ASSIGNMENT-2

NEURAL NETWORKS & DEEP LEARNING

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Github link:

https://github.com/GayathriKeshamoni/Neural-Assignment4--Keshamoni-Gayathri--700742488

Video Link: https://youtu.be/GUfGtgJFQao

Programming elements:

1. Basics of Autoencoders
2. Role of Autoencoders in unsupervised learning
3. Types of Autoencoders
4. Use case: Simple autoencoder-Reconstructing the existing image, which will contain most important features of the image
5. Use case: Stacked autoencoder

In class programming:

1. Add one more hidden layer to autoencoder

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 3. Repeat the question 2 on the denoisening autoencoder 4. plot loss and accuracy using the history object

jupyter Neural Assignment 4 - 700742488 Last Checkpoint: 7 minutes ago (autosaved)

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)

In [13]:
```
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', 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.
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:])))

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

- Imported the required packages.
- Fixed the size of the encoded representations.
- Encoded the input representation
- Decoded i.e the lossy reconstruction of the input
- Autoencoded using the model().

- ‘fashion_mnist’ is a dataset , which is a part of the Keras library.The load_data() returns two tuples: (x_train, y_train) and (x_test, y_test).
- .astype(‘float32’) used to convert the data type of the elements in x_train to 32 bit floating point numbers.
- /255 is used to normalse the pixel values of the images.
- Using train and test data samples and target labels to evaluate the performance of the model.

```
                shuffle=True,
                validation_data=(x_test, x_test))

Epoch 1/5
235/235 [==============================] - 4s 12ms/step - loss: 0.6937 - accu
racy: 0.0036 - val_loss: 0.6936 - val_accuracy: 0.0045
Epoch 2/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6935 - accu
racy: 0.0037 - val_loss: 0.6935 - val_accuracy: 0.0046
Epoch 3/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6934 - accu
racy: 0.0037 - val_loss: 0.6933 - val_accuracy: 0.0045
Epoch 4/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6933 - accu
racy: 0.0037 - val_loss: 0.6932 - val_accuracy: 0.0044
Epoch 5/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6931 - accu
racy: 0.0037 - val_loss: 0.6931 - val_accuracy: 0.0044

Out[13]: <keras.callbacks.History at 0x2b9d0410e50>
```

In [14]:

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

# This is the size of our encoded representation
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
encoded1 = Dense(128, activation='relu')(input_img)
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)

# "decoded" is the lossy reconstruction of the input
decoded1 = Dense(128, activation='relu')(encoded2)
decoded2 = Dense(784, activation='sigmoid')(decoded1)

# This model maps an input to its reconstruction
autoencoder = Model(input_img, decoded2)

# This model maps an input to its encoded representation
encoder = Model(input_img, encoded2)

# This is our decoder model
encoded_input = Input(shape=(encoding_dim,))
decoder_layer1 = autoencoder.layers[-2]
decoder_layer2 = autoencoder.layers[-1]
decoder = Model(encoded_input, decoder_layer2(decoder_layer1(encoded_input)))

# Compile the model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy',metrics ='accuracy')

# Load the MNIST dataset
from keras.datasets import mnist, fashion_mnist
import numpy as np
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

# Normalize and flatten the data
x_train = x_train.astype('float32') / 255.
```

```python
decoder_layer1 = autoencoder.layers[-2]
decoder_layer2 = autoencoder.layers[-1]
decoder = Model(encoded_input, decoder_layer2(decoder_layer1(encoded_input)))

# Compile the model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy',metrics ='accuracy')

# Load the MNIST dataset
from keras.datasets import mnist, fashion_mnist
import numpy as np
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

# Normalize and flatten the 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:])))

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

```
Epoch 1/5
235/235 [==============================] - 7s 22ms/step - loss: 0.6939 - accuracy: 0.0027 - val_loss: 0.6938 - val_accuracy: 0.0025
Epoch 2/5
235/235 [==============================] - 4s 19ms/step - loss: 0.6938 - accuracy: 0.0028 - val_loss: 0.6937 - val_accuracy: 0.0025
Epoch 3/5
235/235 [==============================] - 4s 17ms/step - loss: 0.6937 - accuracy: 0.0027 - val_loss: 0.6936 - val_accuracy: 0.0026
Epoch 4/5
235/235 [==============================] - 4s 17ms/step - loss: 0.6936 - accuracy: 0.0027 - val_loss: 0.6935 - val_accuracy: 0.0026
Epoch 5/5
235/235 [==============================] - 4s 17ms/step - loss: 0.6935 - accuracy: 0.0027 - val_loss: 0.6934 - val_accuracy: 0.0028
```

Out[14]:

