CS156 (Introduction to AI), Spring 2022

Homework 10 submission

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

References and sources

+ Code + Text

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

Solution

Load libraries and set random number generator seed

```
import numpy as np
from tensorflow import keras
from tensorflow.keras.datasets.mnist import load_data
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import LeakyReLU
from tensorflow.keras.utils import plot_model
from tensorflow.keras.layers import Reshape
from tensorflow.keras.layers import Conv2DTranspose
```

```
from numpy import expand_dims
from numpy import ones
from numpy import zeros
from numpy.random import rand
from numpy.random import randint
from numpy.random import randn
from numpy import vstack
from numpy import asarray


np.random.seed(42)


input_shape = (28, 28, 1)

# load into train and test splits:
(x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

#combine into a single dataset
mnist = np.concatenate([x_train, x_test], axis=0)
mnist = expand_dims(mnist, axis=-1)

# Scale images to the [0, 1] range
mnist = mnist.astype("float32") / 255

mnist.shape
```

```
(70000, 28, 28, 1)
```

```
# define the standalone discriminator model
def define_discriminator(in_shape=(28,28,1)):
    model = Sequential()

    model.add(Conv2D(64, (3,3), strides=(2, 2), padding='same', input_shape=in_shape))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dropout(0.4))

    model.add(Conv2D(64, (3,3), strides=(2, 2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dropout(0.4))

    model.add(Conv2D(64, (5,5), strides=(1, 1), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dropout(0.4))

    model.add(Flatten())
    model.add(Dense(1, activation='sigmoid'))

    # compile model
    opt = Adam(learning_rate=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
```

```
    return model

# define the discriminator model
discriminator = define_discriminator()
discriminator.summary()
```

```
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
_________________________________________________________________
conv2d_2 (Conv2D)           (None, 7, 7, 64)          102464
_________________________________________________________________
leaky_re_lu_2 (LeakyReLU)   (None, 7, 7, 64)          0
_________________________________________________________________
dropout_2 (Dropout)         (None, 7, 7, 64)          0
_________________________________________________________________
flatten (Flatten)           (None, 3136)              0
_________________________________________________________________
dense (Dense)               (None, 1)                 3137
=================================================================
Total params: 143,169
Trainable params: 143,169
Non-trainable params: 0
_________________________________________________________________
```

```
# define the standalone generator model
def define_generator(latent_dim):
    model = Sequential()

    # foundation for 7x7 image
    n_nodes = 128 * 7 * 7

    model.add(Dense(n_nodes, input_dim=latent_dim))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Reshape((7, 7, 128)))

    # upsample to 14x14
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))

    # add additional Conv2DTranspose layer
    model.add(Conv2DTranspose(128, (1,1), strides=(1,1), padding='same'))
```

```
    model.add(LeakyReLU(alpha=0.2))

    # upsample to 28x28
    model.add(Conv2DTranspose(128, (4,4), strides=(2,2), padding='same'))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Conv2D(1, (7,7), activation='sigmoid', padding='same'))

    return model

# size of the latent space
latent_dim = 100

# define the discriminator model
generator = define_generator(latent_dim)
generator.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 6272)              633472
_________________________________________________________________
leaky_re_lu_3 (LeakyReLU)    (None, 6272)              0
_________________________________________________________________
reshape (Reshape)            (None, 7, 7, 128)         0
_________________________________________________________________
conv2d_transpose (Conv2DTran (None, 14, 14, 128)       262272
_________________________________________________________________
leaky_re_lu_4 (LeakyReLU)    (None, 14, 14, 128)       0
_________________________________________________________________
conv2d_transpose_1 (Conv2DTr (None, 14, 14, 128)       16512
_________________________________________________________________
leaky_re_lu_5 (LeakyReLU)    (None, 14, 14, 128)       0
_________________________________________________________________
conv2d_transpose_2 (Conv2DTr (None, 28, 28, 128)       262272
_________________________________________________________________
leaky_re_lu_6 (LeakyReLU)    (None, 28, 28, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 28, 28, 1)         6273
=================================================================
Total params: 1,180,801
Trainable params: 1,180,801
Non-trainable params: 0
_________________________________________________________________
```

```
# define the combined generator and discriminator model, for updating the generator
def define_gan(g_model, d_model):
    # make weights in the discriminator not trainable
    d_model.trainable = False

    # connect them
    model = Sequential()
```

```
    # add generator
    model.add(g_model)

    # add the discriminator
    model.add(d_model)

    # compile model
    opt = Adam(learning_rate=0.0002, beta_1=0.5)
    model.compile(loss='binary_crossentropy', optimizer=opt)

    return model

gan_model = define_gan(generator, discriminator)
gan_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
sequential_1 (Sequential)   (None, 28, 28, 1)         1180801

_________________________________________________________________
sequential (Sequential)     (None, 1)                 143169
=================================================================
Total params: 1,323,970
Trainable params: 1,180,801
Non-trainable params: 143,169
_________________________________________________________________
```

