

Andrew Vu - CS156_HW9_GPU

April 30, 2022

1 CS156 (Introduction to AI), Spring 2022

2 Homework 9 submission

2.0.1 Roster Name: Andrew Vu

2.0.2 Student ID: 015055911

2.0.3 Email address: andrew.k.vu@sjsu.edu

Any special notes or anything you would like to communicate to me about this homework submission goes in here.

2.1 References and sources

List all your references and sources here. This includes all sites/discussion boards/blogs/posts/etc. where you grabbed some code examples.

- Autoencoders file

2.2 Solution

Load libraries and set random number generator seed

```
[64]: import numpy as np
import tensorflow as tf
from tensorflow import keras
from sklearn.model_selection import train_test_split

from tensorflow.keras import layers
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Reshape
from tensorflow.keras.layers import Input
from tensorflow.keras.models import Model

import matplotlib.pyplot as plt
```

```
[65]: np.random.seed(42)
```

Code the solution

2.2.1 Load and prepare image data

```
[66]: (x_train_valid, y_train_valid), (x_test, y_test) = keras.datasets.fashion_mnist.  
      ↪load_data()  
  
x_train, x_validation, y_train, y_validation = train_test_split(x_train_valid,   
      ↪y_train_valid, test_size=0.2, random_state=0)  
  
x_train = x_train.astype("float32") / 255  
x_validation = x_validation.astype("float32") / 255  
x_test = x_test.astype("float32") / 255  
  
x_train.shape, x_validation.shape, x_test.shape  
# scale images to the [0,1] range
```

```
[66]: ((48000, 28, 28), (12000, 28, 28), (10000, 28, 28))
```

2.2.2 Autoencoder model and its performance for first 10 images in test set

```
[67]: # Reshape images into flat ANN layers  
x_train = x_train.reshape(-1, 784)  
x_validation = x_validation.reshape(-1, 784)  
x_test = x_test.reshape(-1, 784)  
  
x_train.shape, x_validation.shape, x_test.shape
```

```
[67]: ((48000, 784), (12000, 784), (10000, 784))
```

```
[68]: input_layer = Input(shape=(784,)) # 28 * 28  
encoded = layers.Dense(128, activation='relu')(input_layer)  
encoded = layers.Dense(64, activation='relu')(encoded)  
encoded = layers.Dense(32, activation='relu')(encoded)  
  
decoded = layers.Dense(64, activation='sigmoid')(encoded)  
decoded = layers.Dense(128, activation='sigmoid')(decoded)  
decoded = layers.Dense(784, activation='sigmoid')(decoded)  
  
# reconstruction model:  
autoencoder = keras.Model(input_layer, decoded)  
autoencoder.summary()  
  
# encoder model  
encoder = keras.Model(input_layer, encoded)  
  
# decoder model:  
encoded_input = keras.Input(shape=(128,))  
decoder_layer = autoencoder.layers[-1] # last layer of autoencoder model
```

```
decoder = keras.Model(encoded_input, decoder_layer(encoded_input))
```

Model: "functional_57"

Layer (type)	Output Shape	Param #
input_16 (InputLayer)	[(None, 784)]	0
dense_30 (Dense)	(None, 128)	100480
dense_31 (Dense)	(None, 64)	8256
dense_32 (Dense)	(None, 32)	2080
dense_33 (Dense)	(None, 64)	2112
dense_34 (Dense)	(None, 128)	8320
dense_35 (Dense)	(None, 784)	101136
Total params: 222,384		
Trainable params: 222,384		
Non-trainable params: 0		

```
[69]: # Fitting/training the model

autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

autoencoder.fit(x_train, x_train,
                epochs=30,
                batch_size=2048,
                shuffle=True,
                validation_data=(x_test, x_test))
```

```
Epoch 1/30
24/24 [=====] - 1s 42ms/step - loss: 0.5879 - val_loss: 0.5141
Epoch 2/30
24/24 [=====] - 1s 37ms/step - loss: 0.4989 - val_loss: 0.4915
Epoch 3/30
24/24 [=====] - 1s 41ms/step - loss: 0.4867 - val_loss: 0.4828
Epoch 4/30
24/24 [=====] - 1s 46ms/step - loss: 0.4747 - val_loss: 0.4646
Epoch 5/30
```

