NEURAL NETWORK DEEP LEARNING ICP 6

Autoencoders

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```
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 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))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
29515/29515 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
```

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```
Epoch 2/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6948 - val_loss: 0.6946
Epoch 3/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6946 - val_loss: 0.6944
Epoch 4/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6943 - val_loss: 0.6941
Epoch 5/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6941 - val_loss: 0.6939
<keras.src.callbacks.history.History at 0x7b4b3bb33d50>
```

+ Code + Text

```
[3] 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
    encoding_dim2 = 64

    # 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)
    encoded2 = Dense(encoding_dim2, activation='relu')(encoded)

    # "decoded" is the lossy reconstruction of the input
    decoded = Dense(784, activation='sigmoid')(encoded)
    decoded2 = Dense(784, activation='sigmoid')(decoded)

    # 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 mnist, fashion_mnist
    import numpy as np
```

```python
# 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 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))

# Prediction on the test data
decoded_imgs = autoencoder.predict(x_test)
# Choosing an index to a test image for visualizing
idx = 10

# Reshaping the test image
test_image = x_test[idx].reshape(28, 28)

# Reshape the reconstructed image
reconstructed_image = decoded_imgs[idx].reshape(28, 28)

# Plotting the original and reconstructed images side by side
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.imshow(test_image, cmap='Blues_r')
plt.title('Original Image')
plt.subplot(1, 2, 2)
```

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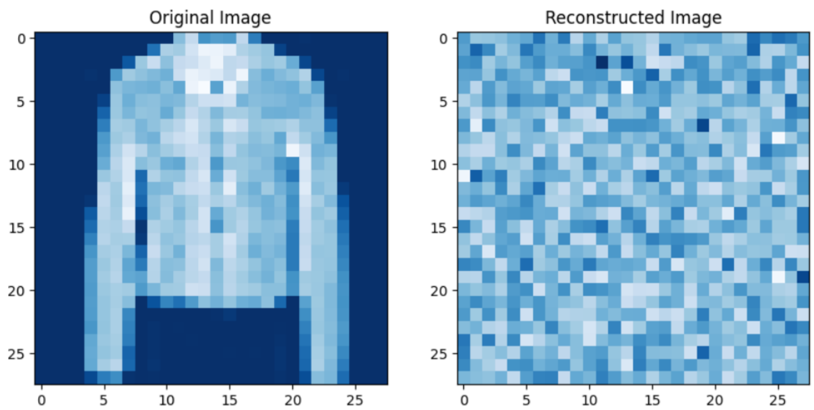
```python
plt.show()
```

```
Epoch 1/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - loss: 0.6951 - val_loss: 0.6949
Epoch 2/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6948 - val_loss: 0.6946
Epoch 3/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6945 - val_loss: 0.6943
Epoch 4/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6943 - val_loss: 0.6940
Epoch 5/5
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.6940 - val_loss: 0.6938
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



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

# this is the size of our encoded representations
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# "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)

history = autoencoder.fit(x_train_noisy, x_train,
                epochs=10,
                batch_size=256
```

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```
Epoch 1/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.0013 - loss: 0.6999 - val_accuracy: 0.0016 - val_loss: 0.6997
Epoch 2/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.0014 - loss: 0.6995 - val_accuracy: 0.0016 - val_loss: 0.6994
Epoch 3/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.0013 - loss: 0.6992 - val_accuracy: 0.0016 - val_loss: 0.6990
Epoch 4/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 9.9282e-04 - loss: 0.6988 - val_accuracy: 0.0016 - val_loss: 0.6987
Epoch 5/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.0016 - loss: 0.6985 - val_accuracy: 0.0015 - val_loss: 0.6984
Epoch 6/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.0017 - loss: 0.6982 - val_accuracy: 0.0016 - val_loss: 0.6981
Epoch 7/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.0013 - loss: 0.6979 - val_accuracy: 0.0015 - val_loss: 0.6978
Epoch 8/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.0013 - loss: 0.6976 - val_accuracy: 0.0015 - val_loss: 0.6975
Epoch 9/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.0013 - loss: 0.6973 - val_accuracy: 0.0015 - val_loss: 0.6972
Epoch 10/10
235/235 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.0012 - loss: 0.6970 - val_accuracy: 0.0015 - val_loss: 0.6970
```

[5]

```python
import matplotlib.pyplot as plt

# Get the reconstructed images
reconstructed_images = autoencoder.predict(x_test_noisy)

# Select one image to display
img_to_display = 0

# Display the original, noisy, and reconstructed images side by side
plt.subplot(1, 3, 1)
plt.imshow(x_test[img_to_display].reshape(28, 28))
plt.title('Original Image')

plt.subplot(1, 3, 2)
```

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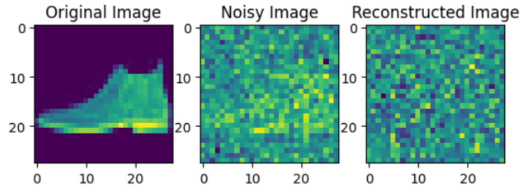
```
plt.title('Noisy Image')

plt.subplot(1, 3, 3)
plt.imshow(reconstructed_images[img_to_display].reshape(28, 28))
plt.title('Reconstructed Image')

plt.show()
```

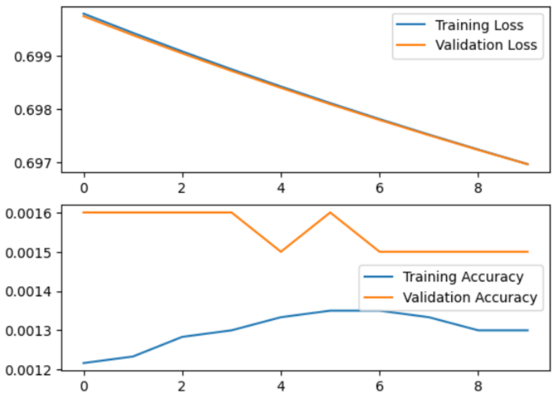
```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```




```
# Plot the loss and accuracy over epochs
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()

plt.subplot(2, 1, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.legend()

plt.show()
```



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