CS5720

Neural Networks & Deep Learning- ICP-4

Name: Madhavi Mamidala

#700: 700744319

Username: MXM43190

GitHub Link: https://github.com/MadhaviMamidala/CS5720_ASSIGNMENT4_700744319/tree/main

+ Code + Text

[1]
```
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')
```

[2]
```
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))
```

```
Epoch 1/5
235/235 [==============================] - 6s 13ms/step - loss: 0.6943 - accuracy: 7.3333e-04 - val_loss: 0.6942 - val_accuracy: 0.0012
Epoch 2/5
235/235 [==============================] - 2s 8ms/step - loss: 0.6942 - accuracy: 7.5000e-04 - val_loss: 0.6941 - val_accuracy: 0.0012
Epoch 3/5
```

```
Epoch 3/5
235/235 [==============================] - 2s 8ms/step - loss: 0.6940 - accuracy: 7.1667e-04 - val_loss: 0.6940 - val_accuracy: 0.0012
Epoch 4/5
235/235 [==============================] - 2s 9ms/step - loss: 0.6939 - accuracy: 7.3333e-04 - val_loss: 0.6938 - val_accuracy: 0.0011
Epoch 5/5
235/235 [==============================] - 2s 8ms/step - loss: 0.6938 - accuracy: 7.6667e-04 - val_loss: 0.6937 - val_accuracy: 0.0011
<keras.callbacks.History at 0x78edfbb92b90>
```

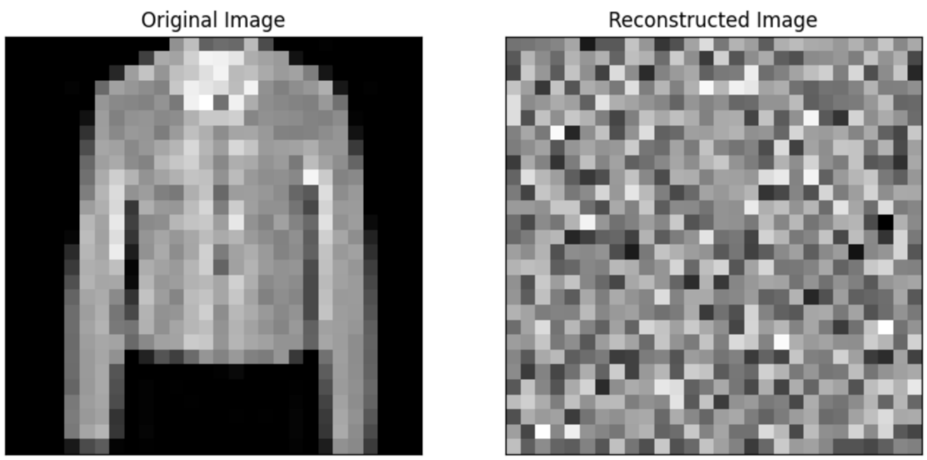
```python
from keras.layers import Input, Dense
from keras.models import Model

# 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')
```

7

```python
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
```

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



[6]

```python
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')
```

[7]

```python
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))
```

```
Epoch 1/10
235/235 [==============================] - 2s 6ms/step - loss: 0.6966 - accuracy: 7.1667e-04 - val_loss: 0.6964 - val_accuracy: 8.0000e-04
Epoch 2/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6963 - accuracy: 7.0000e-04 - val_loss: 0.6962 - val_accuracy: 7.0000e-04
Epoch 3/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6961 - accuracy: 7.0000e-04 - val_loss: 0.6959 - val_accuracy: 7.0000e-04
Epoch 4/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6959 - accuracy: 7.0000e-04 - val_loss: 0.6957 - val_accuracy: 7.0000e-04
```

+ Code + Text

```
235/235 [==============================] - 1s 6ms/step - loss: 0.6953 - accuracy: 7.0000e-04 - val_loss: 0.6951 - val_accuracy: 7.0000e-04
Epoch 8/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6951 - accuracy: 7.0000e-04 - val_loss: 0.6949 - val_accuracy: 7.0000e-04
Epoch 9/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6949 - accuracy: 7.3333e-04 - val_loss: 0.6948 - val_accuracy: 7.0000e-04
Epoch 10/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6947 - accuracy: 7.5000e-04 - val_loss: 0.6946 - val_accuracy: 7.0000e-04
<keras.callbacks.History at 0x78edf13352a0>
```

+ Code + Text

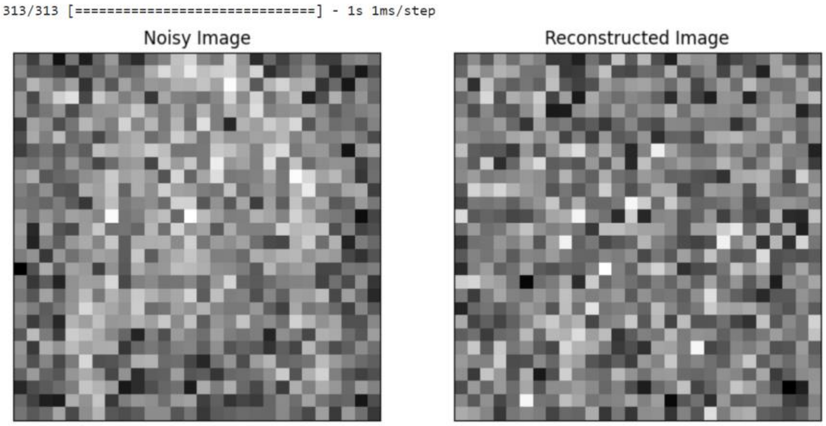
[8]

```
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 1ms/step
```



