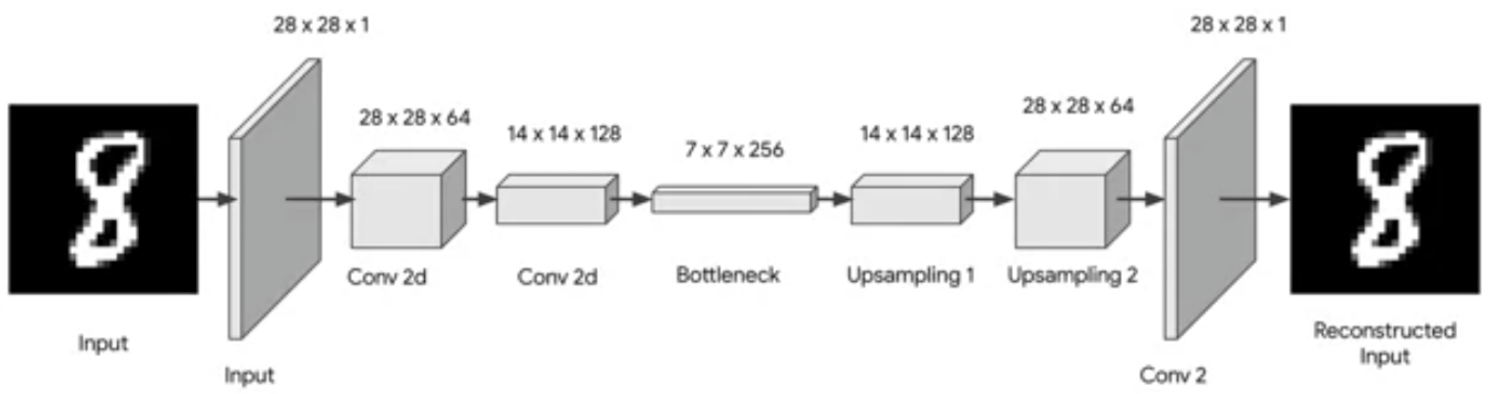
Dl Size...: 100% 29/29 [00:04<00:00, 11.15 MiB/s]

Extraction completed...: 100% 4/4 [00:04<00:00, 1.29s/ file]

```
Dataset fashion_mnist downloaded and prepared to ~/tensorflow_datasets/fashion_mnist/3.0.1. Subsequent
```

Define the Model

As mentioned, you will use convolutional layers to build the model. This is composed of three main parts: encoder, bottleneck, and decoder. You will follow the configuration shown in the image below.



The encoder, just like in previous labs, will contract with each additional layer. The features are generated with the Conv2D layers while the max pooling layers reduce the dimensionality.

```
def encoder(inputs):
  '''Defines the encoder with two Conv2D and max pooling layers.'''
  conv_1 = tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same')(inputs)
  max_pool_1 = tf.keras.layers.MaxPooling2D(pool_size=(2,2))(conv_1)

  conv_2 = tf.keras.layers.Conv2D(filters=128, kernel_size=(3,3), activation='relu', padding='same')(max_pool_1)
  max_pool_2 = tf.keras.layers.MaxPooling2D(pool_size=(2,2))(conv_2)

  return max_pool_2
```

A bottleneck layer is used to get more features but without further reducing the dimension afterwards. Another layer is inserted here for visualizing the encoder output.

```
def bottle_neck(inputs):
  '''Defines the bottleneck.'''
  bottle_neck = tf.keras.layers.Conv2D(filters=256, kernel_size=(3,3), activation='relu', padding='same')(inputs)
  encoder_visualization = tf.keras.layers.Conv2D(filters=1, kernel_size=(3,3), activation='sigmoid', padding='same')(bottle_neck)

  return bottle_neck, encoder_visualization
```

The decoder will upsample the bottleneck output back to the original image size.

```
def decoder(inputs):
  '''Defines the decoder path to upsample back to the original image size.'''
  conv_1 = tf.keras.layers.Conv2D(filters=128, kernel_size=(3,3), activation='relu', padding='same')(inputs)
  up_sample_1 = tf.keras.layers.UpSampling2D(size=(2,2))(conv_1)

  conv_2 = tf.keras.layers.Conv2D(filters=64, kernel_size=(3,3), activation='relu', padding='same')(up_sample_1)
  up_sample_2 = tf.keras.layers.UpSampling2D(size=(2,2))(conv_2)

  conv_3 = tf.keras.layers.Conv2D(filters=1, kernel_size=(3,3), activation='sigmoid', padding='same')(up_sample_2)

  return conv_3
```

