

▼ CS156 (Introduction to AI), Spring 2021

Homework Assignment #11 submission

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Solution

```
1 import numpy as np
2 from tensorflow import keras
3 from tensorflow.keras.datasets.mnist import load_data
4 import matplotlib.pyplot as plt
5 from tensorflow.keras.models import Sequential
6 from tensorflow.keras.optimizers import Adam
7 from tensorflow.keras.layers import Dense
8 from tensorflow.keras.layers import Conv2D
9 from tensorflow.keras.layers import Flatten
10 from tensorflow.keras.layers import Dropout
11 from tensorflow.keras.layers import LeakyReLU
12 from tensorflow.keras.utils import plot_model
13 from tensorflow.keras.layers import Reshape
14 from tensorflow.keras.layers import Conv2DTranspose
15 from numpy import expand_dims
16 from numpy import ones
17 from numpy import zeros
18 from numpy.random import rand
19 from numpy.random import randint
20 from numpy.random import randn
21 from numpy import vstack
22 from numpy import asarray

1
2 (x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()
3 input_shape = (28, 28, 1)
4
5 #combine into a single dataset
6 mnist = np.concatenate([x_train, x_test], axis=0)
7 mnist = expand_dims(mnist, axis=-1)
8
9 # Scale images to the [0, 1] range
10 mnist = mnist.astype("float32") / 255
```

```
11
12 mnist.shape
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-32768/29515 [=====] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-26427392/26421880 [=====] - 1s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-8192/5148 [=====] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-4423680/4422102 [=====] - 0s 0us/step
(70000, 28, 28, 1)
```



```
1 for i in range(25):
2     plt.subplot(5, 5, 1 + i)
3     plt.axis('off')
4     plt.imshow(x_train[i], cmap='gray')
5 plt.show()
```



```
1 # plot reverse gray scale:
2 for i in range(25):
3     plt.subplot(5, 5, 1 + i)
4     plt.axis('off')
5     plt.imshow(x_train[i], cmap='gray_r')
6 plt.show()
```



```
1 # define the standalone discriminator model
2 def define_discriminator(in_shape=(28, 28, 1)):
3     model = Sequential()
4     model.add(Conv2D(64, (3, 3), strides=(2, 2), padding='same', input_shape=in_shape))
5     model.add(LeakyReLU(alpha=0.2))
6     model.add(Dropout(0.4))
7     model.add(Conv2D(64, (3, 3), strides=(2, 2), padding='same'))
8     model.add(LeakyReLU(alpha=0.2))
9     model.add(Dropout(0.4))
10    model.add(Flatten())
11    model.add(Dense(1, activation='sigmoid'))
12    # compile model
13    opt = Adam(lr=0.0002, beta_1=0.5)
14    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
15    return model
16
17
18 # define the discriminator model
19 discriminator = define_discriminator()
20 discriminator.summary()
21
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 14, 14, 64)	640

leaky_re_lu (LeakyReLU)	(None, 14, 14, 64)	0

dropout (Dropout)	(None, 14, 14, 64)	0

conv2d_1 (Conv2D)	(None, 7, 7, 64)	36928

leaky_re_lu_1 (LeakyReLU)	(None, 7, 7, 64)	0

dropout_1 (Dropout)	(None, 7, 7, 64)	0

flatten (Flatten)	(None, 3136)	0

dense (Dense)	(None, 1)	3137
=====		
Total params: 40,705		
Trainable params: 40,705		
Non-trainable params: 0		

```
1 # define the standalone generator model
2 def define_generator(latent_dim):
3     model = Sequential()
4     # foundation for 7x7 image
```

```

5     n_nodes = 128 * 7 * 7
6     model.add(Dense(n_nodes, input_dim=latent_dim))
7     model.add(LeakyReLU(alpha=0.2))
8     model.add(Reshape((7, 7, 128)))
9     # upsample to 14x14
10    model.add(Conv2DTranspose(128, (4, 4), strides=(2, 2), padding='same'))
11    model.add(LeakyReLU(alpha=0.2))
12    # upsample to 28x28
13    model.add(Conv2DTranspose(128, (4, 4), strides=(2, 2), padding='same'))
14    model.add(LeakyReLU(alpha=0.2))
15    model.add(Conv2D(1, (7, 7), activation='sigmoid', padding='same'))
16    return model
17
18
19 # size of the latent space
20 latent_dim = 100
21 # define the discriminator model
22 generator = define_generator(latent_dim)
23 generator.summary()

