<u>Spring 2024: CS5720 Neural Networks & Deep Learning - ICP-8</u> <u>Sai Deva Pranay Kumar Rao Guddity (700745063)</u>

Programming elements:

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

In class programming:

- Add one more hidden layer to autoencoder
- 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
- Repeat the question 2 on the denoisening autoencoder
- plot loss and accuracy using the history object

```
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
encoding_dim = 32 # 32 floats -> compression factor 24.5, assuming the input is 784 floats
input_img = Input(shape=(784,))
encoded = Dense(encoding_dim, activation='relu')(input_img)
decoded = Dense(784, activation='sigmoid')(encoded)
autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy', metrics=['accuracy'])
(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:])))
```

```
from keras.layers import Input, Dense
from keras.models import Model
encoding_dim = 32 # 32 floats -> compression of factor 24.5, assuming the input is 784 floats
input_img = Input(shape=(784,))
encoded1 = Dense(128, activation='relu')(input_img)
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)
decoded1 = Dense(128, activation='relu')(encoded2)
decoded2 = Dense(784, activation='sigmoid')(decoded1)
autoencoder = Model(input_img, decoded2)
```

```
encoder = Model(input img, encoded2)
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)))
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 \text{ test} = x \text{ test.reshape}((len(x \text{ test}), np.prod(x \text{ test.shape}[1:])))
autoencoder.fit(x train, x train,
epochs=5,
batch size=256,
shuffle=True,
validation data=(x test, x test))
```

```
import matplotlib.pyplot as plt
reconstructed imgs = autoencoder.predict(x test)
```

```
n = 10 # index of the image to be plotted

plt.figure(figsize=(10, 5))

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")

ax = plt.subplot(1, 2, 2)

plt.imshow(reconstructed_imgs[n].reshape(28, 28))

plt.gray()

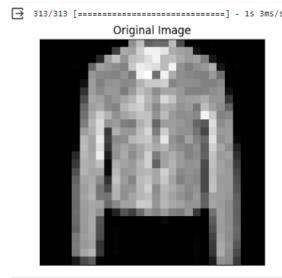
ax.get_xaxis().set_visible(False)

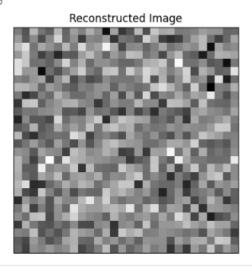
ax.get_yaxis().set_visible(False)

ax.get_yaxis().set_visible(False)

ax.set_title("Reconstructed Image")

plt.show()
```





Code:

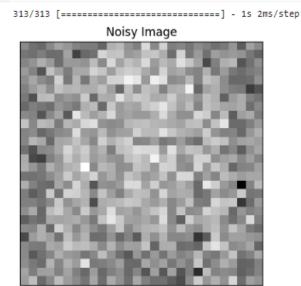
```
from keras.layers import Input, Dense
from keras.models import Model
encoding dim = 32 # 32 floats -> compression of factor 24.5, assuming the input is 784 floats
input img = Input(shape=(784,))
encoded = Dense(encoding dim, activation='relu')(input img)
decoded = Dense(784, activation='sigmoid')(encoded)
autoencoder = Model(input img, decoded)
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 \text{ test} = x \text{ test.astype('float32')} / 255.
x train = x train.reshape((len(x train), np.prod(x train.shape[1:])))
x \text{ test} = x \text{ test.reshape}((len(x \text{ test}), np.prod(x \text{ test.shape}[1:])))
noise factor = 0.5
x train noisy = x train + noise factor * np.random.normal(loc=0.0, scale=loc=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))
```

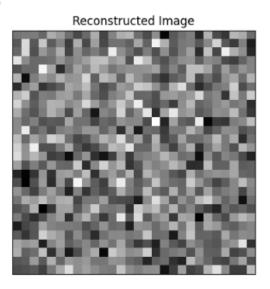
Output:

```
235/235 [===========] - 2s &ms/step - loss: 0.6957 - accuracy: 0.0017 - val_loss: 0.6955 - val_accuracy: 0.0013
 Epoch 3/10
       235/235 [==
 235/235 [=============] - 1s Gms/step - loss: 0.6952 - accuracy: 0.0016 - val_loss: 0.6951 - val_accuracy: 0.0013
 Enoch 5/10
 Epoch 7/10
 235/235 [===========] - 1s 6ms/step - loss: 0.6944 - accuracy: 0.0017 - val_loss: 0.6943 - val_accuracy: 0.0013
 Epoch 9/10
 235/235 [===========] - 1s 6ms/step - loss: 0.6940 - accuracy: 0.0017 - val_loss: 0.6939 - val_accuracy: 0.0012
 <keras.src.callbacks.History at 0x7bb30f5a8250>
```

```
import matplotlib.pyplot as plt
```

```
reconstructed imgs = autoencoder.predict(x test noisy)
n = 10 # index of the image to be plotted
plt.figure(figsize=(10, 5))
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")
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()
```





```
import matplotlib.pyplot as plt
history = autoencoder.fit(x_train_noisy, x_train,
          epochs=10,
          batch_size=256,
          shuffle=True,
          validation_data=(x_test_noisy, x_test_noisy))
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()
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()
```

```
Epoch 1/10
235/235 [==
           Epoch 2/10
Epoch 3/10
235/235 [===
           :=========] - 1s Gms/step - loss: 0.6934 - accuracy: 0.0017 - val_loss: 0.6933 - val_accuracy: 0.0011
Epoch 4/10
235/235 [===
        Epoch 5/10
235/235 [=========] - 1s 6ms/step - loss: 0.6930 - accuracy: 0.0017 - val_loss: 0.6929 - val_accuracy: 0.0011
Epoch 6/10
           :=========] - 1s 6ms/step - loss: 0.6929 - accuracy: 0.0017 - val_loss: 0.6927 - val_accuracy: 0.0012
235/235 [===
Epoch 7/10
Epoch 8/10
235/235 [============== ] - 1s Gms/step - loss: 0.6925 - accuracy: 0.0017 - val_loss: 0.6924 - val_accuracy: 0.0013
Epoch 9/10
             =========] - 3s 15ms/step - loss: 0.6923 - accuracy: 0.0017 - val_loss: 0.6922 - val_accuracy: 0.0013
235/235 [==
Epoch 10/10
```

