

4 Additional Functions with Keras 2

- 4.1 LSTM with MNIST
- 4.2 GAN with MNIST

4.1 LSTM with MNIST

(1) 데이터셋

```
In [1]: import tensorflow.keras.utils as utils
from tensorflow.keras import datasets
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import LSTM, Dense

import os
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

In [2]: (X_train, Y_train), (X_test, Y_test) = datasets.mnist.load_data()
X_train_norm = X_train.astype('float32')/255.0
X_test_norm = X_test.astype('float32')/255.0
Y_train_onehot = utils.to_categorical(Y_train)
Y_test_onehot = utils.to_categorical(Y_test)

print(X_train_norm.shape, Y_train_onehot.shape)
n_in = X_train.shape[1:]
n_out = Y_train_onehot.shape[-1]

(60000, 28, 28) (60000, 10)
```

(2) 모델링

```
In [3]: def lstm(n_in, n_out):
# Coding Time
    model = Sequential()
    model.add(LSTM(30, input_shape=n_in))
    model.add(Dense(n_out, activation='softmax'))
    return model

model = lstm(n_in, n_out)
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 30)	7080
dense (Dense)	(None, 10)	310

Total params: 7,390
Trainable params: 7,390
Non-trainable params: 0

(3) 모델의 학습과정 설정

```
In [4]: model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
```

(4) 모델 학습