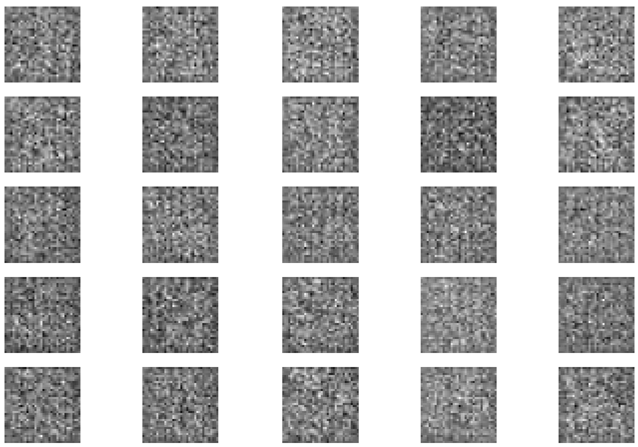
```
# without training, our generator model produces really bad images (they are not very good):

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
    return x_input

# use the generator to generate n fake examples, with class labels
def generate_fake_generator_samples(g_model, latent_dim, n_samples):
    # generate points in latent space
    x_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    X = g_model.predict(x_input)
    # create 'fake' class labels (0)
    y = zeros((n_samples, 1))
    return X, y

# generate samples
n_samples = 25
X, _ = generate_fake_generator_samples(generator, latent_dim, n_samples)
```

```
    # plot the generated samples
    for i in range(n_samples):
        # define subplot
        plt.subplot(5, 5, 1 + i)
        # turn off axis labels
        plt.axis('off')
        # plot single image
        plt.imshow(X[i, :, :, 0], cmap='gray_r')
    # show the figure
    plt.show()
```



```
# select real samples
def generate_real_samples(dataset, n_samples):
    # choose random instances
    ix = randint(0, dataset.shape[0], n_samples)
    # retrieve selected images
    X = dataset[ix]
    # generate 'real' class labels (1)
    y = ones((n_samples, 1))
    return X, y

# use the generator to generate n fake examples, with class labels
def generate_fake_samples(g_model, latent_dim, n_samples):
    # generate points in latent space
    x_input = generate_latent_points(latent_dim, n_samples)
    # predict outputs
    X = g_model.predict(x_input)
    # create 'fake' class labels (0)
    y = zeros((n_samples, 1))
    return X, y

# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
```

```
        return x_input

    # evaluate the discriminator, plot generated images, save generator model
    def summarize_performance(epoch, g_model, d_model, dataset, latent_dim, n_samples=100):
        # prepare real samples
        X_real, y_real = generate_real_samples(dataset, n_samples)
        # evaluate discriminator on real examples
        _, acc_real = d_model.evaluate(X_real, y_real, verbose=0)
        # prepare fake examples
        x_fake, y_fake = generate_fake_samples(g_model, latent_dim, n_samples)
        # evaluate discriminator on fake examples
        _, acc_fake = d_model.evaluate(x_fake, y_fake, verbose=0)
        # summarize discriminator performance
        print('>Accuracy real: %.0f%%, fake: %.0f%%' % (acc_real*100, acc_fake*100))
        # save plot
        #save_plot(x_fake, epoch)
        # save the generator model tile file
        #filename = 'generator_model_%03d.h5' % (epoch + 1)
        #g_model.save(filename)  # serializing the model: https://www.tensorflow.org/tutorials/ke

    # train the generator and discriminator together
    def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=256):
        bat_per_epo = int(dataset.shape[0] / n_batch)
        half_batch = int(n_batch / 2)
        # manually enumerate epochs
        for i in range(n_epochs):
            # enumerate batches over the training set
            for j in range(bat_per_epo):
                # get randomly selected 'real' samples
                X_real, y_real = generate_real_samples(dataset, half_batch)
                # generate 'fake' examples
                X_fake, y_fake = generate_fake_samples(g_model, latent_dim, half_batch)
                # create training set for the discriminator
                X, y = vstack((X_real, X_fake)), vstack((y_real, y_fake))
                # update discriminator model weights
                d_loss, _ = d_model.train_on_batch(X, y)
                # prepare points in latent space as input for the generator
                X_gan = generate_latent_points(latent_dim, n_batch)