```
<keras.callbacks.History at 0x2b9d7038350>
```

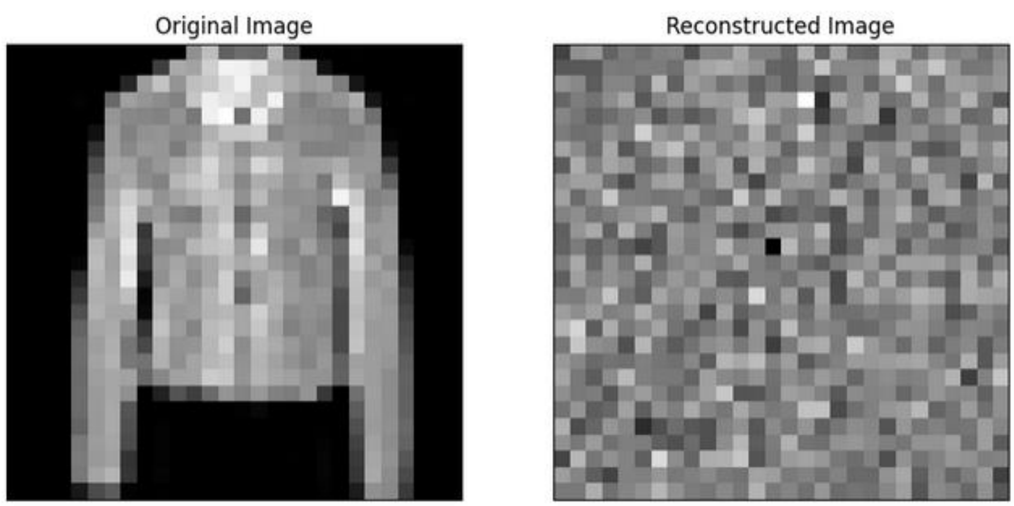
In [15]:

```
import matplotlib.pyplot as plt

# Get the reconstructed images for the test set
reconstructed_imgs = autoencoder.predict(x_test)

# Choose a random image from the test set
n = 10  # index of the image to be plotted
plt.figure(figsize=(10, 5))

# Plot the original image
ax = plt.subplot(1, 2, 1)
plt.imshow(x_test[n].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
ax.set_title("Original Image")

# Plot the reconstructed image
ax = plt.subplot(1, 2, 2)
plt.imshow(reconstructed_imgs[n].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
ax.set_title("Reconstructed Image")

plt.show()
```

```
313/313 [==============================] - 1s 2ms/step
```

```
plt.show()
```

```
313/313 [==============================] - 1s 2ms/step
```



```
In [16]: 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',metrics ='accuracy')
         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:])))

         #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))
```

- ‘fashion_mnist’ is a dataset , which is a part of the Keras library.The load_data() returns two tuples: (x_train, y_train) and (x_test, y_test).
- .astype(‘float32’) used to convert the data type of the elements in x_train to 32 bit floating point numbers.
- /255 is used to normalse the pixel values of the images.