```
In [5]: from tensorflow.keras.callbacks import EarlyStopping
# Coding Time
earlystopper = EarlyStopping(monitor='val_accuracy', patience=7, verbose=1, mode='auto', restore_best_weights=True)
history = model.fit(X_train_norm, Y_train_onehot, batch_size=128, epochs=50, validation_split=0.2, callbacks = [earlystopper])
```

Epoch 1/50
375/375 [=====] - 5s 8ms/step - loss: 1.1792 - accuracy: 0.6231 - val_loss: 0.6155 - val_accuracy: 0.8192
Epoch 2/50
375/375 [=====] - 2s 6ms/step - loss: 0.4904 - accuracy: 0.8541 - val_loss: 0.3766 - val_accuracy: 0.8913
Epoch 3/50
375/375 [=====] - 2s 6ms/step - loss: 0.3345 - accuracy: 0.9032 - val_loss: 0.2773 - val_accuracy: 0.9226
Epoch 4/50
375/375 [=====] - 2s 6ms/step - loss: 0.2614 - accuracy: 0.9243 - val_loss: 0.2302 - val_accuracy: 0.9339
Epoch 5/50
375/375 [=====] - 2s 6ms/step - loss: 0.2190 - accuracy: 0.9375 - val_loss: 0.2008 - val_accuracy: 0.9448
Epoch 6/50
375/375 [=====] - 2s 7ms/step - loss: 0.1907 - accuracy: 0.9450 - val_loss: 0.1739 - val_accuracy: 0.9495
Epoch 7/50
375/375 [=====] - 2s 6ms/step - loss: 0.1671 - accuracy: 0.9518 - val_loss: 0.1695 - val_accuracy: 0.9499
Epoch 8/50
375/375 [=====] - 2s 6ms/step - loss: 0.1500 - accuracy: 0.9567 - val_loss: 0.1549 - val_accuracy: 0.9561
Epoch 9/50
375/375 [=====] - 2s 6ms/step - loss: 0.1361 - accuracy: 0.9599 - val_loss: 0.1406 - val_accuracy: 0.9607
Epoch 10/50
375/375 [=====] - 2s 6ms/step - loss: 0.1239 - accuracy: 0.9640 - val_loss: 0.1242 - val_accuracy: 0.9645
Epoch 11/50
375/375 [=====] - 2s 6ms/step - loss: 0.1146 - accuracy: 0.9669 - val_loss: 0.1250 - val_accuracy: 0.9650
Epoch 12/50
375/375 [=====] - 2s 6ms/step - loss: 0.1077 - accuracy: 0.9681 - val_loss: 0.1103 - val_accuracy: 0.9696
Epoch 13/50
375/375 [=====] - 2s 6ms/step - loss: 0.1002 - accuracy: 0.9703 - val_loss: 0.1140 - val_accuracy: 0.9672
Epoch 14/50
375/375 [=====] - 2s 6ms/step - loss: 0.0928 - accuracy: 0.9722 - val_loss: 0.1041 - val_accuracy: 0.9700
Epoch 15/50
375/375 [=====] - 2s 6ms/step - loss: 0.0881 - accuracy: 0.9731 - val_loss: 0.0980 - val_accuracy: 0.9719
Epoch 16/50
375/375 [=====] - 2s 6ms/step - loss: 0.0830 - accuracy: 0.9749 - val_loss: 0.1006 - val_accuracy: 0.9712
Epoch 17/50
375/375 [=====] - 2s 6ms/step - loss: 0.0780 - accuracy: 0.9766 - val_loss: 0.1003 - val_accuracy: 0.9733
Epoch 18/50
375/375 [=====] - 2s 6ms/step - loss: 0.0748 - accuracy: 0.9771 - val_loss: 0.1051 - val_accuracy: 0.9693
Epoch 19/50
375/375 [=====] - 2s 6ms/step - loss: 0.0711 - accuracy: 0.9789 - val_loss: 0.1044 - val_accuracy: 0.9711
Epoch 20/50
375/375 [=====] - 2s 6ms/step - loss: 0.0686 - accuracy: 0.9790 - val_loss: 0.1042 - val_accuracy: 0.9717
Epoch 21/50
375/375 [=====] - 2s 6ms/step - loss: 0.0647 - accuracy: 0.9804 - val_loss: 0.0849 - val_accuracy: 0.9769
Epoch 22/50
375/375 [=====] - 2s 6ms/step - loss: 0.0629 - accuracy: 0.9813 - val_loss: 0.0912 - val_accuracy: 0.9744
Epoch 23/50
375/375 [=====] - 2s 6ms/step - loss: 0.0600 - accuracy: 0.9818 - val_loss: 0.0910 - val_accuracy: 0.9755
Epoch 24/50
375/375 [=====] - 2s 6ms/step - loss: 0.0578 - accuracy: 0.9826 - val_loss: 0.0916 - val_accuracy: 0.9743
