Neural Networks & Deep Learning - ICP-5

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GITHUB LINK:

https://github.com/Venkatesh-Spandan/ICP_5

Lesson Overview:
In this lesson, we are going to discuss types and applications of Autoencoder.

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

```
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.
```

```
               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
26421880/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
5148/5148 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4422102/4422102 [==============================] - 0s 0us/step
Epoch 1/5
235/235 [==============================] - 13s 41ms/step - loss: 0.6944 - val_loss: 0.6944
Epoch 2/5
235/235 [==============================] - 6s 24ms/step - loss: 0.6943 - val_loss: 0.6942
Epoch 3/5
235/235 [==============================] - 5s 21ms/step - loss: 0.6942 - val_loss: 0.6941
Epoch 4/5
235/235 [==============================] - 5s 22ms/step - loss: 0.6941 - val_loss: 0.6940
Epoch 5/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6939 - val_loss: 0.6939
```

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1.Adding hidden layer to Autoencoder :

Program :

1.Adding hidden layer to Autoencoder

```
[ ]  Start coding or generate with AI.
```

```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np

# this is the size of our encoded representations
encoding_dim = 32
# 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 an additional hidden layer
hidden_layer_dim = 64
hidden_layer = Dense(hidden_layer_dim, activation='relu')(encoded)
```

```python
# Adding an additional hidden layer
hidden_layer_dim = 64
hidden_layer = Dense(hidden_layer_dim, activation='relu')(encoded)

# "decoded" is the lossy reconstruction of the input, now connected to the hidden layer instead of 'encoded'
decoded = Dense(784, activation='sigmoid')(hidden_layer)

# 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')
# Load and prepare the data
(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:])))
```

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

Output:

```
Epoch 1/5
235/235 [==============================] - 5s 18ms/step - loss: 0.6937 - val_loss: 0.6937
Epoch 2/5
235/235 [==============================] - 6s 27ms/step - loss: 0.6937 - val_loss: 0.6936
Epoch 3/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6936 - val_loss: 0.6936
Epoch 4/5
235/235 [==============================] - 3s 13ms/step - loss: 0.6935 - val_loss: 0.6935
Epoch 5/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6935 - val_loss: 0.6934
<keras.src.callbacks.History at 0x7eb477464520>
```

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

Program :

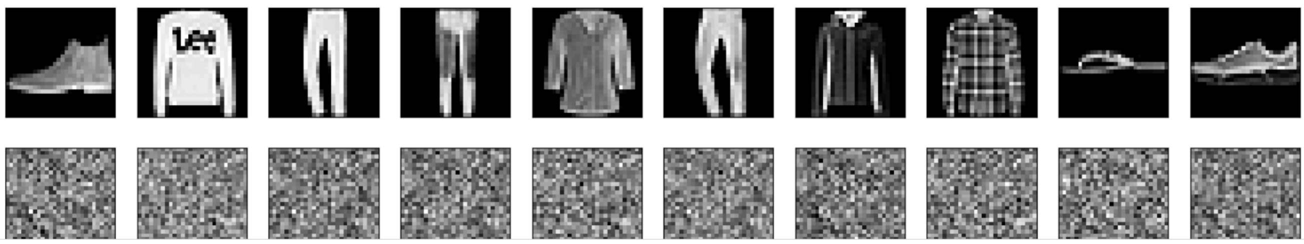
```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

# Define the model architecture
encoding_dim = 32
hidden_layer_dim = 64

input_img = Input(shape=(784,))
encoded = Dense(encoding_dim, activation='relu')(input_img)
hidden_layer = Dense(hidden_layer_dim, activation='relu')(encoded)  # Additional hidden layer
decoded = Dense(784, activation='sigmoid')(hidden_layer)

autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
```

```
# Load and prepare data
(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:])))

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

# Predict on the test data
decoded_imgs = autoencoder.predict(x_test)

# Visualize the original and reconstructed data
n = 10  # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
```

```
for i in range(n):
    # display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # display reconstruction
    ax = plt.subplot(2, n, i + n + 1)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```

Output :