```
Epoch 1/10
235/235 [==============================] - 4s 14ms/step - loss: 0.6964 - accuracy: 7.8333e-04 - val_loss: 0.6963 - val_accuracy: 8.
0000e-04
Epoch 2/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6962 - accuracy: 8.0000e-04 - val_loss: 0.6961 - val_accuracy: 8.
0000e-04
Epoch 3/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6959 - accuracy: 8.1667e-04 - val_loss: 0.6959 - val_accuracy: 8.
0000e-04
Epoch 4/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6957 - accuracy: 8.6667e-04 - val_loss: 0.6956 - val_accuracy: 7.
0000e-04
Epoch 5/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6955 - accuracy: 8.6667e-04 - val_loss: 0.6954 - val_accuracy: 7.
0000e-04
Epoch 6/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6952 - accuracy: 8.6667e-04 - val_loss: 0.6952 - val_accuracy: 8.
0000e-04
Epoch 7/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6950 - accuracy: 9.0000e-04 - val_loss: 0.6950 - val_accuracy: 9.
0000e-04
Epoch 8/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6948 - accuracy: 8.6667e-04 - val_loss: 0.6948 - val_accuracy: 0.
0011
Epoch 9/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6946 - accuracy: 8.6667e-04 - val_loss: 0.6946 - val_accuracy: 0.
0013
Epoch 10/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6944 - accuracy: 8.3333e-04 - val_loss: 0.6944 - val_accuracy: 0.
0013
```

5]: <keras.callbacks.History at 0x2b9da289810>

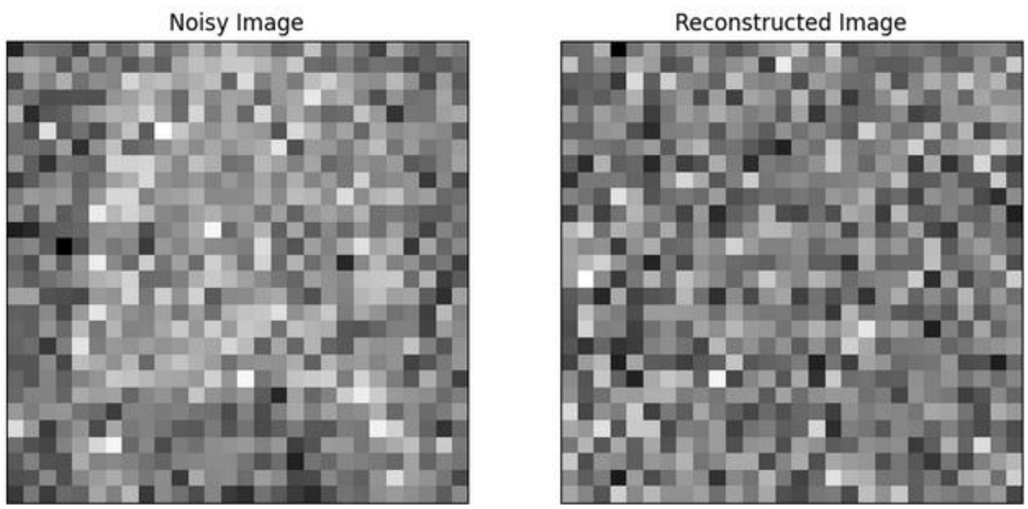
In [17]:

```
import matplotlib.pyplot as plt

# Get the reconstructed images for the test set
reconstructed_imgs = autoencoder.predict(x_test_noisy)

# Choose a random image from the test set
n = 10  # index of the image to be plotted
plt.figure(figsize=(10, 5))

# Plot the original noisy image
ax = plt.subplot(1, 2, 1)
plt.imshow(x_test_noisy[n].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
ax.set_title("Noisy Image")

# Plot the reconstructed image
ax = plt.subplot(1, 2, 2)
plt.imshow(reconstructed_imgs[n].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
ax.set_title("Reconstructed Image")

plt.show()
```

```
313/313 [==============================] - 1s 3ms/step
```

- With the use of autoencoder.predict(), tried to get reconstructed images for the test set.
- Plotting the original noisy image and reconstructed one.

```
313/313 [==============================] - 1s 3ms/step
```

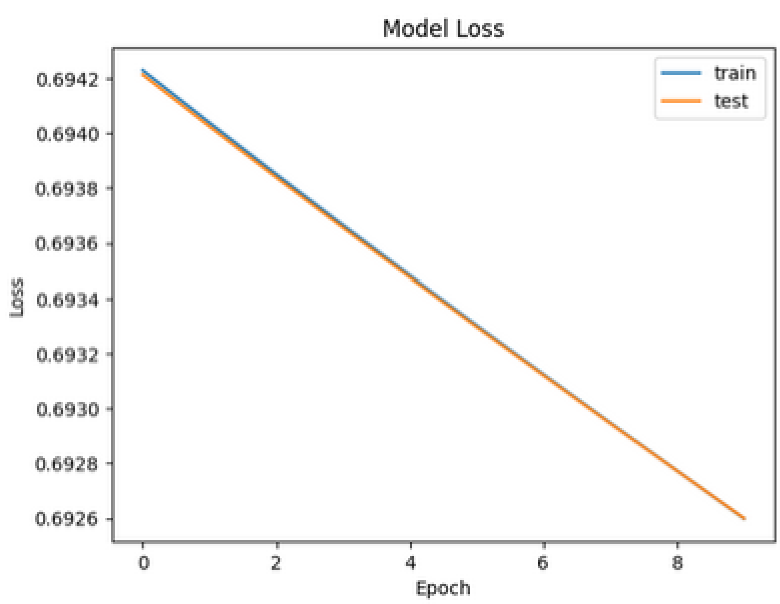


