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NN&DeepLearning_Lesson: Autoencoders

Assignment-4

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Github Link: https://github.com/sxm26790/Assignment4_neural/tree/main

1. Add one more hidden layer to autoencoder

```
from keras.layers import Input, Dense
from keras.models import Model
import matplotlib.pyplot as plt


# this is the size of our encoded representations
encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

# this is our input placeholder
input_img = Input(shape=(784,))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img)
# Adding of one more layer to the encoder
encoded_1 = Dense(4, activation='relu')(encoded)
# Adding of one more layer to the decoder
decoded_1 = Dense(encoding_dim, activation='sigmoid')(encoded_1)
# "decoded" is the lossy reconstruction of the input
decoded = Dense(784, activation='sigmoid')(encoded)
# this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# this model maps an input to its encoded representation
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy' ,metrics=['accuracy'])
from keras.datasets import mnist, fashion_mnist
import numpy as np
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
#Visualize the data before reconstructed.
plt.imshow(x_test[15].reshape(28,28))
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

history=autoencoder.fit(x_train, x_train,
                epochs=5,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))
```

```
Epoch 1/5
235/235 [==============================] - 9s 32ms/step - loss: 0.6943 - accuracy: 0.0010 - val_loss: 0.6942 - val_accuracy:
Epoch 2/5
235/235 [==============================] - 4s 18ms/step - loss: 0.6941 - accuracy: 0.0011 - val_loss: 0.6940 - val_accuracy:
Epoch 3/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6939 - accuracy: 0.0011 - val_loss: 0.6939 - val_accuracy:
Epoch 4/5
235/235 [==============================] - 4s 18ms/step - loss: 0.6938 - accuracy: 0.0011 - val_loss: 0.6937 - val_accuracy:
Epoch 5/5
235/235 [==============================] - 3s 13ms/step - loss: 0.6936 - accuracy: 0.0012 - val_loss: 0.6936 - val_accuracy:
```

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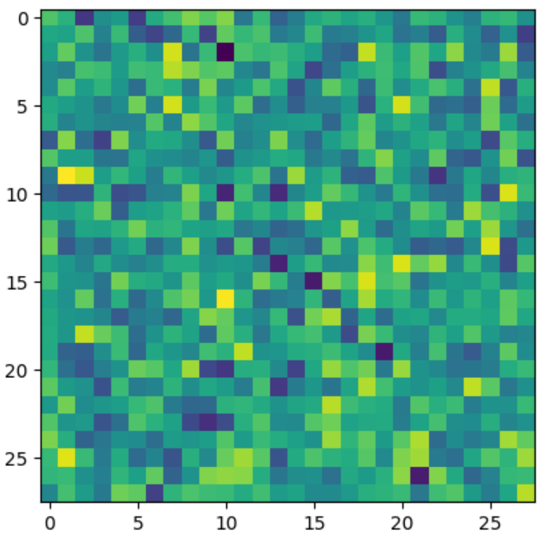
2. Do the prediction on the test data and then visualize one of the reconstructed version of that test data. Also, visualize the same test data before reconstruction using Matplotlib

```
#After reconstructed version of that test data.
X_test = autoencoder.predict(x_test)
plt.imshow(X_test[15].reshape(28,28))
```

```
313/313 [==============================] - 1s 2ms/step
<matplotlib.image.AxesImage at 0x7d328e26e8f0>
```

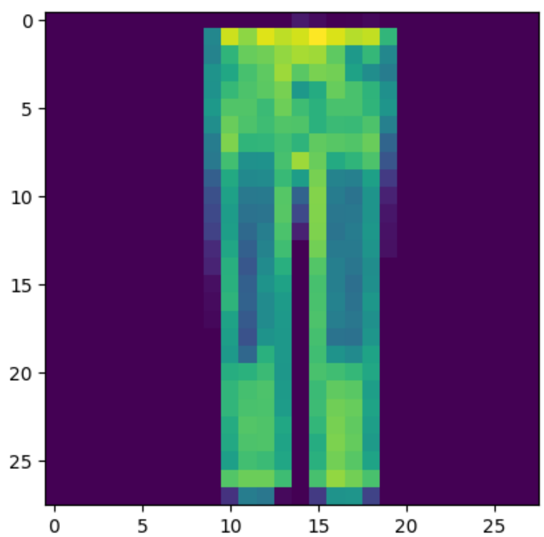


3. Repeat the question 2 on the denoisening autoencoder

```
from keras.layers import Input, Dense
from keras.models import Model

# this is the size of our encoded representations
encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

# this is our input placeholder
input_img = Input(shape=(784,))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img)
# "decoded" is the lossy reconstruction of the input
decoded = Dense(784, activation='sigmoid')(encoded)
# this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# this model maps an input to its encoded representation
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
from keras.datasets import fashion_mnist
import numpy as np
(x_train, _), (x_test, _) = fashion_mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
#Visualize the data before reconstruction
plt.imshow(x_test[15].reshape(28,28))
```

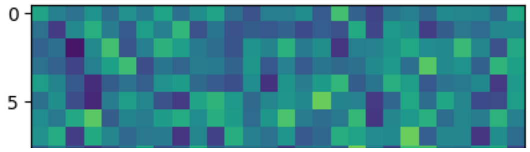
```
#introducing noise
noise_factor = 0.5
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_train.shape)
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)

autoencoder.fit(x_train_noisy, x_train,
                epochs=10,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test_noisy))
```

```
Epoch 1/10
235/235 [==============================] - 4s 13ms/step - loss: 0.6994 - val_loss: 0.6992
Epoch 2/10
235/235 [==============================] - 4s 16ms/step - loss: 0.6991 - val_loss: 0.6988
Epoch 3/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6987 - val_loss: 0.6985
Epoch 4/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6984 - val_loss: 0.6982
Epoch 5/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6981 - val_loss: 0.6979
Epoch 6/10
235/235 [==============================] - 4s 15ms/step - loss: 0.6978 - val_loss: 0.6976
Epoch 7/10
235/235 [==============================] - 3s 14ms/step - loss: 0.6975 - val_loss: 0.6973
Epoch 8/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6972 - val_loss: 0.6970
Epoch 9/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6969 - val_loss: 0.6967
Epoch 10/10
235/235 [==============================] - 4s 15ms/step - loss: 0.6966 - val_loss: 0.6964
<keras.callbacks.History at 0x7d328e19fee0>
```




```
#After reconstructed version of that test data.
X_test = autoencoder.predict(x_test)
plt.imshow(X_test[15].reshape(28,28))
```

```
313/313 [==============================] - 2s 5ms/step
<matplotlib.image.AxesImage at 0x7d328de17b20>
```



4. plot loss and accuracy using the history object

```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```