

**Spring 2024: CS5720 Neural Networks & Deep Learning – Autoencoders**  
**Assignment- Autoencoders**  
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**GitHub link:**

<https://github.com/Sangeetha-Baddam/Assignment-8>

**Video link:**

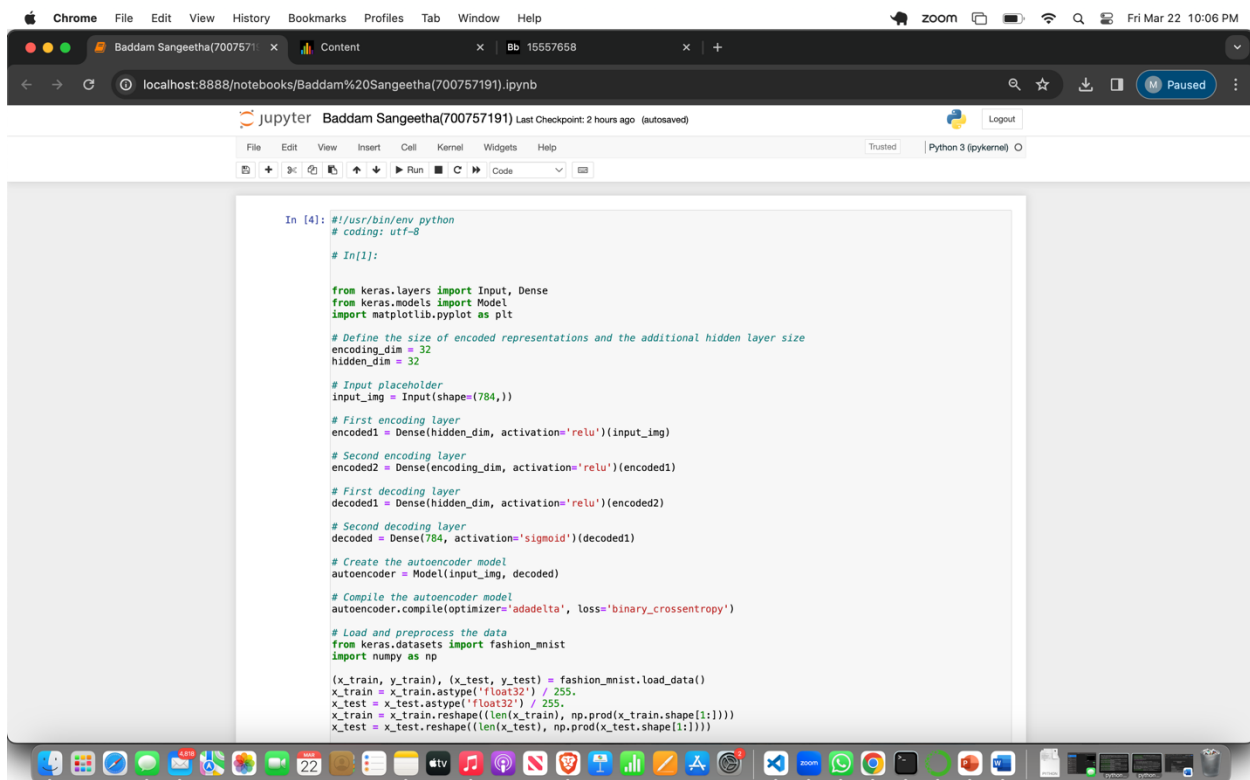
[https://drive.google.com/file/d/1Jq67MamyNzLV3OI2Srmnc1Oj4nsiWVZX/view?usp=drive\\_link](https://drive.google.com/file/d/1Jq67MamyNzLV3OI2Srmnc1Oj4nsiWVZX/view?usp=drive_link)

**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 [4]: #!/usr/bin/env python
# coding: utf-8

# In[1]:

from keras.layers import Input, Dense
from keras.models import Model
import matplotlib.pyplot as plt