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 6272)	633472
leaky_re_lu_2 (LeakyReLU)	(None, 6272)	0
reshape (Reshape)	(None, 7, 7, 128)	0
conv2d_transpose (Conv2DTran	(None, 14, 14, 128)	262272
leaky_re_lu_3 (LeakyReLU)	(None, 14, 14, 128)	0
conv2d_transpose_1 (Conv2DTr	(None, 28, 28, 128)	262272
leaky_re_lu_4 (LeakyReLU)	(None, 28, 28, 128)	0
conv2d_2 (Conv2D)	(None, 28, 28, 1)	6273
Total params: 1,164,289		
Trainable params: 1,164,289		
Non-trainable params: 0		

```

1 # define the combined generator and discriminator model, for updating the generator
2 def define_gan(g_model, d_model):
3     # make weights in the discriminator not trainable
4     d_model.trainable = False
5     # connect them
6     model = Sequential()
7     # add generator
8     model.add(g_model)
9     # add the discriminator

```

```

9     # add the discriminator
10    model.add(d_model)
11    # compile model
12    opt = Adam(lr=0.0002, beta_1=0.5)
13    model.compile(loss='binary_crossentropy', optimizer=opt)
14    return model
15
16
17 gan_model = define_gan(generator, discriminator)
18 gan_model.summary()

```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
=====		
sequential_1 (Sequential)	(None, 28, 28, 1)	1164289
=====		
sequential (Sequential)	(None, 1)	40705
=====		
Total params: 1,204,994		
Trainable params: 1,164,289		
Non-trainable params: 40,705		
=====		

```

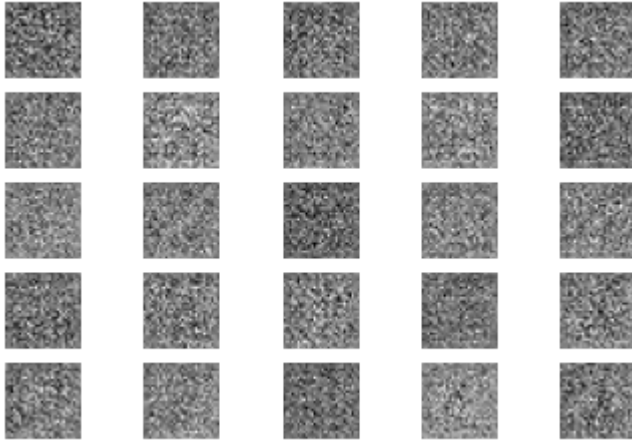
1 # without training, our generator model produces really bad images (they are not very good
2
3 # generate points in latent space as input for the generator
4 def generate_latent_points(latent_dim, n_samples):
5     # generate points in the latent space
6     x_input = randn(latent_dim * n_samples)
7     # reshape into a batch of inputs for the network
8     x_input = x_input.reshape(n_samples, latent_dim)
9     return x_input
10
11
12 # use the generator to generate n fake examples, with class labels
13 def generate_fake_generator_samples(g_model, latent_dim, n_samples):
14     # generate points in latent space
15     x_input = generate_latent_points(latent_dim, n_samples)
16     # predict outputs
17     X = g_model.predict(x_input)
18     # create 'fake' class labels (0)
19     y = zeros((n_samples, 1))
20     return X, y
21
22
23 # generate samples
24 n_samples = 25
25 X, _ = generate_fake_generator_samples(generator, latent_dim, n_samples)
26 # plot the generated samples
27 for i in range(n_samples):
28     # define subplot
29     plt.subplot(5, 5, 1 + i)

```

```

29 plt.subplot(5, 5, i + 1),
30 # turn off axis labels
31 plt.axis('off')
32 # plot single image
33 plt.imshow(X[i, :, :, 0], cmap='gray_r')
34 # show the figure
35 plt.show()

