

1. What you learned in the ICP:

I learned to use the Autoencoder algorithm and built the 3 components such as encoder, code, and c decoder. The Autoencoder is used to compress the input into a lower-dimensional code and then reconstruct the output from this representation.

2. Screen shots that shows the successful execution of each required step of your code:

Since the source code has been given by the instructor and asked us to add only 2 encoder and decoder layers I did not take a screenshot for the part that I did not change.

a. Encoder:

In this part, I have added Conv2D with 32 filters and 1 strides in order to move the filters to 1 pixel at a time. The reason that I increased the filter size is to capture more combinations. Also, I have added BatchNormalization in order to maintain the mean output close to 0 and the output standard deviation close to 1 and enhance the neural network performance.

```
# Encoder Definition
i = Input(shape=input_shape, name='encoder_input')
cx = Conv2D(filters=8, kernel_size=3, strides=2, padding='same', activation='relu')(i)
cx = BatchNormalization()(cx)
cx = Conv2D(filters=16, kernel_size=3, strides=2, padding='same', activation='relu')(cx)
cx = BatchNormalization()(cx)
# New 2 layer: I added Conv2D with 32 filters and BatchNormalization to help coordinate the update of multiple layers in the model.
cx = Conv2D(filters=32, kernel_size=3, strides=1, padding='same', activation='relu')(cx)
cx = BatchNormalization()(cx)
x = Flatten()(cx)
x = Dense(20, activation='relu')(x)
x = BatchNormalization()(x)
mu = Dense(latent_dim, name='latent_mu')(x)
sigma = Dense(latent_dim, name='latent_sigma')(x)
```

Encoder summary:

```
[ ] # Instantiate encoder
encoder = Model(i, [mu, sigma, z], name='encoder')
encoder.summary()
```

Model: "encoder"

Layer (type)	Output Shape	Param #	Connected to
encoder_input (InputLayer)	[(None, 28, 28, 1)]	0	
conv2d_6 (Conv2D)	(None, 14, 14, 8)	80	encoder_input[0][0]
batch_normalization_16 (Batch Normalization)	(None, 14, 14, 8)	32	conv2d_6[0][0]
conv2d_7 (Conv2D)	(None, 7, 7, 16)	1168	batch_normalization_16[0][0]
batch_normalization_17 (Batch Normalization)	(None, 7, 7, 16)	64	conv2d_7[0][0]
conv2d_8 (Conv2D)	(None, 7, 7, 32)	4640	batch_normalization_17[0][0]
batch_normalization_18 (Batch Normalization)	(None, 7, 7, 32)	128	conv2d_8[0][0]
flatten_2 (Flatten)	(None, 1568)	0	batch_normalization_18[0][0]
dense_4 (Dense)	(None, 20)	31380	flatten_2[0][0]
batch_normalization_19 (Batch Normalization)	(None, 20)	80	dense_4[0][0]
latent_mu (Dense)	(None, 2)	42	batch_normalization_19[0][0]
latent_sigma (Dense)	(None, 2)	42	batch_normalization_19[0][0]
z (Lambda)	(None, 2)	0	latent_mu[0][0] latent_sigma[0][0]

=====
 Total params: 37,656
 Trainable params: 37,504
 Non-trainable params: 152
 =====

b. Decoder:

In this part, I have the same layers that I added to the encoder. After the model has trained I used the Conv2DTranspose in the decoder to upsample its input and to arise from the desire to use a transformation going in the opposite direction of a normal convolution.

```
# Decoder Definition
d_i = Input(shape=(latent_dim, ), name='decoder_input')
x = Dense(conv_shape[1] * conv_shape[2] * conv_shape[3], activation='relu')(d_i)
x = BatchNormalization()(x)
x = Reshape((conv_shape[1], conv_shape[2], conv_shape[3]))(x)
# I start the decoder with the one that I have added in the encoder.
cx = Conv2DTranspose(filters=32, kernel_size=3, strides=1, padding='same', activation='relu')(x)
cx = BatchNormalization()(cx)
cx = Conv2DTranspose(filters=16, kernel_size=3, strides=2, padding='same', activation='relu')(cx)
cx = BatchNormalization()(cx)
cx = Conv2DTranspose(filters=8, kernel_size=3, strides=2, padding='same', activation='relu')(cx)
cx = BatchNormalization()(cx)
o = Conv2DTranspose(filters=num_channels, kernel_size=3, activation='sigmoid', padding='same', name='decoder_output')(cx)
```