Epoch 25/50
375/375 [=====] - 2s 6ms/step - loss: 0.0559 - accuracy: 0.9829 - val_loss: 0.0835 - val_accuracy: 0.9772
Epoch 26/50
375/375 [=====] - 2s 6ms/step - loss: 0.0536 - accuracy: 0.9836 - val_loss: 0.0943 - val_accuracy: 0.9749
Epoch 27/50
375/375 [=====] - 2s 6ms/step - loss: 0.0515 - accuracy: 0.9846 - val_loss: 0.0916 - val_accuracy: 0.9748
Epoch 28/50
375/375 [=====] - 2s 6ms/step - loss: 0.0494 - accuracy: 0.9848 - val_loss: 0.0871 - val_accuracy: 0.9759
Epoch 29/50
375/375 [=====] - 2s 6ms/step - loss: 0.0485 - accuracy: 0.9854 - val_loss: 0.0918 - val_accuracy: 0.9756
Epoch 30/50
375/375 [=====] - 2s 6ms/step - loss: 0.0466 - accuracy: 0.9854 - val_loss: 0.0838 - val_accuracy: 0.9773
Epoch 31/50
375/375 [=====] - 2s 6ms/step - loss: 0.0454 - accuracy: 0.9861 - val_loss: 0.0861 - val_accuracy: 0.9773
Epoch 32/50
375/375 [=====] - 2s 6ms/step - loss: 0.0442 - accuracy: 0.9867 - val_loss: 0.0826 - val_accuracy: 0.9778
Epoch 33/50
375/375 [=====] - 2s 6ms/step - loss: 0.0427 - accuracy: 0.9872 - val_loss: 0.0918 - val_accuracy: 0.9770
Epoch 34/50
375/375 [=====] - 2s 6ms/step - loss: 0.0411 - accuracy: 0.9870 - val_loss: 0.0856 - val_accuracy: 0.9771
Epoch 35/50
375/375 [=====] - 2s 6ms/step - loss: 0.0398 - accuracy: 0.9879 - val_loss: 0.0797 - val_accuracy: 0.9784
Epoch 36/50
375/375 [=====] - 2s 6ms/step - loss: 0.0390 - accuracy: 0.9884 - val_loss: 0.0887 - val_accuracy: 0.9772
Epoch 37/50
375/375 [=====] - 2s 6ms/step - loss: 0.0387 - accuracy: 0.9888 - val_loss: 0.0851 - val_accuracy: 0.9781
Epoch 38/50
375/375 [=====] - 2s 6ms/step - loss: 0.0372 - accuracy: 0.9888 - val_loss: 0.0851 - val_accuracy: 0.9772
Epoch 39/50
375/375 [=====] - 2s 6ms/step - loss: 0.0367 - accuracy: 0.9890 - val_loss: 0.0822 - val_accuracy: 0.9790
Epoch 40/50
375/375 [=====] - 2s 6ms/step - loss: 0.0358 - accuracy: 0.9894 - val_loss: 0.0821 - val_accuracy: 0.9796
Epoch 41/50
375/375 [=====] - 2s 6ms/step - loss: 0.0348 - accuracy: 0.9895 - val_loss: 0.0849 - val_accuracy: 0.9772
Epoch 42/50
375/375 [=====] - 2s 6ms/step - loss: 0.0333 - accuracy: 0.9898 - val_loss: 0.0806 - val_accuracy: 0.9797
Epoch 43/50
375/375 [=====] - 2s 6ms/step - loss: 0.0326 - accuracy: 0.9900 - val_loss: 0.0883 - val_accuracy: 0.9778
Epoch 44/50
375/375 [=====] - 2s 6ms/step - loss: 0.0314 - accuracy: 0.9903 - val_loss: 0.0859 - val_accuracy: 0.9791
Epoch 45/50
375/375 [=====] - 2s 6ms/step - loss: 0.0305 - accuracy: 0.9907 - val_loss: 0.0876 - val_accuracy: 0.9772
Epoch 46/50
375/375 [=====] - 2s 6ms/step - loss: 0.0299 - accuracy: 0.9910 - val_loss: 0.0844 - val_accuracy: 0.9793
Epoch 47/50
375/375 [=====] - 2s 6ms/step - loss: 0.0295 - accuracy: 0.9909 - val_loss: 0.0779 - val_accuracy: 0.9807
Epoch 48/50
375/375 [=====] - 2s 6ms/step - loss: 0.0285 - accuracy: 0.9914 - val_loss: 0.0806 - val_accuracy: 0.9788
Epoch 49/50
375/375 [=====] - 2s 6ms/step - loss: 0.0284 - accuracy: 0.9912 - val_loss: 0.0800 - val_accuracy: 0.9793
Epoch 50/50
375/375 [=====] - 2s 6ms/step - loss: 0.0273 - accuracy: 0.9916 - val_loss: 0.0870 - val_accuracy: 0.9786