```



```

1 # select real samples
2 def generate_real_samples(dataset, n_samples):
3     # choose random instances
4     ix = randint(0, dataset.shape[0], n_samples)
5     # retrieve selected images
6     X = dataset[ix]
7     # generate 'real' class labels (1)
8     y = ones((n_samples, 1))
9     return X, y
10
11
12 # use the generator to generate n fake examples, with class labels
13 def generate_fake_samples(g_model, latent_dim, n_samples):
14     # generate points in latent space
15     x_input = generate_latent_points(latent_dim, n_samples)
16     # predict outputs
17     X = g_model.predict(x_input)
18     # create 'fake' class labels (0)
19     y = zeros((n_samples, 1))
20     return X, y
21
22
23 # generate points in latent space as input for the generator
24 def generate_latent_points(latent_dim, n_samples):
25     # generate points in the latent space
26     x_input = randn(latent_dim * n_samples)
27     # reshape into a batch of inputs for the network
28     x_input = x_input.reshape(n_samples, latent_dim)
29     return x_input
30
31

```

```

51
52 # evaluate the discriminator, plot generated images, save generator model
53 def summarize_performance(epoch, g_model, d_model, dataset, latent_dim, n_samples=100):
54     # prepare real samples
55     X_real, y_real = generate_real_samples(dataset, n_samples)
56     # evaluate discriminator on real examples
57     _, acc_real = d_model.evaluate(X_real, y_real, verbose=0)
58     # prepare fake examples
59     x_fake, y_fake = generate_fake_samples(g_model, latent_dim, n_samples)
60     # evaluate discriminator on fake examples
61     _, acc_fake = d_model.evaluate(x_fake, y_fake, verbose=0)
62     # summarize discriminator performance
63     print('>Accuracy real: %.0f%%, fake: %.0f%%' % (acc_real * 100, acc_fake * 100))
64     # save plot
65     #save_plot(x_fake, epoch)
66     # save the generator model tile file
67     #filename = 'generator_model_%03d.h5' % (epoch + 1)
68     #g_model.save(filename) # serializing the model: https://www.tensorflow.org/tutorials
69
70
71 # train the generator and discriminator together
72 def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=256):
73     bat_per_epo = int(dataset.shape[0] / n_batch)
74     half_batch = int(n_batch / 2)
75     # manually enumerate epochs
76     for i in range(n_epochs):
77         # enumerate batches over the training set
78         for j in range(bat_per_epo):
79             # get randomly selected 'real' samples
80             X_real, y_real = generate_real_samples(dataset, half_batch)
81             # generate 'fake' examples
82             X_fake, y_fake = generate_fake_samples(g_model, latent_dim, half_batch)
83             # create training set for the discriminator
84             X, y = vstack((X_real, X_fake)), vstack((y_real, y_fake))
85             # update discriminator model weights
86             d_loss, _ = d_model.train_on_batch(X, y)
87             # prepare points in latent space as input for the generator
88             X_gan = generate_latent_points(latent_dim, n_batch)
89             # create inverted labels for the fake samples
90             y_gan = ones((n_batch, 1))
91             # update the generator via the discriminator's error
92             g_loss = gan_model.train_on_batch(X_gan, y_gan)
93             # summarize loss on this batch
94             print('>%d, %d/%d, d_loss=%.3f, g_loss=%.3f' % (i + 1, j + 1, bat_per_epo, d_l
95             # evaluate the model performance, sometimes
96             #if (i+1) % 10 == 0:
97             summarize_performance(i, g_model, d_model, dataset, latent_dim)
98
99     return g_model

