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NEURAL NETWORK AND DEEP LEARNING ASSIGNMENT-9

GITHUB LINK: https://github.com/SucharithaAeluri/NNAssign9.git

Use Case Description:

1. Sentiment Analysis on the Twitter dataset

Programming elements:

1. Basics of LSTM

2. Types of RNN

3. Use case: Sentiment Analysis on the Twitter data set

In class programming:

1. Save the model and use the saved model to predict on new text data (ex, “A lot of good things are happening. We are respected again throughout the world, and that's a great thing.@realDonaldTrump”)

2. Apply GridSearchCV on the source code provided in the class

```
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))
```

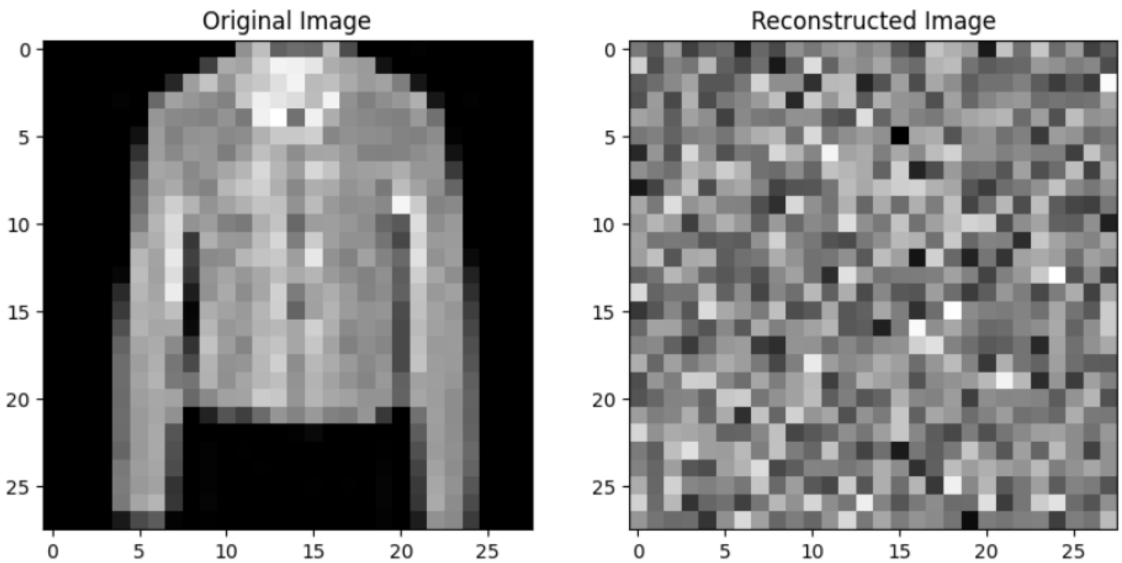
```
Epoch 1/5
235/235 [==============================] - 4s 12ms/step - loss: 0.6967 - val_loss: 0.6965
Epoch 2/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6964 - val_loss: 0.6962
Epoch 3/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6961 - val_loss: 0.6959
Epoch 4/5
235/235 [==============================] - 3s 11ms/step - loss: 0.6958 - val_loss: 0.6956
Epoch 5/5
235/235 [==============================] - 4s 15ms/step - loss: 0.6955 - val_loss: 0.6953
<keras.src.callbacks.History at 0x7b95b6a79390>
```

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

# Define input shape
input_shape = (784,)

# Define encoding dimensions
encoding_dim1 = 64
encoding_dim2 = 32

# Define input layer
input_img = Input(shape=input_shape)

encoded1 = Dense(encoding_dim1, activation='relu')(input_img)
encoded2 = Dense(encoding_dim2, activation='relu')(encoded1)
decoded1 = Dense(encoding_dim1, activation='relu')(encoded2)
decoded2 = Dense(input_shape[0], activation='sigmoid')(decoded1)
autoencoder = Model(input_img, decoded2)
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:])))
```

```python
# Train model
history = autoencoder.fit(x_train, x_train,
                          epochs=20,
                          batch_size=256,
                          shuffle=True,
                          validation_data=(x_test, x_test))

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

# Visualize reconstructed image and original image
import matplotlib.pyplot as plt

# Choose an index of a test image to visualize
idx = 10

# Reshape the test image
test_img = x_test[idx].reshape(28, 28)

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

# Plot the original and reconstructed images side by side
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.imshow(test_img, cmap='gray')
plt.title('Original Image')
plt.subplot(1, 2, 2)
plt.imshow(reconstructed_img, cmap='gray')
plt.title('Reconstructed Image')
plt.show()
```