You can now build the full autoencoder using the functions above.

```
def convolutional_auto_encoder():
  '''Builds the entire autoencoder model.'''
  inputs = tf.keras.layers.Input(shape=(28, 28, 1,))
  encoder_output = encoder(inputs)
  bottleneck_output, encoder_visualization = bottle_neck(encoder_output)
  decoder_output = decoder(bottleneck_output)

  model = tf.keras.Model(inputs =inputs, outputs=decoder_output)
  encoder_model = tf.keras.Model(inputs=inputs, outputs=encoder_visualization)
  return model, encoder_model
```

```
convolutional_model, convolutional_encoder_model = convolutional_auto_encoder()
convolutional_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 28, 28, 1)]       0

 conv2d (Conv2D)             (None, 28, 28, 64)        640

 max_pooling2d (MaxPooling2D  (None, 14, 14, 64)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 128)       73856

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 128)        0
 2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 256)         295168

 conv2d_4 (Conv2D)           (None, 7, 7, 128)         295040

 up_sampling2d (UpSampling2D  (None, 14, 14, 128)      0
 )
```

```
 conv2d_5 (Conv2D)           (None, 14, 14, 64)        73792

 up_sampling2d_1 (UpSampling  (None, 28, 28, 64)       0
 2D)

 conv2d_6 (Conv2D)           (None, 28, 28, 1)         577

=================================================================
Total params: 739,073
Trainable params: 739,073
Non-trainable params: 0
_________________________________________________________________
```

Compile and Train the model

```
train_steps = 60000 // BATCH_SIZE
valid_steps = 60000 // BATCH_SIZE

convolutional_model.compile(optimizer=tf.keras.optimizers.Adam(), loss='binary_crossentropy')
conv_model_history = convolutional_model.fit(train_dataset, steps_per_epoch=train_steps, validation_data=test_dataset, validation_steps=valid_s
```

```
Epoch 12/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2472 - val_loss: 0.2496
Epoch 13/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2470 - val_loss: 0.2490
Epoch 14/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2468 - val_loss: 0.2486
Epoch 15/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2465 - val_loss: 0.2485
Epoch 16/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2463 - val_loss: 0.2482
Epoch 17/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2462 - val_loss: 0.2480
Epoch 18/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2460 - val_loss: 0.2479
Epoch 19/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2458 - val_loss: 0.2478
Epoch 20/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2457 - val_loss: 0.2477
Epoch 21/40
468/468 [==============================] - 13s 28ms/step - loss: 0.2456 - val_loss: 0.2479
Epoch 22/40
468/468 [==============================] - 15s 31ms/step - loss: 0.2454 - val_loss: 0.2478
Epoch 23/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2453 - val_loss: 0.2473
Epoch 24/40
468/468 [==============================] - 12s 26ms/step - loss: 0.2452 - val_loss: 0.2473
Epoch 25/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2451 - val_loss: 0.2473
Epoch 26/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2450 - val_loss: 0.2470
Epoch 27/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2449 - val_loss: 0.2469
Epoch 28/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2449 - val_loss: 0.2469
Epoch 29/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2448 - val_loss: 0.2474
Epoch 30/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2447 - val_loss: 0.2467
Epoch 31/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2446 - val_loss: 0.2467
Epoch 32/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2446 - val_loss: 0.2466
Epoch 33/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2445 - val_loss: 0.2467

Epoch 34/40
468/468 [==============================] - 13s 28ms/step - loss: 0.2445 - val_loss: 0.2465
Epoch 35/40
468/468 [==============================] - 12s 27ms/step - loss: 0.2444 - val_loss: 0.2465
Epoch 36/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2444 - val_loss: 0.2464
Epoch 37/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2443 - val_loss: 0.2465
Epoch 38/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2443 - val_loss: 0.2463
Epoch 39/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2442 - val_loss: 0.2463
Epoch 40/40
468/468 [==============================] - 13s 27ms/step - loss: 0.2442 - val_loss: 0.2463
```

Display sample results

As usual, let's see some sample results from the trained model.

```
def display_one_row(disp_images, offset, shape=(28, 28)):
  '''Display sample outputs in one row.'''
  for idx, test_image in enumerate(disp_images):
    plt.subplot(3, 10, offset + idx + 1)
    plt.xticks([])
    plt.yticks([])
    test_image = np.reshape(test_image, shape)
    plt.imshow(test_image, cmap='gray')


def display_results(disp_input_images, disp_encoded, disp_predicted, enc_shape=(8,4)):
  '''Displays the input, encoded, and decoded output values.'''
  plt.figure(figsize=(15, 5))
  display_one_row(disp_input_images, 0, shape=(28,28,))
  display_one_row(disp_encoded, 10, shape=enc_shape)
  display_one_row(disp_predicted, 20, shape=(28,28,))
```

```
# take 1 batch of the dataset
test_dataset = test_dataset.take(1)

# take the input images and put them in a list
output_samples = []
for input_image, image in tfds.as_numpy(test_dataset):
      output_samples = input_image

# pick 10 indices
idxs = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])

# prepare test samples as a batch of 10 images
conv_output_samples = np.array(output_samples[idxs])
conv_output_samples = np.reshape(conv_output_samples, (10, 28, 28, 1))

# get the encoder ouput
encoded = convolutional_encoder_model.predict(conv_output_samples)

# get a prediction for some values in the dataset
predicted = convolutional_model.predict(conv_output_samples)

# display the samples, encodings and decoded values!
display_results(conv_output_samples, encoded, predicted, enc_shape=(7,7))
```

```
1/1 [==============================] - 0s 138ms/step
1/1 [==============================] - 0s 113ms/step
```