ICP-9 Neural Networks & Deep Learning

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GitHub link: https://github.com/niryarjessy22/ICP-9.git

Video link:
https://drive.google.com/file/d/1k8qcaag4ug5TwBwNNoQW4rllq5FOclRS/view?usp=share_link

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

```
ICP Assignment 9
```

```
## 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 [ ]:
```
## 1. Add one more hidden layer to autoencoder##
```

In [1]:
```
from keras.layers import Input, Dense
from keras.models import Model

# input layer
input_img = Input(shape=(784,))

## encoding architecture
encode_layer1 = Dense(256, activation='relu')(input_img)
encode_layer2 = Dense(128, activation='relu')(encode_layer1)
encode_layer3 = Dense(64, activation='relu')(encode_layer2)

## latent view
latent_view   = Dense(32, activation='sigmoid')(encode_layer3)

## decoding architecture
decode_layer1 = Dense(64, activation='relu')(latent_view)
decode_layer2 = Dense(128, activation='relu')(decode_layer1)
decode_layer3 = Dense(128, activation='relu')(decode_layer2)

## output layer
output_layer  = Dense(784)(decode_layer3)

model = Model(input_img, output_layer)
```

In [2]:
```python
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:])))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
29515/29515 [==============================] - 0s 1us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
26421880/26421880 [==============================] - 1s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
5148/5148 [==============================] - 0s 0s/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4422102/4422102 [==============================] - 0s 0us/step
```

In [3]:
```python
model.compile(optimizer='adam', loss='mse',metrics=['accuracy'])