```
Epoch 1/20
235/235 [==============================] - 7s 22ms/step - loss: 0.6944 - val_loss: 0.6943
Epoch 2/20
235/235 [==============================] - 4s 17ms/step - loss: 0.6942 - val_loss: 0.6941
Epoch 3/20
235/235 [==============================] - 3s 14ms/step - loss: 0.6940 - val_loss: 0.6939
Epoch 4/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6939 - val_loss: 0.6938
Epoch 5/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6937 - val_loss: 0.6936
Epoch 6/20
235/235 [==============================] - 4s 17ms/step - loss: 0.6936 - val_loss: 0.6935
Epoch 7/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6934 - val_loss: 0.6934
Epoch 8/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6933 - val_loss: 0.6932
Epoch 9/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6932 - val_loss: 0.6931
Epoch 10/20
235/235 [==============================] - 4s 18ms/step - loss: 0.6931 - val_loss: 0.6930
Epoch 11/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6930 - val_loss: 0.6929
Epoch 12/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6928 - val_loss: 0.6928
Epoch 13/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6927 - val_loss: 0.6927
Epoch 14/20
235/235 [==============================] - 4s 18ms/step - loss: 0.6926 - val_loss: 0.6926
Epoch 15/20
235/235 [==============================] - 3s 14ms/step - loss: 0.6925 - val_loss: 0.6925
```

```
'
Epoch 16/20
235/235 [==============================] - 3s 14ms/step - loss: 0.6924 - val_loss: 0.6924
Epoch 17/20
235/235 [==============================] - 4s 18ms/step - loss: 0.6923 - val_loss: 0.6923
Epoch 18/20
235/235 [==============================] - 4s 16ms/step - loss: 0.6922 - val_loss: 0.6922
Epoch 19/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6922 - val_loss: 0.6921
Epoch 20/20
235/235 [==============================] - 3s 13ms/step - loss: 0.6921 - val_loss: 0.6920
313/313 [==============================] - 1s 2ms/step
```



```python
from keras.layers import Input, Dense
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encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

# this is our input placeholder
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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)
```
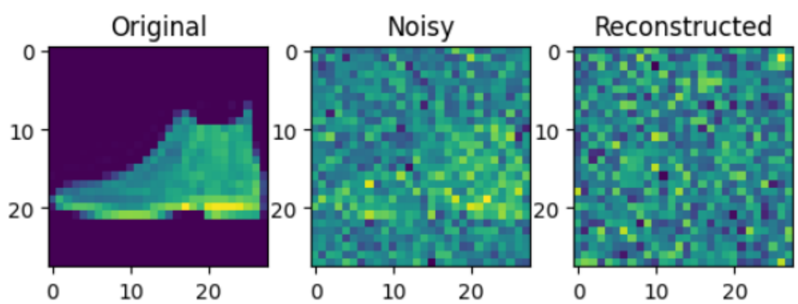

```python
history=autoencoder.fit(x_train_noisy, x_train,
                epochs=10,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test_noisy))
```

```
Epoch 1/10
235/235 [==============================] - 4s 15ms/step - loss: 0.6966 - accuracy: 0.0017 - val_loss: 0.6965 - val_accuracy: 0.0013
Epoch 2/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6964 - accuracy: 0.0017 - val_loss: 0.6963 - val_accuracy: 0.0013
Epoch 3/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6961 - accuracy: 0.0018 - val_loss: 0.6960 - val_accuracy: 0.0013
Epoch 4/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6959 - accuracy: 0.0018 - val_loss: 0.6958 - val_accuracy: 0.0013
Epoch 5/10
235/235 [==============================] - 4s 16ms/step - loss: 0.6957 - accuracy: 0.0018 - val_loss: 0.6956 - val_accuracy: 0.0013
Epoch 6/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6954 - accuracy: 0.0018 - val_loss: 0.6954 - val_accuracy: 0.0012
Epoch 7/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6952 - accuracy: 0.0018 - val_loss: 0.6951 - val_accuracy: 0.0012
Epoch 8/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6950 - accuracy: 0.0018 - val_loss: 0.6949 - val_accuracy: 0.0012
Epoch 9/10
235/235 [==============================] - 3s 14ms/step - loss: 0.6948 - accuracy: 0.0018 - val_loss: 0.6947 - val_accuracy: 0.0012
Epoch 10/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6946 - accuracy: 0.0018 - val_loss: 0.6945 - val_accuracy: 0.0012
```

```python
import matplotlib.pyplot as plt

# Get the reconstructed images
reconstructed_imgs = 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')

plt.subplot(1, 3, 2)
plt.imshow(x_test_noisy[img_to_display].reshape(28, 28))
plt.title('Noisy')

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

plt.show()
```

```
313/313 [==============================] - 1s 3ms/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()
```