Decoder summary:

```
[ ] # Instantiate decoder
decoder = Model(d_i, o, name='decoder')
decoder.summary()
```

Model: "decoder"

Layer (type)	Output Shape	Param #
decoder_input (InputLayer)	[(None, 2)]	0
dense_5 (Dense)	(None, 1568)	4704
batch_normalization_20 (Batch Normalization)	(None, 1568)	6272
reshape_2 (Reshape)	(None, 7, 7, 32)	0
conv2d_transpose_6 (Conv2DTranspose)	(None, 7, 7, 32)	9248
batch_normalization_21 (Batch Normalization)	(None, 7, 7, 32)	128
conv2d_transpose_7 (Conv2DTranspose)	(None, 14, 14, 16)	4624
batch_normalization_22 (Batch Normalization)	(None, 14, 14, 16)	64
conv2d_transpose_8 (Conv2DTranspose)	(None, 28, 28, 8)	1160
batch_normalization_23 (Batch Normalization)	(None, 28, 28, 8)	32
decoder_output (Conv2DTranspose)	(None, 28, 28, 1)	73
Total params: 26,305		
Trainable params: 23,057		
Non-trainable params: 3,248		

In this screenshot (Instantiate VAE) we can see the shape of the input and output is the same.

```
# Instantiate VAE
vae_outputs = decoder(encoder(i)[2])
vae = Model(i, vae_outputs, name='vae')
vae.summary()
```

Model: "vae"

Layer (type)	Output Shape	Param #
encoder_input (InputLayer)	[(None, 28, 28, 1)]	0
encoder (Functional)	[(None, 2), (None, 2), (N 37656	
decoder (Functional)	(None, 28, 28, 1)	26305

Total params: 63,961
 Trainable params: 60,561
 Non-trainable params: 3,400

Then I trained the model using fit function and I got (loss: 0.1874 - val_loss: 0.1929) which means the model's performance is good.

```
tf.config.run_functions_eagerly(True)
# Compile VAE
vae.compile(optimizer='adam', loss='binary_crossentropy')

# Train autoencoder
vae.fit(input_train, input_train, epochs = no_epochs, batch_size = batch_size, validation_split = validation_split)
```