```
In [6]: fig, loss_ax = plt.subplots()
acc_ax = loss_ax.twinx()

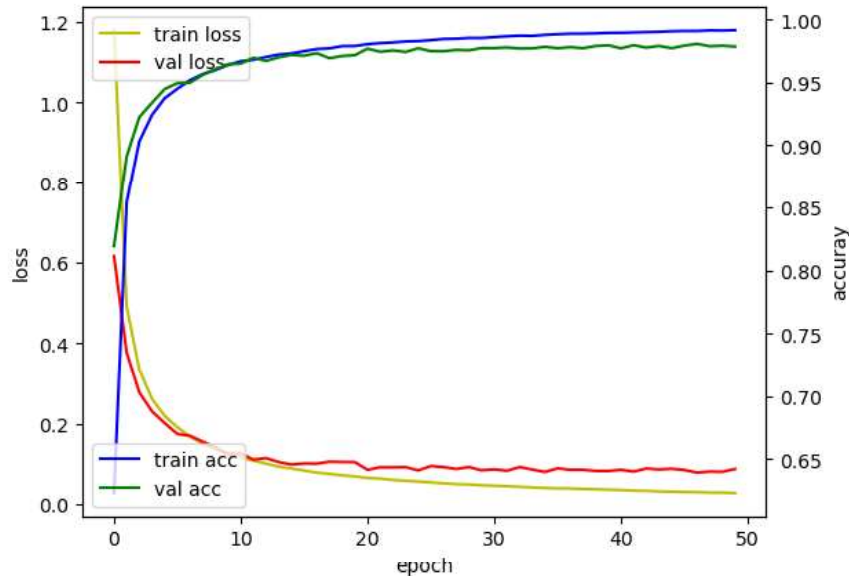
loss_ax.plot(history.history['loss'], 'y', label='train loss')
loss_ax.plot(history.history['val_loss'], 'r', label='val loss')

acc_ax.plot(history.history['accuracy'], 'b', label='train acc')
acc_ax.plot(history.history['val_accuracy'], 'g', label='val acc')

loss_ax.set_xlabel('epoch')
loss_ax.set_ylabel('loss')
acc_ax.set_ylabel('accuracy')

loss_ax.legend(loc='upper left')
acc_ax.legend(loc='lower left')

plt.show()
```



(5) 모델 평가하기

```
In [7]: loss_and_accuracy = model.evaluate(X_test_norm, Y_test_onehot, batch_size=128, verbose=1)
print('loss : %.4f, accuracy : %.4f'%(loss_and_accuracy[0], loss_and_accuracy[1]))

79/79 [=====] - 0s 4ms/step - loss: 0.0777 - accuracy: 0.9805
loss : 0.0777, accuracy : 0.9805
```

4.2 GAN with MNIST

```
In [8]: import os
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
```

```
In [9]: from keras.layers import Input, Dense, Dropout, LeakyReLU
from keras.models import Model, Sequential
from keras.datasets import mnist
from tensorflow.keras.optimizers import Adam
from keras import initializers
```

```
In [10]: # 실험을 재현하고 동일한 결과를 얻을 수 있는지 확인하기 위해 seed 를 설정합니다.
np.random.seed(10)

# 우리의 랜덤 노이즈 벡터의 차원을 설정합니다.
random_dim = 100
```

(1) 데이터셋

```
In [11]: def load_mnist_data():
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train = (x_train.astype(np.float32) - 127.5)/127.5 # -1~1 사이의 값
x_train = x_train.reshape(60000, 784)
return (x_train, y_train, x_test, y_test) # Label에 대한 진행이 없어도 됨
```

(2-3) 모델링 / 모델 학습과정 설정

```
In [12]: # Adam Optimizer를 사용합니다.
def get_optimizer():
    return Adam(learning_rate=0.0002, beta_1=0.5)

# Generator 만들기
def get_generator(optimizer):
    generator = Sequential()
    generator.add(Dense(256, input_dim=random_dim, kernel_initializer=initializers.RandomNormal(stddev=0.02)))
    generator.add(LeakyReLU(0.2))

    generator.add(Dense(512))
```

```

generator.add(LeakyReLU(0.2))

generator.add(Dense(1024))
generator.add(LeakyReLU(0.2))

generator.add(Dense(784, activation='tanh'))
generator.compile(loss='binary_crossentropy', optimizer=optimizer)
return generator