```

1 # size of the latent space

2 latent_dim = 100

```
2 latent_dim = 100
3 # train model
4 trained_generator = train(generator, discriminator, gan_model, mnist, latent_dim, 30)

>30, 161/273, d_loss=0.690, g_loss=0.694
>30, 162/273, d_loss=0.685, g_loss=0.709
>30, 163/273, d_loss=0.691, g_loss=0.726
>30, 164/273, d_loss=0.693, g_loss=0.742
>30, 165/273, d_loss=0.689, g_loss=0.751
>30, 166/273, d_loss=0.688, g_loss=0.748
>30, 167/273, d_loss=0.692, g_loss=0.729
>30, 168/273, d_loss=0.695, g_loss=0.705
>30, 169/273, d_loss=0.691, g_loss=0.679
>30, 170/273, d_loss=0.688, g_loss=0.660
>30, 171/273, d_loss=0.691, g_loss=0.653

>30, 172/273, d_loss=0.686, g_loss=0.658
>30, 173/273, d_loss=0.696, g_loss=0.683
>30, 174/273, d_loss=0.692, g_loss=0.703
>30, 175/273, d_loss=0.696, g_loss=0.722
>30, 176/273, d_loss=0.693, g_loss=0.740
>30, 177/273, d_loss=0.693, g_loss=0.743
>30, 178/273, d_loss=0.696, g_loss=0.744
>30, 179/273, d_loss=0.688, g_loss=0.739
>30, 180/273, d_loss=0.695, g_loss=0.718
>30, 181/273, d_loss=0.699, g_loss=0.703
>30, 182/273, d_loss=0.690, g_loss=0.692
>30, 183/273, d_loss=0.692, g_loss=0.670
>30, 184/273, d_loss=0.684, g_loss=0.663
>30, 185/273, d_loss=0.686, g_loss=0.658
>30, 186/273, d_loss=0.692, g_loss=0.666
>30, 187/273, d_loss=0.694, g_loss=0.683
>30, 188/273, d_loss=0.693, g_loss=0.720
>30, 189/273, d_loss=0.698, g_loss=0.749
>30, 190/273, d_loss=0.685, g_loss=0.762
>30, 191/273, d_loss=0.695, g_loss=0.746
>30, 192/273, d_loss=0.689, g_loss=0.735
>30, 193/273, d_loss=0.691, g_loss=0.719
>30, 194/273, d_loss=0.686, g_loss=0.687
>30, 195/273, d_loss=0.689, g_loss=0.667
>30, 196/273, d_loss=0.693, g_loss=0.649
>30, 197/273, d_loss=0.686, g_loss=0.661
>30, 198/273, d_loss=0.694, g_loss=0.675
>30, 199/273, d_loss=0.687, g_loss=0.693
>30, 200/273, d_loss=0.691, g_loss=0.698
>30, 201/273, d_loss=0.690, g_loss=0.726
>30, 202/273, d_loss=0.688, g_loss=0.732
>30, 203/273, d_loss=0.692, g_loss=0.739
>30, 204/273, d_loss=0.690, g_loss=0.730
>30, 205/273, d_loss=0.692, g_loss=0.720
>30, 206/273, d_loss=0.696, g_loss=0.695
>30, 207/273, d_loss=0.692, g_loss=0.684
>30, 208/273, d_loss=0.693, g_loss=0.681
>30, 209/273, d_loss=0.685, g_loss=0.683
>30, 210/273, d_loss=0.687, g_loss=0.693
>30, 211/273, d_loss=0.692, g_loss=0.689
>30, 212/273, d_loss=0.698, g_loss=0.690
>30, 213/273, d_loss=0.691, g_loss=0.688
```



```

>30, 214/273, d_loss=0.697, g_loss=0.693
>30, 215/273, d_loss=0.690, g_loss=0.696
>30, 216/273, d_loss=0.696, g_loss=0.710
>30, 217/273, d_loss=0.694, g_loss=0.715
>30, 218/273, d_loss=0.690, g_loss=0.740
>30, 219/273, d_loss=0.692, g_loss=0.730

```

```

1 ##### 30 epochs
2
3 # generate points in latent space as input for the generator
4 def generate_latent_points(latent_dim, n_samples):
5     # generate points in the latent space
6     x_input = randn(latent_dim * n_samples)
7     # reshape into a batch of inputs for the network
8     x_input = x_input.reshape(n_samples, latent_dim)
9     return x_input
10
11
12 # create and display a plot of generated images (reversed grayscale)
13 def display_plot(examples, n):
14     for i in range(n * n):
15         plt.subplot(n, n, 1 + i)
16         plt.axis('off')
17         plt.imshow(examples[i, :, :, 0], cmap='gray_r')
18     plt.show()
19
20
21 # load model
22 #model = load_model('generator_model_100.h5') #load the last seralized model (latest versi
23 # generate images
24 latent_points = generate_latent_points(100, 25)
25 # generate images
26 X = trained_generator.predict(latent_points)
27 # plot the result
28 display_plot(X, 5)

```



```

1
2 # generate points in latent space as input for the generator
3 def generate_latent_points(latent_dim, n_samples):

```

```

3 def generate_latent_points(latent_dim, n_samples):
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17     plt.show()
18
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20 # load model
21 #model = load_model('generator_model_100.h5') #load the last seralized model (latest versi
22 # generate images
23 latent_points = generate_latent_points(100, 25)
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25 X = trained_generator.predict(latent_points)
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```



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