```
Epoch 1/5
235/235 [==============================] - 5s 20ms/step - loss: 0.6937 - val_loss: 0.6937
Epoch 2/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6936 - val_loss: 0.6936
Epoch 3/5
235/235 [==============================] - 3s 13ms/step - loss: 0.6935 - val_loss: 0.6935
Epoch 4/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6934 - val_loss: 0.6934
Epoch 5/5
235/235 [==============================] - 4s 15ms/step - loss: 0.6933 - val_loss: 0.6933
313/313 [==============================] - 1s 2ms/step
```



3.Denoising Autoencoder - prediction on the test data and then visualize one of the reconstructed versions of that test data. Also, visualize the same test data before reconstruction using Matplotlib.

Program :

```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

# Define the model architecture
encoding_dim = 32

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')
# Load data
(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:])))
```

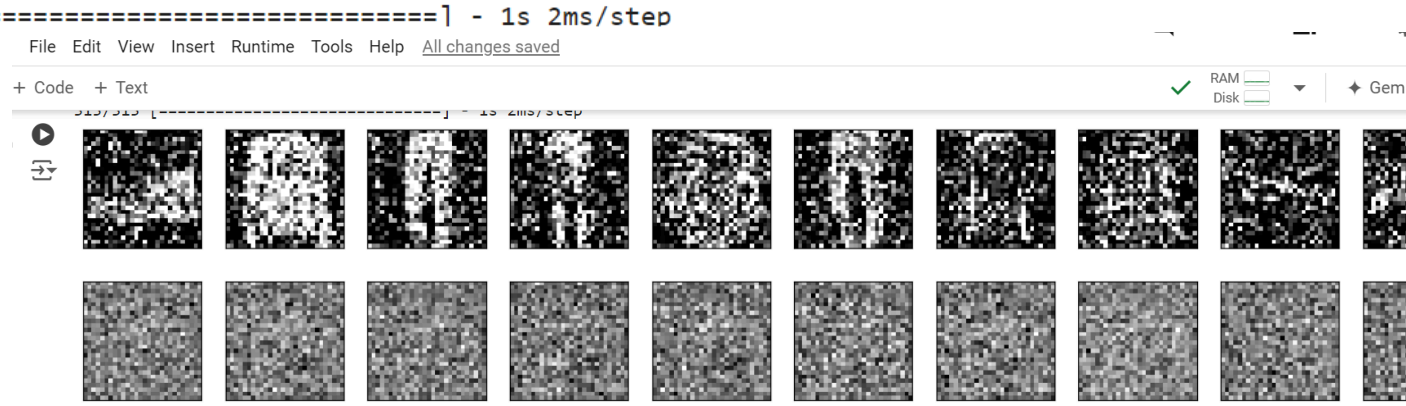
```python
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
# Introducing noise
noise_factor = 0.5
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_train.shape)
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)
x_train_noisy = np.clip(x_train_noisy, 0., 1.)
x_test_noisy = np.clip(x_test_noisy, 0., 1.)

# Train the model
autoencoder.fit(x_train_noisy, x_train,
                epochs=20,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test))

# Predict on the noisy test data
decoded_imgs = autoencoder.predict(x_test_noisy)

# Visualize the noisy input and the reconstructed data
n = 10  # How many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
```

```python
# Visualize the noisy input and the reconstructed data
n = 10  # How many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display noisy input
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test_noisy[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
```

Output :

```
Epoch 1/20
235/235 [==============================] - 4s 13ms/step - loss: 0.6949 - val_loss: 0.6948
Epoch 2/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6947 - val_loss: 0.6946
Epoch 3/20
235/235 [==============================] - 2s 11ms/step - loss: 0.6945 - val_loss: 0.6944
Epoch 4/20
235/235 [==============================] - 3s 14ms/step - loss: 0.6943 - val_loss: 0.6942
Epoch 5/20
235/235 [==============================] - 3s 12ms/step - loss: 0.6941 - val_loss: 0.6940
Epoch 6/20
235/235 [==============================] - 3s 12ms/step - loss: 0.6939 - val_loss: 0.6939
Epoch 7/20
235/235 [==============================] - 2s 10ms/step - loss: 0.6938 - val_loss: 0.6937
Epoch 8/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6936 - val_loss: 0.6935
Epoch 9/20
235/235 [==============================] - 4s 18ms/step - loss: 0.6934 - val_loss: 0.6933
Epoch 10/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6933 - val_loss: 0.6932
Epoch 11/20
235/235 [==============================] - 3s 12ms/step - loss: 0.6931 - val_loss: 0.6930
Epoch 12/20
```