history=model.fit(x_train, x_train,epochs=10,batch_size=256, shuffle=True,validation_data=(x_test, x_test))
```

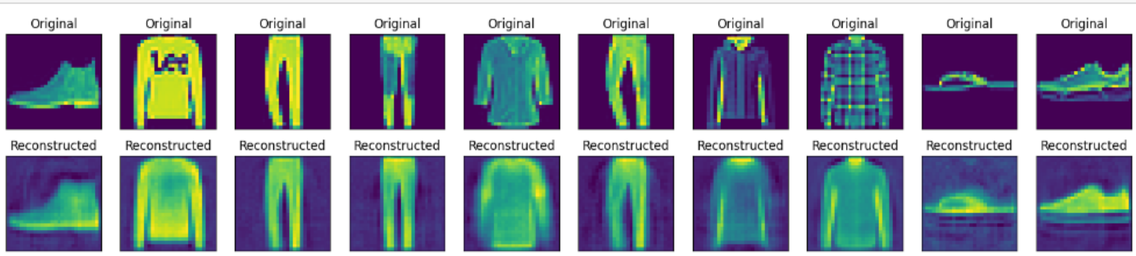
```
Epoch 1/10
235/235 [==============================] - 4s 10ms/step - loss: 0.0525 - accuracy: 0.0077 - val_loss: 0.0286 - val_accuracy: 0.
0139
Epoch 2/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0256 - accuracy: 0.0122 - val_loss: 0.0240 - val_accuracy: 0.0
146
Epoch 3/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0229 - accuracy: 0.0132 - val_loss: 0.0221 - val_accuracy: 0.0
186
Epoch 4/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0211 - accuracy: 0.0140 - val_loss: 0.0204 - val_accuracy: 0.0
146
Epoch 5/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0199 - accuracy: 0.0145 - val_loss: 0.0193 - val_accuracy: 0.0
146
Epoch 6/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0188 - accuracy: 0.0144 - val_loss: 0.0184 - val_accuracy: 0.0
125
Epoch 7/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0180 - accuracy: 0.0156 - val_loss: 0.0180 - val_accuracy: 0.0
162
Epoch 8/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0174 - accuracy: 0.0160 - val_loss: 0.0172 - val_accuracy: 0.0
176
Epoch 9/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0169 - accuracy: 0.0170 - val_loss: 0.0167 - val_accuracy: 0.0
142
Epoch 10/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0164 - accuracy: 0.0181 - val_loss: 0.0163 - val_accuracy: 0.0
```

In [4]:
```python
predictions = model.predict(x_test)
```

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

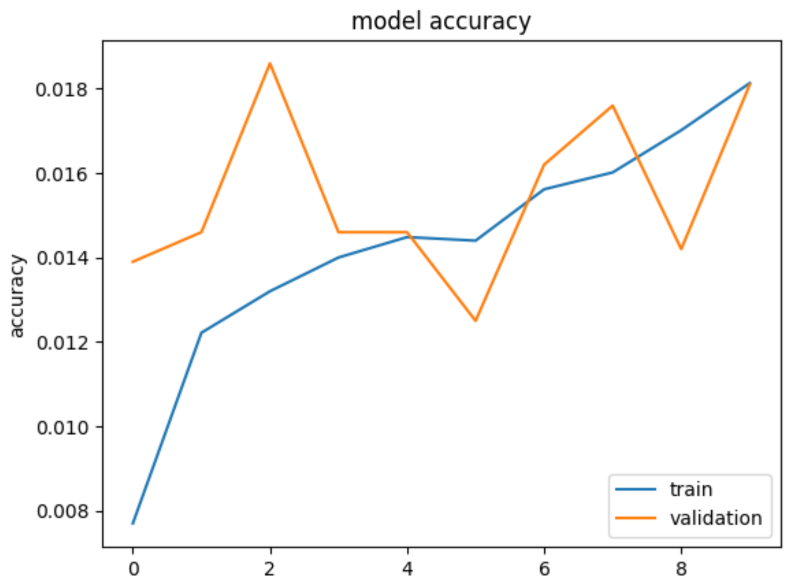
In [ ]:
```python
## 2. Do the prediction on the test data and then visualize one of the reconstructed version of that test data.
## Also, visualize the same test data before reconstruction using Matplotlib
```

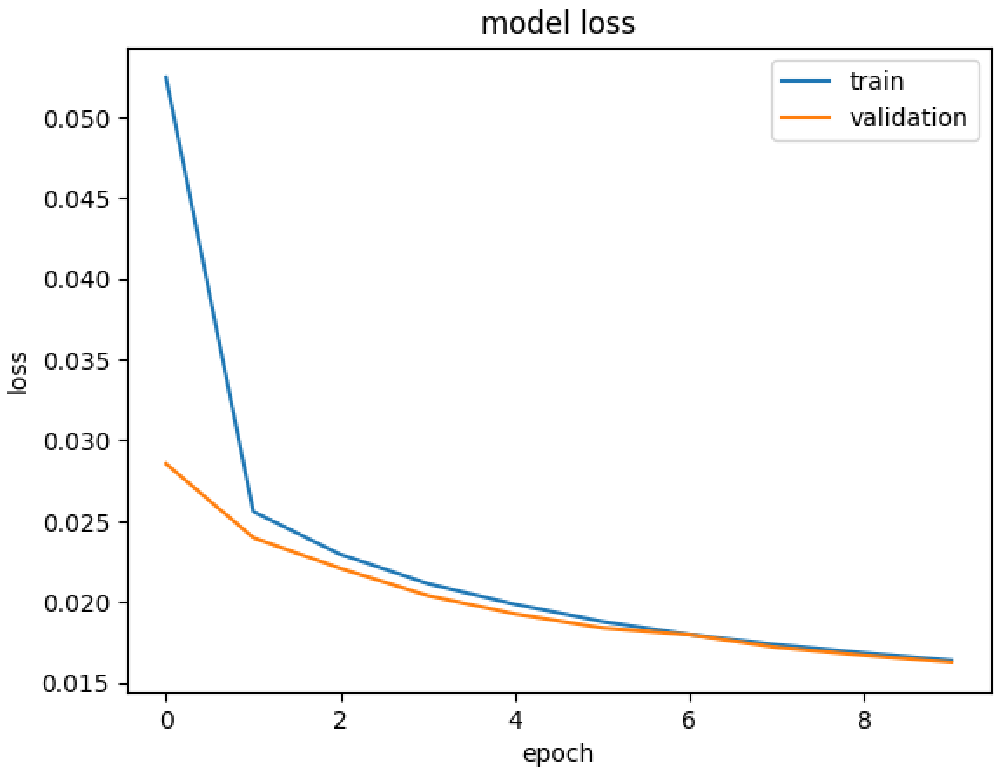
In [5]:
```python
import matplotlib.pyplot as plt

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.title("Original")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(predictions[i].reshape(28, 28))
    plt.title("Reconstructed")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



In [ ]:
```
## 3. Repeat the question 2 on the denoisening autoencoder
## 4. plot loss and accuracy using the history object
```