24/24 [=====] - 1s 46ms/step - loss: 0.4506 - val_loss: 0.4371
Epoch 6/30
24/24 [=====] - 1s 47ms/step - loss: 0.4261 - val_loss: 0.4161
Epoch 7/30
24/24 [=====] - 1s 40ms/step - loss: 0.4075 - val_loss: 0.4020
Epoch 8/30
24/24 [=====] - 1s 41ms/step - loss: 0.3966 - val_loss: 0.3937
Epoch 9/30
24/24 [=====] - 1s 40ms/step - loss: 0.3895 - val_loss: 0.3892
Epoch 10/30
24/24 [=====] - 1s 42ms/step - loss: 0.3859 - val_loss: 0.3850
Epoch 11/30
24/24 [=====] - 1s 44ms/step - loss: 0.3818 - val_loss: 0.3815
Epoch 12/30
24/24 [=====] - 1s 39ms/step - loss: 0.3784 - val_loss: 0.3785
Epoch 13/30
24/24 [=====] - 1s 38ms/step - loss: 0.3756 - val_loss: 0.3753
Epoch 14/30
24/24 [=====] - 1s 39ms/step - loss: 0.3720 - val_loss: 0.3714
Epoch 15/30
24/24 [=====] - 1s 40ms/step - loss: 0.3683 - val_loss: 0.3673
Epoch 16/30
24/24 [=====] - 1s 39ms/step - loss: 0.3638 - val_loss: 0.3629
Epoch 17/30
24/24 [=====] - 1s 37ms/step - loss: 0.3599 - val_loss: 0.3592
Epoch 18/30
24/24 [=====] - 1s 37ms/step - loss: 0.3562 - val_loss: 0.3564
Epoch 19/30
24/24 [=====] - 1s 37ms/step - loss: 0.3535 - val_loss: 0.3540
Epoch 20/30
24/24 [=====] - 1s 37ms/step - loss: 0.3510 - val_loss: 0.3518
Epoch 21/30

```

24/24 [=====] - 1s 37ms/step - loss: 0.3493 - val_loss:
0.3493
Epoch 22/30
24/24 [=====] - 1s 36ms/step - loss: 0.3473 - val_loss:
0.3479
Epoch 23/30
24/24 [=====] - 1s 36ms/step - loss: 0.3455 - val_loss:
0.3464
Epoch 24/30
24/24 [=====] - 1s 37ms/step - loss: 0.3447 - val_loss:
0.3453
Epoch 25/30
24/24 [=====] - 1s 37ms/step - loss: 0.3430 - val_loss:
0.3436
Epoch 26/30
24/24 [=====] - 1s 37ms/step - loss: 0.3414 - val_loss:
0.3422
Epoch 27/30
24/24 [=====] - 1s 37ms/step - loss: 0.3407 - val_loss:
0.3416
Epoch 28/30
24/24 [=====] - 1s 38ms/step - loss: 0.3391 - val_loss:
0.3399
Epoch 29/30
24/24 [=====] - 1s 37ms/step - loss: 0.3378 - val_loss:
0.3387
Epoch 30/30
24/24 [=====] - 1s 36ms/step - loss: 0.3367 - val_loss:
0.3380