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

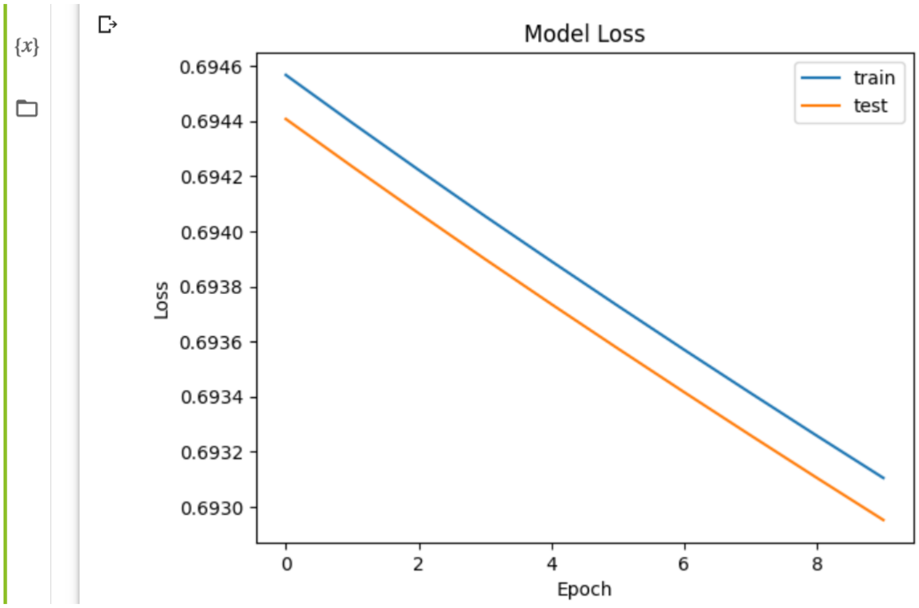



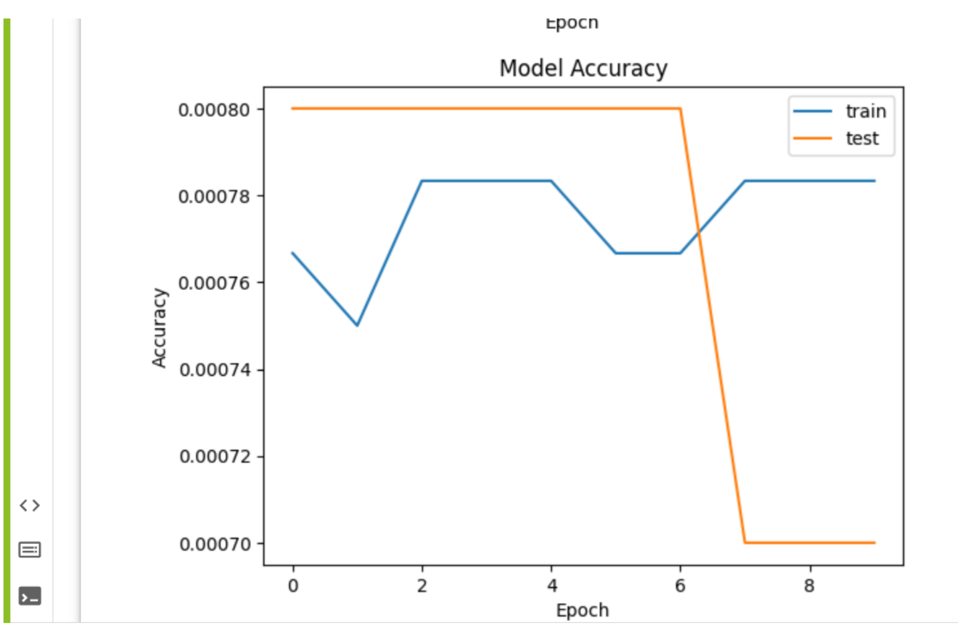
[9]

```python
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))
```

```
Epoch 1/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6946 - accuracy: 7.6667e-04 - val_loss: 0.6944 - val_accuracy: 8.0000e-04
Epoch 2/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6944 - accuracy: 7.5000e-04 - val_loss: 0.6942 - val_accuracy: 8.0000e-04
Epoch 3/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6942 - accuracy: 7.8333e-04 - val_loss: 0.6941 - val_accuracy: 8.0000e-04
Epoch 4/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6941 - accuracy: 7.8333e-04 - val_loss: 0.6939 - val_accuracy: 8.0000e-04
Epoch 5/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6939 - accuracy: 7.8333e-04 - val_loss: 0.6937 - val_accuracy: 8.0000e-04
Epoch 6/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6937 - accuracy: 7.6667e-04 - val_loss: 0.6936 - val_accuracy: 8.0000e-04
Epoch 7/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6936 - accuracy: 7.6667e-04 - val_loss: 0.6934 - val_accuracy: 8.0000e-04
Epoch 8/10
235/235 [==============================] - 1s 6ms/step - loss: 0.6934 - accuracy: 7.8333e-04 - val_loss: 0.6933 - val_accuracy: 7.0000e-04
Epoch 9/10
235/235 [==============================] - 1s 6ms/step - loss: 0.6933 - accuracy: 7.8333e-04 - val_loss: 0.6931 - val_accuracy: 7.0000e-04
Epoch 10/10
235/235 [==============================] - 1s 5ms/step - loss: 0.6931 - accuracy: 7.8333e-04 - val_loss: 0.6930 - val_accuracy: 7.0000e-04
```

```python
# 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()
```


Model Loss
train
test
0.6946
0.6944
0.6942
0.6940
0.6938
0.6936
0.6934
0.6932
0.6930
Loss
0
2
4
6
8
Epoch


Epoch
Model Accuracy
train
test
0.00080
0.00078
0.00076
0.00074
0.00072
0.00070
Accuracy
0
2
4
6
8
Epoch