In [6]:
```
import numpy as np
import matplotlib.pyplot as plt

# plot history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# plot history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()
```





[7]:
```
from keras.layers import Input, Dense
from keras.models import Model

# input layer
input_img = Input(shape=(784,))

## encoding architecture
encode_layer1 = Dense(256, activation='relu')(input_img)
encode_layer2 = Dense(128, activation='relu')(encode_layer1)
encode_layer3 = Dense(64, activation='relu')(encode_layer2)

## latent view
latent_view   = Dense(32, activation='sigmoid')(encode_layer3)

## decoding architecture
decode_layer1 = Dense(64, activation='relu')(latent_view)
decode_layer2 = Dense(128, activation='relu')(decode_layer1)
decode_layer3 = Dense(128, activation='relu')(decode_layer2)

## output layer
output_layer  = Dense(784)(decode_layer3)
```

In [8]:
```
model.compile(optimizer='adadelta', loss='mse',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)
```

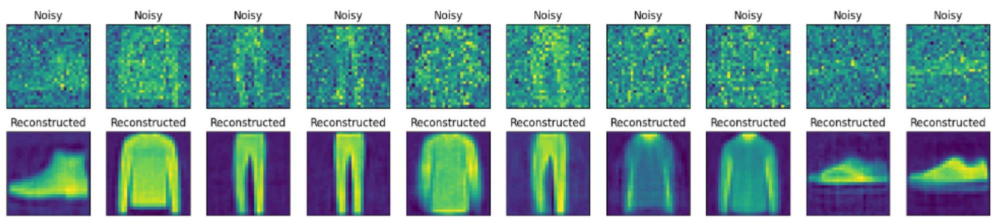
In [9]:
```
model.compile(optimizer='adam', loss='mse',metrics=['accuracy'])

history=model.fit(x_train_noisy, x_train, epochs=10, batch_size=256, validation_data=(x_test_noisy, x_test))
```

```
Epoch 1/10
235/235 [==============================] - 4s 10ms/step - loss: 0.0514 - accuracy: 0.0069 - val_loss: 0.0304 - val_accuracy: 0.
0099
Epoch 2/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0271 - accuracy: 0.0126 - val_loss: 0.0259 - val_accuracy: 0.0
140
Epoch 3/10
235/235 [==============================] - 2s 11ms/step - loss: 0.0246 - accuracy: 0.0132 - val_loss: 0.0242 - val_accuracy: 0.
0128
Epoch 4/10
235/235 [==============================] - 3s 11ms/step - loss: 0.0231 - accuracy: 0.0141 - val_loss: 0.0229 - val_accuracy: 0.
0160
Epoch 5/10
235/235 [==============================] - 3s 11ms/step - loss: 0.0220 - accuracy: 0.0147 - val_loss: 0.0219 - val_accuracy: 0.
0158
Epoch 6/10
235/235 [==============================] - 3s 11ms/step - loss: 0.0212 - accuracy: 0.0157 - val_loss: 0.0214 - val_accuracy: 0.
0145
Epoch 7/10
235/235 [==============================] - 2s 10ms/step - loss: 0.0206 - accuracy: 0.0164 - val_loss: 0.0210 - val_accuracy: 0.
0161
Epoch 8/10
235/235 [==============================] - 3s 12ms/step - loss: 0.0201 - accuracy: 0.0162 - val_loss: 0.0208 - val_accuracy: 0.
0158
Epoch 9/10
235/235 [==============================] - 2s 10ms/step - loss: 0.0197 - accuracy: 0.0162 - val_loss: 0.0204 - val_accuracy: 0.
0187
Epoch 10/10
235/235 [==============================] - 2s 9ms/step - loss: 0.0193 - accuracy: 0.0170 - val_loss: 0.0201 - val_accuracy: 0.0
165
```