```
In [18]: import matplotlib.pyplot as plt

         # Train the autoencoder
         history = autoencoder.fit(x_train_noisy, x_train,
                         epochs=10,
                         batch_size=256,
                         shuffle=True,
                         validation_data=(x_test_noisy, x_test_noisy))

         # Plot the loss
         plt.plot(history.history['loss'], label='train')
         plt.plot(history.history['val_loss'], label='test')
         plt.title('Model Loss')
         plt.ylabel('Loss')
         plt.xlabel('Epoch')
         plt.legend()
         plt.show()

         # Plot the accuracy
         plt.plot(history.history['accuracy'], label='train')
         plt.plot(history.history['val_accuracy'], label='test')
         plt.title('Model Accuracy')
         plt.ylabel('Accuracy')
         plt.xlabel('Epoch')
         plt.legend()
         plt.show()
```

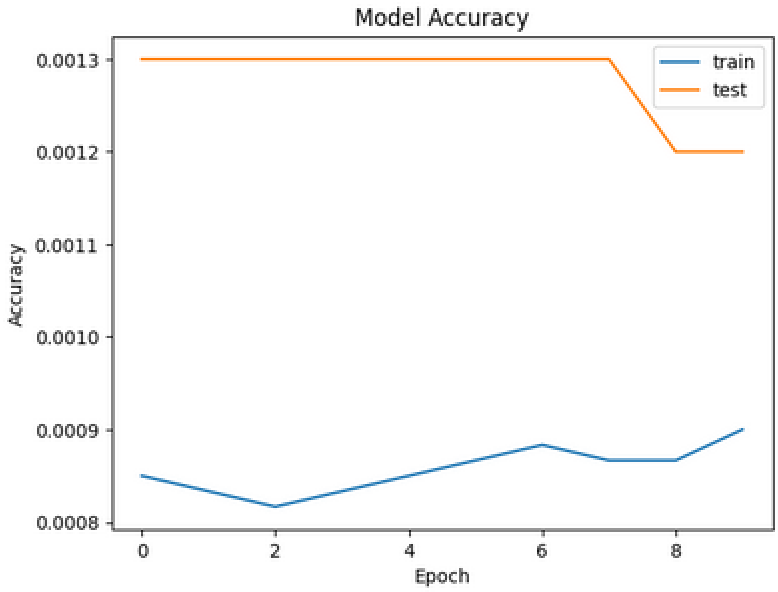
- **P**lotting the Loss by taking histories of loss and validation loss with the labels of train and test.
- Plotting the Accuracy by taking histories of accuracy and validation accuracy with the labels of train and test.

```
Epoch 1/10
235/235 [==============================] - 4s 16ms/step - loss: 0.6942 - accuracy: 8.5000e-04 - val_loss: 0.6942 - val_accuracy: 0.
0013
Epoch 2/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6940 - accuracy: 8.3333e-04 - val_loss: 0.6940 - val_accuracy: 0.
0013
Epoch 3/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6939 - accuracy: 8.1667e-04 - val_loss: 0.6938 - val_accuracy: 0.
0013
Epoch 4/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6937 - accuracy: 8.3333e-04 - val_loss: 0.6937 - val_accuracy: 0.
0013
Epoch 5/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6935 - accuracy: 8.5000e-04 - val_loss: 0.6935 - val_accuracy: 0.
0013
Epoch 6/10
235/235 [==============================] - 4s 16ms/step - loss: 0.6933 - accuracy: 8.6667e-04 - val_loss: 0.6933 - val_accuracy: 0.
0013
Epoch 7/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6931 - accuracy: 8.8333e-04 - val_loss: 0.6931 - val_accuracy: 0.
0013
Epoch 8/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6929 - accuracy: 8.6667e-04 - val_loss: 0.6929 - val_accuracy: 0.
0013
Epoch 9/10
235/235 [==============================] - 3s 14ms/step - loss: 0.6928 - accuracy: 8.6667e-04 - val_loss: 0.6928 - val_accuracy: 0.
0012
Epoch 10/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6926 - accuracy: 9.0000e-04 - val_loss: 0.6926 - val_accuracy: 0.
0012
```


```
235/235 [==============================] - 3s 13ms/step - loss: 0.6926 - accuracy: 9.0000
0012
```


Epoch


Model Accuracy
train
test
Accuracy
0.0013
0.0012
0.0011
0.0010
0.0009
0.0008
0
2
4
6
8
Epoch