# Define the size of encoded representations and the additional hidden layer size
encoding_dim = 32
hidden_dim = 32

# Input placeholder
input_img = Input(shape=(784,))

# First encoding layer
encoded1 = Dense(hidden_dim, activation='relu')(input_img)

# Second encoding layer
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)

# First decoding layer
decoded1 = Dense(hidden_dim, activation='relu')(encoded2)

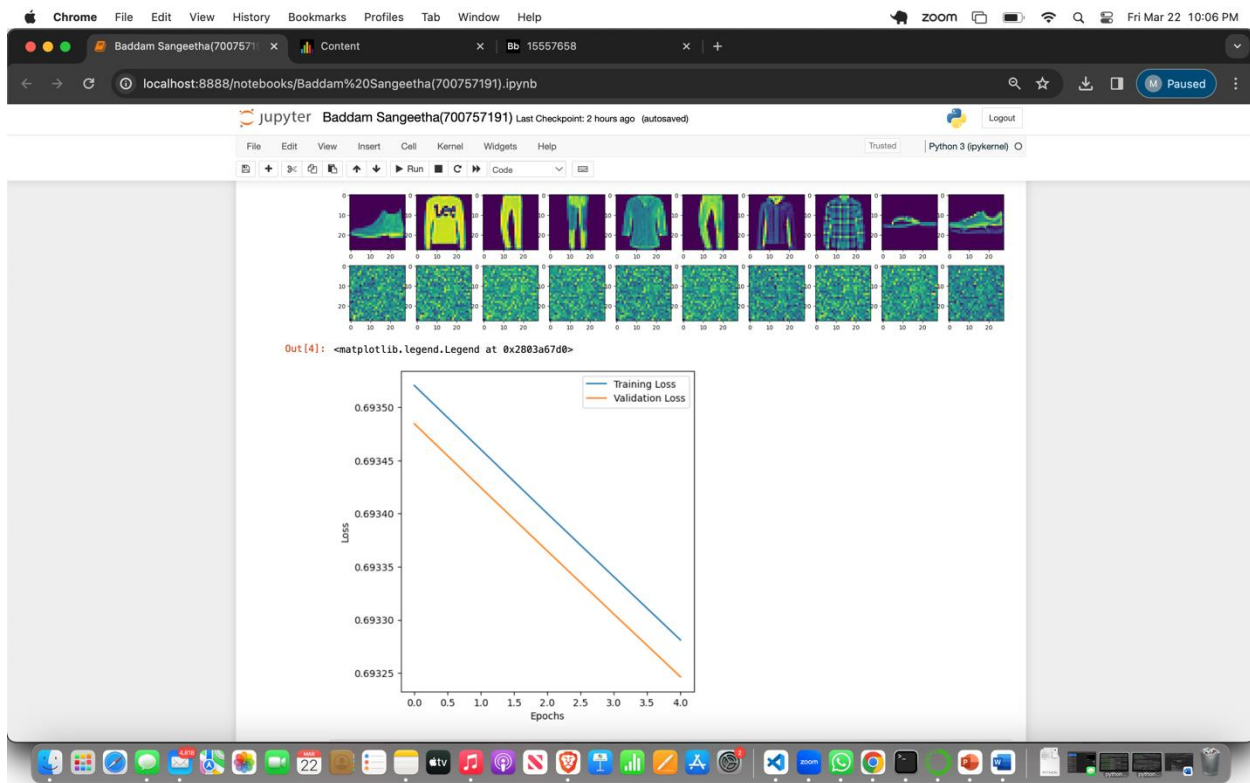
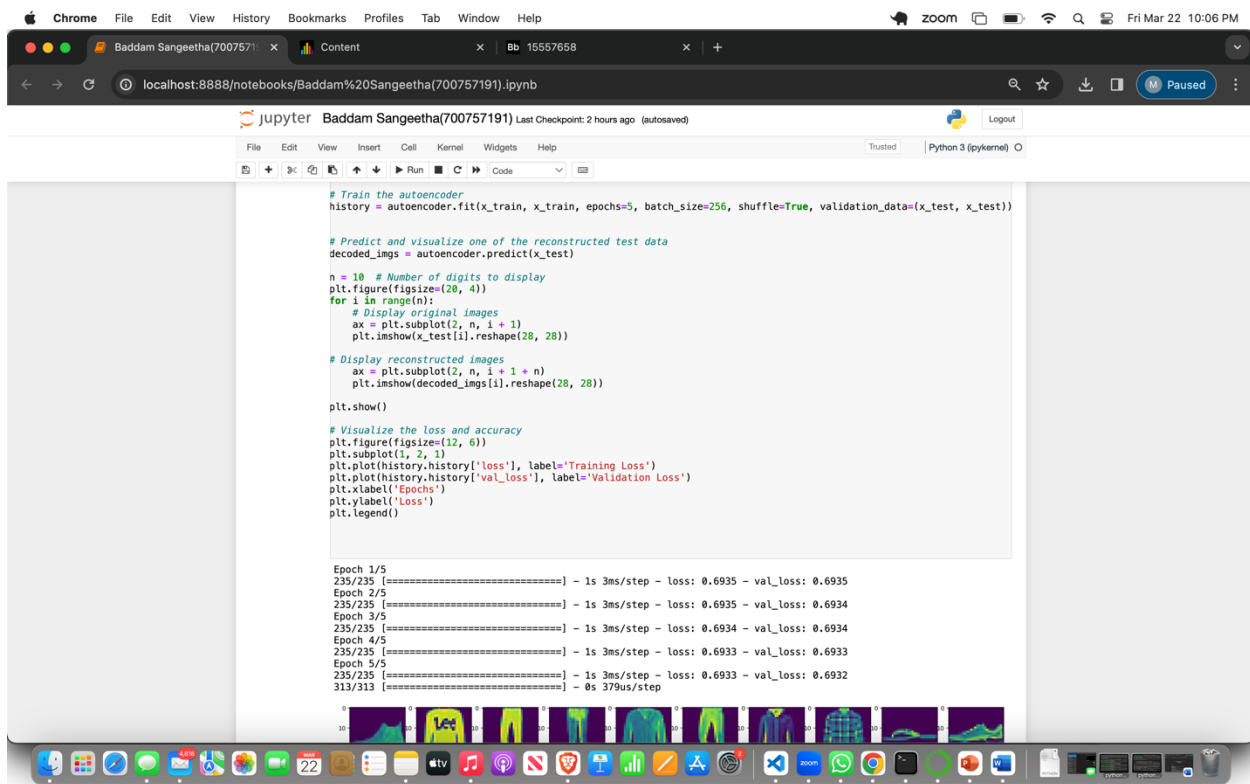
# Second decoding layer
decoded = Dense(784, activation='sigmoid')(decoded1)