                # create inverted labels for the fake samples
                y_gan = ones((n_batch, 1))
                # update the generator via the discriminator's error
                g_loss = gan_model.train_on_batch(X_gan, y_gan)
                # summarize loss on this batch
                print('>%d, %d/%d, d_loss=%.3f, g_loss=%.3f' % (i+1, j+1, bat_per_epo, d_loss, g_
            # evaluate the model performance, sometimes
            #if (i+1) % 10 == 0:
        summarize_performance(i, g_model, d_model, dataset, latent_dim)

        return g_model
```

```
# size of the latent space
latent_dim = 100

# train model
trained_generator = train(generator, discriminator, gan_model, mnist, latent_dim, 10)
```

```
>1, 1/273, d_loss=0.692, g_loss=0.691
>1, 2/273, d_loss=0.690, g_loss=0.717
>1, 3/273, d_loss=0.681, g_loss=0.741
>1, 4/273, d_loss=0.669, g_loss=0.762
>1, 5/273, d_loss=0.658, g_loss=0.776
>1, 6/273, d_loss=0.650, g_loss=0.789
>1, 7/273, d_loss=0.644, g_loss=0.806
>1, 8/273, d_loss=0.633, g_loss=0.822
>1, 9/273, d_loss=0.624, g_loss=0.821
>1, 10/273, d_loss=0.613, g_loss=0.827
>1, 11/273, d_loss=0.601, g_loss=0.816
>1, 12/273, d_loss=0.583, g_loss=0.805
>1, 13/273, d_loss=0.561, g_loss=0.786
>1, 14/273, d_loss=0.536, g_loss=0.772
>1, 15/273, d_loss=0.515, g_loss=0.754
>1, 16/273, d_loss=0.496, g_loss=0.750
>1, 17/273, d_loss=0.495, g_loss=0.782
>1, 18/273, d_loss=0.481, g_loss=0.857
>1, 19/273, d_loss=0.446, g_loss=0.964
>1, 20/273, d_loss=0.456, g_loss=0.987
>1, 21/273, d_loss=0.461, g_loss=0.920
>1, 22/273, d_loss=0.447, g_loss=0.817
>1, 23/273, d_loss=0.442, g_loss=0.764
>1, 24/273, d_loss=0.439, g_loss=0.718
>1, 25/273, d_loss=0.443, g_loss=0.676
>1, 26/273, d_loss=0.485, g_loss=0.687
>1, 27/273, d_loss=0.484, g_loss=0.749
>1, 28/273, d_loss=0.463, g_loss=0.803
>1, 29/273, d_loss=0.484, g_loss=0.746
>1, 30/273, d_loss=0.495, g_loss=0.686
>1, 31/273, d_loss=0.526, g_loss=0.616
>1, 32/273, d_loss=0.559, g_loss=0.607
>1, 33/273, d_loss=0.584, g_loss=0.661
>1, 34/273, d_loss=0.564, g_loss=0.748
>1, 35/273, d_loss=0.596, g_loss=0.726
>1, 36/273, d_loss=0.619, g_loss=0.592
>1, 37/273, d_loss=0.638, g_loss=0.518
>1, 38/273, d_loss=0.712, g_loss=0.625
>1, 39/273, d_loss=0.692, g_loss=0.727
>1, 40/273, d_loss=0.721, g_loss=0.618
>1, 41/273, d_loss=0.729, g_loss=0.581
>1, 42/273, d_loss=0.733, g_loss=0.612
>1, 43/273, d_loss=0.736, g_loss=0.734
>1, 44/273, d_loss=0.767, g_loss=0.703
>1, 45/273, d_loss=0.756, g_loss=0.641
>1, 46/273, d_loss=0.748, g_loss=0.681
>1, 47/273, d_loss=0.731, g_loss=0.758
>1, 48/273, d_loss=0.728, g_loss=0.782
>1, 49/273, d_loss=0.694, g_loss=0.801
```

```
>1, 50/273, d_loss=0.674, g_loss=0.794
>1, 51/273, d_loss=0.651, g_loss=0.830
>1, 52/273, d_loss=0.642, g_loss=0.825
>1, 53/273, d_loss=0.635, g_loss=0.987
>1, 54/273, d_loss=0.615, g_loss=1.147
>1, 55/273, d_loss=0.618, g_loss=1.090
>1, 56/273, d_loss=0.618, g_loss=0.981
>1, 57/273, d_loss=0.646, g_loss=1.285
```

```
# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_samples):
    # generate points in the latent space
    x_input = randn(latent_dim * n_samples)
    # reshape into a batch of inputs for the network
    x_input = x_input.reshape(n_samples, latent_dim)
    return x_input

# create and display a plot of generated images (reversed grayscale)
def display_plot(examples, n):
    for i in range(n * n):
        plt.subplot(n, n, 1 + i)
        plt.axis('off')
        plt.imshow(examples[i, :, :, 0], cmap='gray_r')
    plt.show()

# load model
#model = load_model('generator_model_100.h5') #load the last seralized model (latest version
# generate images
latent_points = generate_latent_points(100, 25)
# generate images
X = trained_generator.predict(latent_points)
# plot the result
display_plot(X, 5)
```