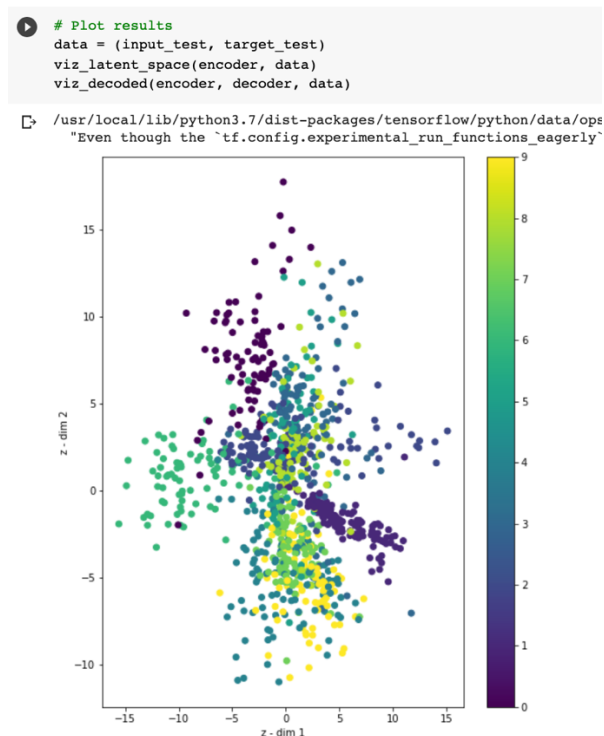
```

40/40 [=====] - 4s 100ms/step - loss: 0.1995 - val_loss: 0.2027
Epoch 23/50
40/40 [=====] - 4s 89ms/step - loss: 0.1980 - val_loss: 0.2036
Epoch 24/50
40/40 [=====] - 3s 88ms/step - loss: 0.1980 - val_loss: 0.2012
Epoch 25/50
40/40 [=====] - 4s 99ms/step - loss: 0.1975 - val_loss: 0.2045
Epoch 26/50
40/40 [=====] - 4s 100ms/step - loss: 0.2009 - val_loss: 0.2176
Epoch 27/50
40/40 [=====] - 4s 91ms/step - loss: 0.1972 - val_loss: 0.2049
Epoch 28/50
40/40 [=====] - 3s 87ms/step - loss: 0.1978 - val_loss: 0.2015
Epoch 29/50
40/40 [=====] - 4s 98ms/step - loss: 0.1951 - val_loss: 0.1994
Epoch 30/50
40/40 [=====] - 4s 100ms/step - loss: 0.1947 - val_loss: 0.1974
Epoch 31/50
40/40 [=====] - 4s 99ms/step - loss: 0.1933 - val_loss: 0.1983
Epoch 32/50
40/40 [=====] - 4s 99ms/step - loss: 0.1944 - val_loss: 0.1970
Epoch 33/50
40/40 [=====] - 4s 90ms/step - loss: 0.1930 - val_loss: 0.1980
Epoch 34/50
40/40 [=====] - 4s 99ms/step - loss: 0.1947 - val_loss: 0.1981
Epoch 35/50
40/40 [=====] - 4s 98ms/step - loss: 0.1931 - val_loss: 0.1967
Epoch 36/50
40/40 [=====] - 4s 99ms/step - loss: 0.1919 - val_loss: 0.1966
Epoch 37/50
40/40 [=====] - 3s 88ms/step - loss: 0.1916 - val_loss: 0.1961
Epoch 38/50
40/40 [=====] - 4s 88ms/step - loss: 0.1915 - val_loss: 0.1968
Epoch 39/50
40/40 [=====] - 4s 98ms/step - loss: 0.1896 - val_loss: 0.1939
Epoch 40/50
40/40 [=====] - 4s 96ms/step - loss: 0.1902 - val_loss: 0.1956

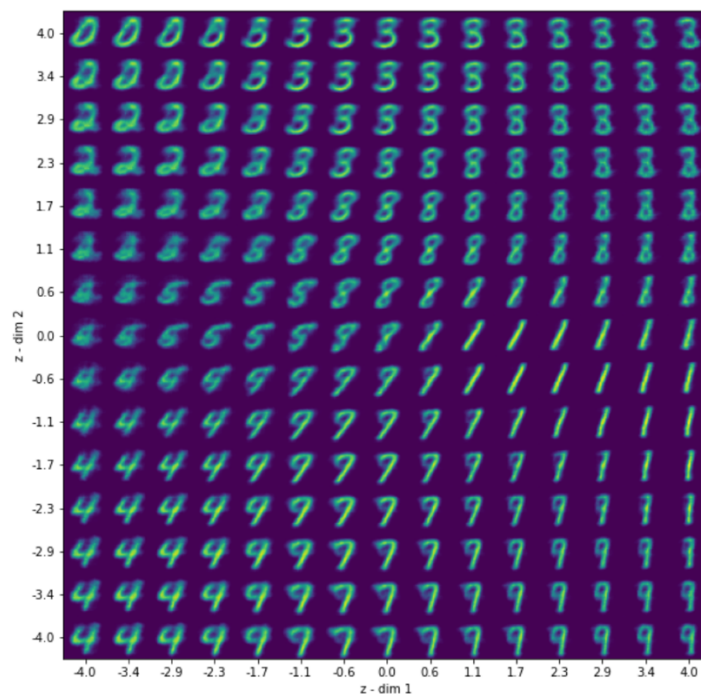
```

From the screenshot below I can notice the model is doing great job because 2 things:

1. The cluster is close to each other and that means the generated value is good.



2. The sampled that is displayed is show how the model is performing. Although there is some noising, but I can see all the numbers.



3. Conclusion:

I have Successfully executed the code and made autoencoder and built the convolutional and denoising autoencoders with the MNIST dataset in Keras. In this ICP I learned more how downsamples the input using the Encoder part, and upsamples its input in Decoder part.

4. Video link:

<https://drive.google.com/file/d/1VLytTwouTeNcIsrG1tClKWpCaPOuJy0/view?usp=sharing>