```

[69]: <tensorflow.python.keras.callbacks.History at 0x21820f4edd8>

```

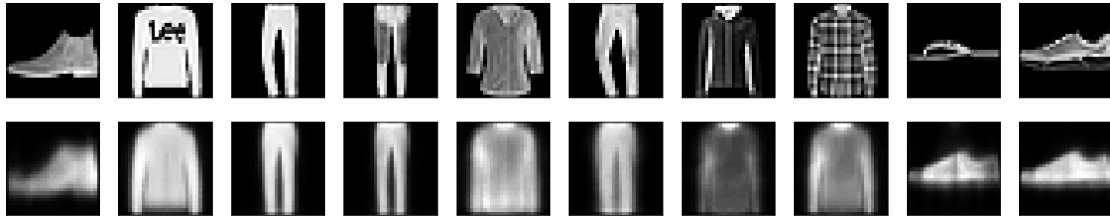
[70]: # Plotting the reconstructed images
predictions = autoencoder.predict(x_test)

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # 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)

    # reconstruction
    ax = plt.subplot(2, n, i + 1 + n)

```

```
plt.imshow(predictions[i].reshape(28, 28))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
```



2.2.3 Reshape + denoise images with an autoencoder model + plotting

```
[71]: x_train = x_train.reshape(-1, 28, 28, 1)
x_validation = x_validation.reshape(-1, 28, 28, 1)
x_test = x_test.reshape(-1, 28, 28, 1)

x_train.shape, x_validation.shape, x_test.shape
```

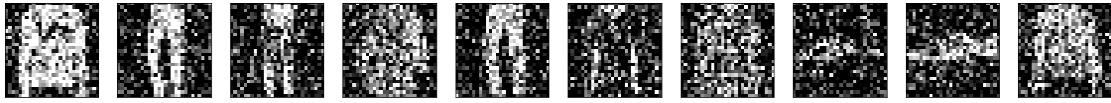
```
[71]: ((48000, 28, 28, 1), (12000, 28, 28, 1), (10000, 28, 28, 1))
```

```
[72]: noise_factor = 0.4
x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0,
↳size=x_train.shape)
x_validation_noisy = x_validation + noise_factor * np.random.normal(loc=0.0,
↳scale=1.0, size=x_validation.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_validation_noisy = np.clip(x_validation_noisy, 0., 1.)
x_test_noisy = np.clip(x_test_noisy, 0., 1.)
```

```
[73]: # Plotting the noised images
n = 10
plt.figure(figsize=(20, 2))
for i in range(1, n + 1):
    ax = plt.subplot(1, n, i)
    plt.imshow(x_test_noisy[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
```

```
plt.show()
```



```
[74]: input_layer = keras.Input(shape=(28, 28, 1))

x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(input_layer)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
encoded = layers.MaxPooling2D((2, 2), padding='same')(x)

# At this point the representation is (7, 7, 32)

x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(encoded)
x = layers.UpSampling2D((2, 2))(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = layers.UpSampling2D((2, 2))(x)
decoded = layers.Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)

autoencoder = keras.Model(input_layer, decoded)
autoencoder.summary()
```

Model: "functional_63"

Layer (type)	Output Shape	Param #
input_18 (InputLayer)	[(None, 28, 28, 1)]	0
conv2d_27 (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d_11 (MaxPooling)	(None, 14, 14, 32)	0
conv2d_28 (Conv2D)	(None, 14, 14, 32)	9248
max_pooling2d_12 (MaxPooling)	(None, 7, 7, 32)	0
conv2d_29 (Conv2D)	(None, 7, 7, 32)	9248
up_sampling2d_11 (UpSampling)	(None, 14, 14, 32)	0
conv2d_30 (Conv2D)	(None, 14, 14, 32)	9248
up_sampling2d_12 (UpSampling)	(None, 28, 28, 32)	0

```

-----
conv2d_31 (Conv2D)                (None, 28, 28, 1)                289
=====
Total params: 28,353
Trainable params: 28,353
Non-trainable params: 0
-----

```

2.2.4 Training the noise model + plotting

```

[75]: autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

autoencoder.fit(x_train_noisy, x_train,
                epochs=30,
                batch_size=2048,
                shuffle=True,
                validation_data=(x_validation_noisy, x_validation))