# Discriminator 만들기
def get_discriminator(optimizer):
    discriminator = Sequential()
    discriminator.add(Dense(1024, input_dim=784, kernel_initializer=initializers.RandomNormal(stddev=0.02)))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(512))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(256))
    discriminator.add(LeakyReLU(0.2))
    discriminator.add(Dropout(0.3))

    discriminator.add(Dense(1, activation='sigmoid'))
    discriminator.compile(loss='binary_crossentropy', optimizer=optimizer)
    return discriminator

```

```

In [13]: def get_gan_network(discriminator, random_dim, generator, optimizer):
# Coding Time
discriminator.trainable = False # Generator와 Discriminator를 동시에 학습시 trainable을 False로 설정

gan_input = Input(shape=(random_dim,)) # gan_input : 노이즈(100 차원)

x = generator(gan_input) # X:이미지

gan_output = discriminator(x) # gan_output : 이미지가 진짜인지 아닌지에 대한 확률

gan = Model(inputs=gan_input, outputs=gan_output)
gan.compile(loss='binary_crossentropy', optimizer=optimizer)
return gan

```

```

In [14]: # 생성된 MNIST 이미지 출력
def plot_generated_images(epoch, generator, examples=100, dim=(10, 10), figsize=(10, 10)):
    noise = np.random.normal(0, 1, size=[examples, random_dim])
    generated_images = generator.predict(noise)
    generated_images = generated_images.reshape(examples, 28, 28)

    plt.figure(figsize=figsize)
    for i in range(generated_images.shape[0]):
        plt.subplot(dim[0], dim[1], i+1)
        plt.imshow(generated_images[i], interpolation='nearest', cmap='gray_r')
        plt.axis('off')
    plt.tight_layout()
    plt.savefig('gan_generated_image_epoch_%d.png' % epoch)

```

(4) 모델 학습

```

In [15]: def train(epochs=1, batch_size=128):
# train 데이터와 test 데이터를 가져옵니다.
x_train, y_train, x_test, y_test = load_mnist_data()

# train 데이터를 128 사이즈의 batch 로 나눕니다.
batch_count = x_train.shape[0] // batch_size

# 우리의 GAN 네트워크를 만듭니다.
adam = get_optimizer()
generator = get_generator(adam)
discriminator = get_discriminator(adam)
gan = get_gan_network(discriminator, random_dim, generator, adam)

for e in range(1, epochs+1):
    print('-'*15, 'Epoch %d' % e, '-'*15)
    for _ in tqdm(range(batch_count)):
        # Coding Time
        # 입력으로 사용할 random 노이즈와 이미지를 가져옵니다.
        noise = np.random.normal(0, 1, size=[batch_size, random_dim])
        image_batch = x_train[np.random.randint(0, x_train.shape[0], size=batch_size)]