# Create the autoencoder model
autoencoder = Model(input_img, decoded)

# Compile the autoencoder model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')

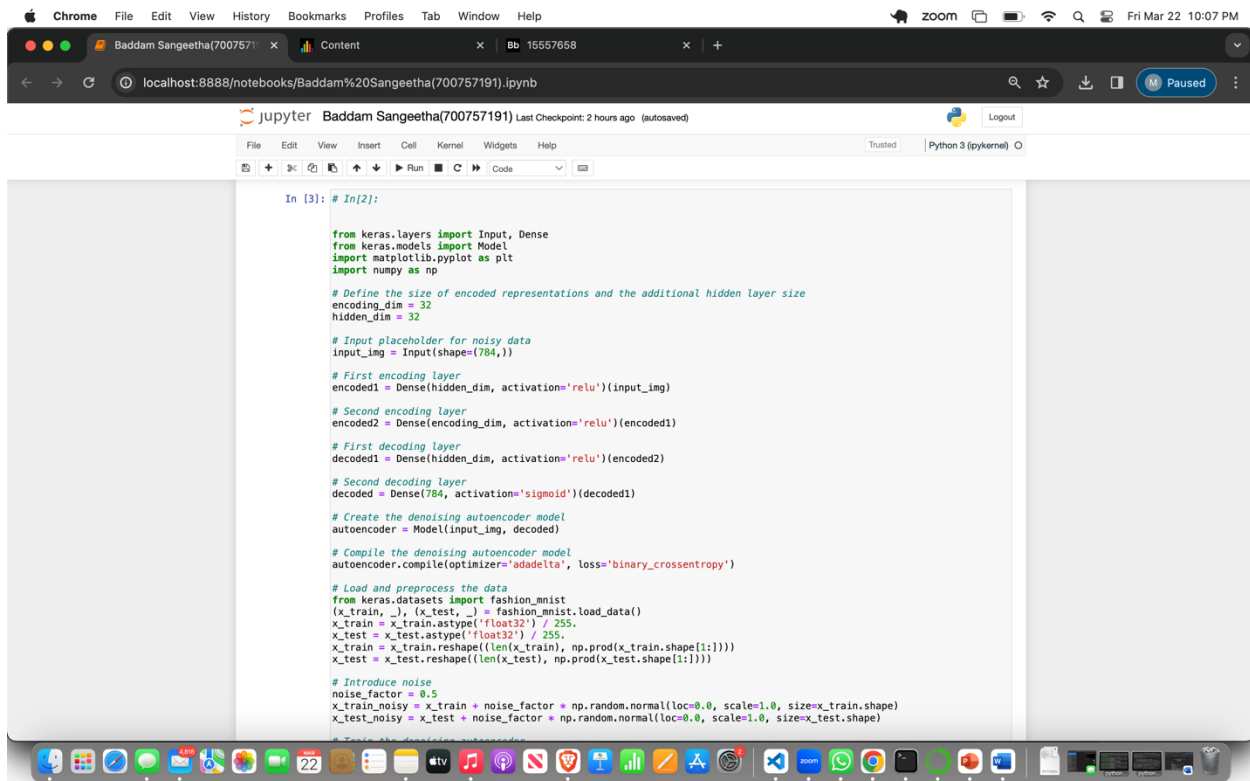
# Load and preprocess the data
from keras.datasets import fashion_mnist
import numpy as np

(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:])))
```



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 denoising autoencoder
4. plot loss and accuracy using the history object



```
In [3]: # In[2]:

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

# Define the size of encoded representations and the additional hidden layer size
encoding_dim = 32
hidden_dim = 32

# Input placeholder for noisy data
input_img = Input(shape=(784,))

# First encoding layer
encoded1 = Dense(hidden_dim, activation='relu')(input_img)

# Second encoding layer
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)

# First decoding layer
decoded1 = Dense(hidden_dim, activation='relu')(encoded2)

# Second decoding layer
decoded = Dense(784, activation='sigmoid')(decoded1)

# Create the denoising autoencoder model
autoencoder = Model(input_img, decoded)

# Compile the denoising autoencoder model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')

# Load and preprocess the data
from keras.datasets import fashion_mnist
(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:])))

# Introduce 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)

# Train the denoising autoencoder
```