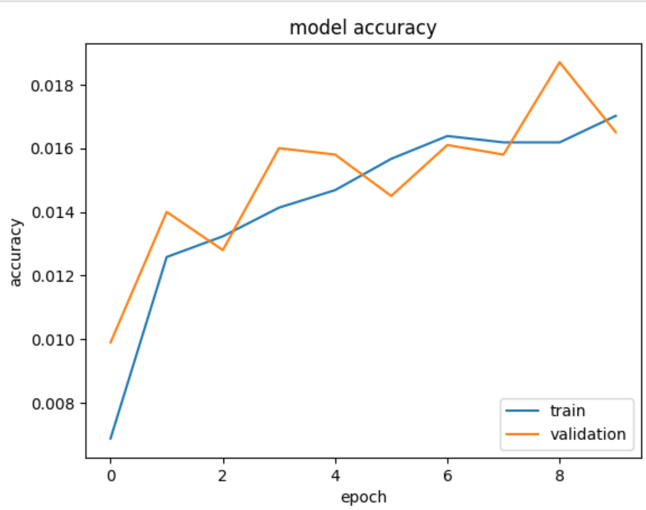
In [10]:
```
predictions = model.predict(x_test)
```

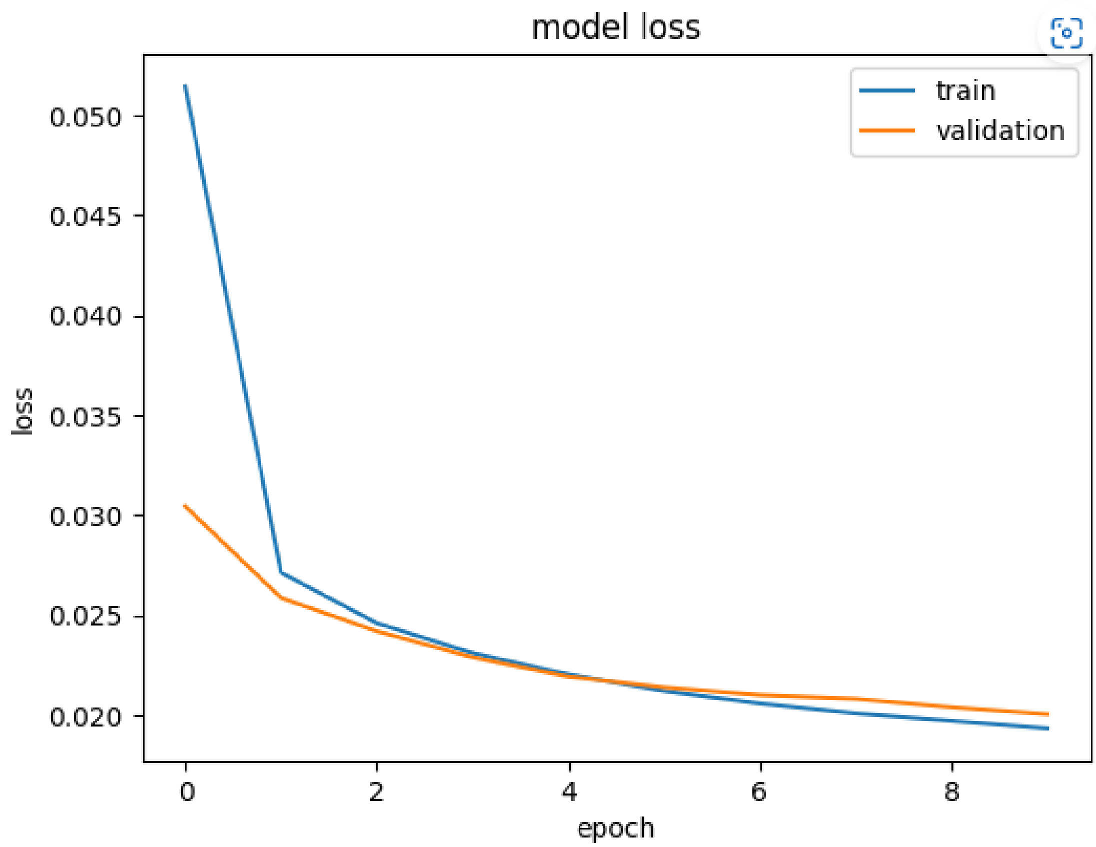
```
313/313 [==============================] - 1s 2ms/step
```

In [11]:
```
import matplotlib.pyplot as plt

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test_noisy[i].reshape(28, 28))
    plt.title("Noisy")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(predictions[i].reshape(28, 28))
    plt.title("Reconstructed")
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



In [12]:
```
import numpy as np
import matplotlib.pyplot as plt

# plot history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='lower right')
plt.show()
# plot history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
plt.show()
```




model loss
train
validation
loss
0.050
0.045
0.040
0.035
0.030
0.025
0.020
0
2
4
6
8
epoch