```
Epoch 12/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6929 - val_loss: 0.6929
Epoch 13/20
235/235 [==============================] - 3s 15ms/step - loss: 0.6928 - val_loss: 0.6927
Epoch 14/20
235/235 [==============================] - 3s 12ms/step - loss: 0.6926 - val_loss: 0.6925
Epoch 15/20
235/235 [==============================] - 2s 10ms/step - loss: 0.6925 - val_loss: 0.6924
Epoch 16/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6923 - val_loss: 0.6922
Epoch 17/20
235/235 [==============================] - 3s 11ms/step - loss: 0.6922 - val_loss: 0.6921
Epoch 18/20
235/235 [==============================] - 3s 14ms/step - loss: 0.6920 - val_loss: 0.6919
Epoch 19/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6919 - val_loss: 0.6918
Epoch 20/20
235/235 [==============================] - 2s 10ms/step - loss: 0.6917 - val_loss: 0.6916
313/313 [==============================] - 1s 2ms/step
```



4.Plot loss and accuracy using the history object

Program :

```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
from keras.utils import to_categorical
import numpy as np
import matplotlib.pyplot as plt
from keras.optimizers import Adam

# Load and prepare the Fashion MNIST data
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
x_train = x_train.reshape(-1, 784).astype('float32') / 255
x_test = x_test.reshape(-1, 784).astype('float32') / 255

# Convert labels to one-hot encoding
num_classes = 10
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)
# Model architecture
input_img = Input(shape=(784,))
encoded = Dense(128, activation='relu')(input_img)
decoded = Dense(10, activation='softmax')(encoded)  # Classification layer
```

```python
# Convert labels to one-hot encoding
num_classes = 10
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)
# Model architecture
input_img = Input(shape=(784,))
encoded = Dense(128, activation='relu')(input_img)
decoded = Dense(10, activation='softmax')(encoded)  # Classification layer

model = Model(input_img, decoded)
model.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=256,
                    shuffle=True,
                    validation_data=(x_test, y_test))
# Plotting the training and validation loss
plt.figure(figsize=(10, 5))

# Plotting training and validation accuracy
```

```python
# Train the model
history = model.fit(x_train, y_train,
                    epochs=10,
                    batch_size=256,
                    shuffle=True,
                    validation_data=(x_test, y_test))
# Plotting the training and validation loss
plt.figure(figsize=(10, 5))

# Plotting training and validation accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Plotting training and validation loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
```

```python
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Plotting training and validation loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```

Output :

```
Epoch 1/10
235/235 [==============================] - 5s 17ms/step - loss: 0.6046 - accuracy: 0.7962 - val_loss: 0.4747 - val_accuracy: 0.8354
Epoch 2/10
235/235 [==============================] - 2s 7ms/step - loss: 0.4266 - accuracy: 0.8513 - val_loss: 0.4316 - val_accuracy: 0.8485
Epoch 3/10
235/235 [==============================] - 2s 7ms/step - loss: 0.3868 - accuracy: 0.8639 - val_loss: 0.4146 - val_accuracy: 0.8529
Epoch 4/10
235/235 [==============================] - 2s 7ms/step - loss: 0.3614 - accuracy: 0.8733 - val_loss: 0.4012 - val_accuracy: 0.8586
Epoch 5/10
235/235 [==============================] - 1s 6ms/step - loss: 0.3419 - accuracy: 0.8802 - val_loss: 0.3815 - val_accuracy: 0.8639
Epoch 6/10
235/235 [==============================] - 1s 6ms/step - loss: 0.3269 - accuracy: 0.8837 - val_loss: 0.3720 - val_accuracy: 0.8679
Epoch 7/10
235/235 [==============================] - 2s 7ms/step - loss: 0.3127 - accuracy: 0.8880 - val_loss: 0.3613 - val_accuracy: 0.8717
Epoch 8/10
235/235 [==============================] - 3s 12ms/step - loss: 0.3023 - accuracy: 0.8923 - val_loss: 0.3586 - val_accuracy: 0.8729
Epoch 9/10
235/235 [==============================] - 2s 7ms/step - loss: 0.2921 - accuracy: 0.8950 - val_loss: 0.3588 - val_accuracy: 0.8712
Epoch 10/10
235/235 [==============================] - 1s 6ms/step - loss: 0.2839 - accuracy: 0.8968 - val_loss: 0.3522 - val_accuracy: 0.8727
```