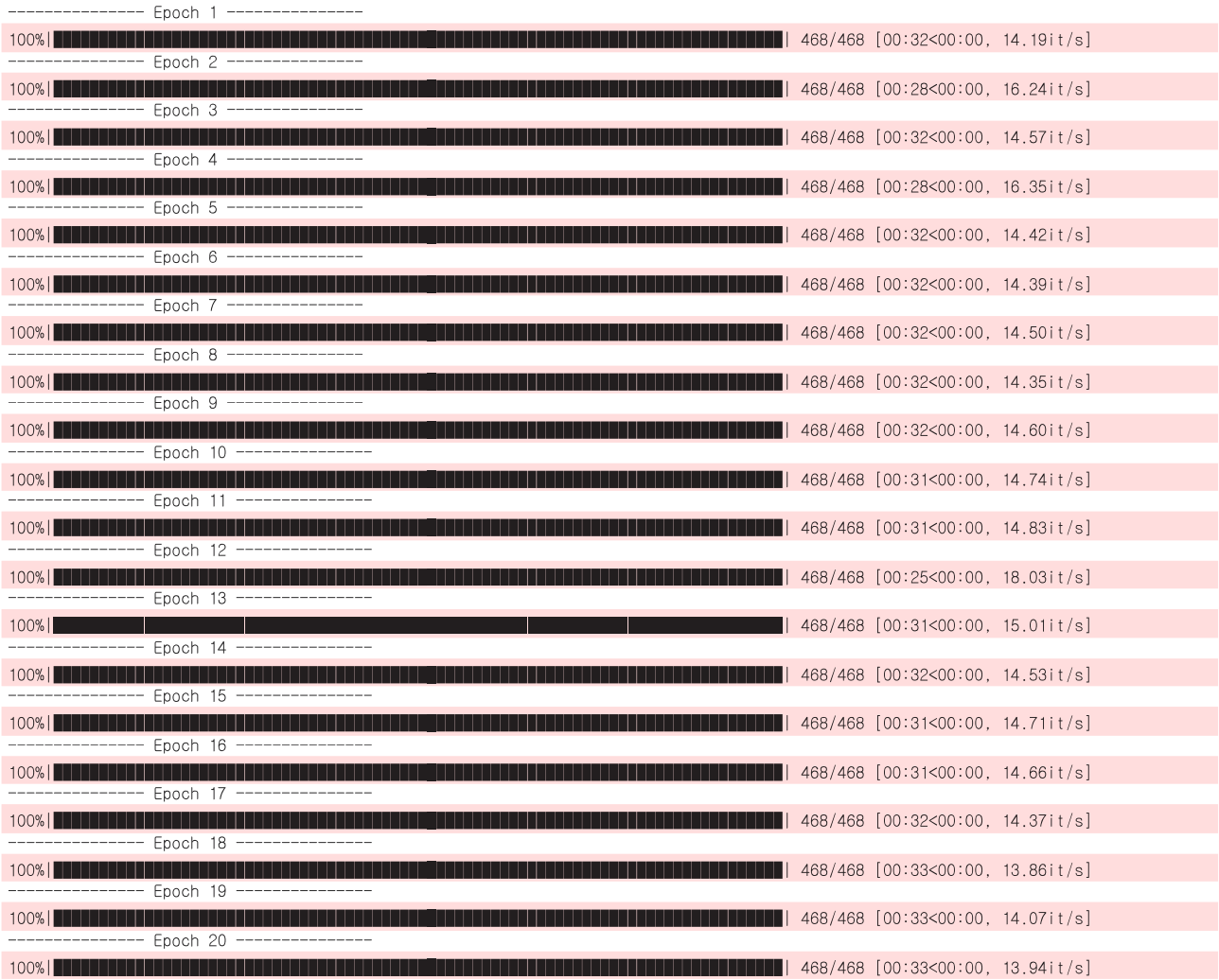
        # Generator를 통해 MNIST 이미지를 생성
        generated_images = generator.predict(noise, verbose =0)
        X = np.concatenate([image_batch, generated_images])