```

```

Epoch 1/30
24/24 [=====] - 34s 1s/step - loss: 0.5513 - val_loss: 0.3879
Epoch 2/30
24/24 [=====] - 34s 1s/step - loss: 0.3605 - val_loss: 0.3408
Epoch 3/30
24/24 [=====] - 34s 1s/step - loss: 0.3311 - val_loss: 0.3226
Epoch 4/30
24/24 [=====] - 34s 1s/step - loss: 0.3192 - val_loss: 0.3152
Epoch 5/30
24/24 [=====] - 35s 1s/step - loss: 0.3132 - val_loss: 0.3108
Epoch 6/30
24/24 [=====] - 34s 1s/step - loss: 0.3097 - val_loss: 0.3079
Epoch 7/30
24/24 [=====] - 34s 1s/step - loss: 0.3071 - val_loss: 0.3059
Epoch 8/30
24/24 [=====] - 34s 1s/step - loss: 0.3055 - val_loss: 0.3052
Epoch 9/30
24/24 [=====] - 34s 1s/step - loss: 0.3038 - val_loss: 0.3029
Epoch 10/30
24/24 [=====] - 34s 1s/step - loss: 0.3025 - val_loss: 0.3018

```


Epoch 11/30
24/24 [=====] - 34s 1s/step - loss: 0.3016 - val_loss: 0.3015

Epoch 12/30
24/24 [=====] - 35s 1s/step - loss: 0.3008 - val_loss: 0.3002

Epoch 13/30
24/24 [=====] - 34s 1s/step - loss: 0.2999 - val_loss: 0.2992

Epoch 14/30
24/24 [=====] - 34s 1s/step - loss: 0.2996 - val_loss: 0.2991

Epoch 15/30
24/24 [=====] - 35s 1s/step - loss: 0.2987 - val_loss: 0.2980

Epoch 16/30
24/24 [=====] - 34s 1s/step - loss: 0.2981 - val_loss: 0.2975

Epoch 17/30
24/24 [=====] - 34s 1s/step - loss: 0.2976 - val_loss: 0.2975

Epoch 18/30
24/24 [=====] - 34s 1s/step - loss: 0.2974 - val_loss: 0.2966

Epoch 19/30
24/24 [=====] - 34s 1s/step - loss: 0.2966 - val_loss: 0.2962

Epoch 20/30
24/24 [=====] - 34s 1s/step - loss: 0.2962 - val_loss: 0.2964

Epoch 21/30
24/24 [=====] - 34s 1s/step - loss: 0.2964 - val_loss: 0.2958

Epoch 22/30
24/24 [=====] - 34s 1s/step - loss: 0.2957 - val_loss: 0.2960

Epoch 23/30
24/24 [=====] - 34s 1s/step - loss: 0.2953 - val_loss: 0.2947

Epoch 24/30
24/24 [=====] - 34s 1s/step - loss: 0.2948 - val_loss: 0.2944

Epoch 25/30
24/24 [=====] - 34s 1s/step - loss: 0.2945 - val_loss: 0.2941

Epoch 26/30
24/24 [=====] - 34s 1s/step - loss: 0.2942 - val_loss: 0.2938

```

Epoch 27/30
24/24 [=====] - 34s 1s/step - loss: 0.2943 - val_loss: 0.2935
Epoch 28/30
24/24 [=====] - 34s 1s/step - loss: 0.2936 - val_loss: 0.2933
Epoch 29/30
24/24 [=====] - 34s 1s/step - loss: 0.2935 - val_loss: 0.2931
Epoch 30/30
24/24 [=====] - 34s 1s/step - loss: 0.2932 - val_loss: 0.2929

```

[75]: <tensorflow.python.keras.callbacks.History at 0x21823c1c7b8>

```

[76]: # Plotting the reconstructed images
predictions = autoencoder.predict(x_test)

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # noisy
    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)

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

```