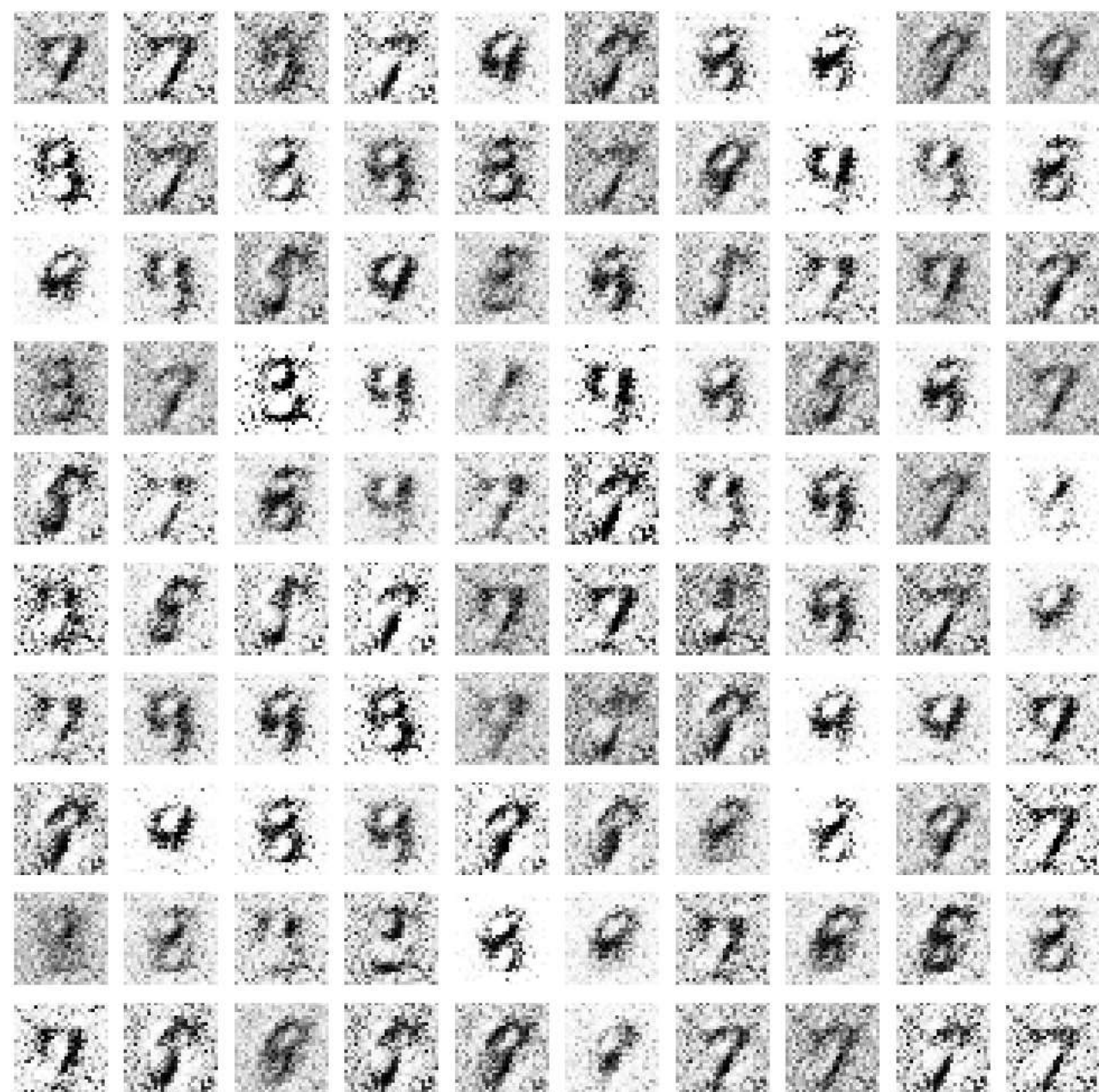
        # Discriminator 학습
        y_dis = np.zeros(2*batch_size)
        y_dis[:batch_size] = 0.9
        discriminator.trainable = True
        discriminator.train_on_batch(X, y_dis)

        # Generator 학습
        noise = np.random.normal(0, 1, size=[batch_size, random_dim])
        y_gen = np.ones(batch_size)
        discriminator.trainable = False
        gan.train_on_batch(noise, y_gen)
    if e == 1 or e % 20 == 0:
        plot_generated_images(e, generator)

```

```
In [16]: train(20, 128)
```





7	6	2	8	1	1	5	4	4	1
1	1	7	5	3	2	3	7	8	9
1	3	3	0	6	7	9	0	4	7
6	9	3	1	9	4	9	1	7	0
3	2	2	9	0	6	8	9	3	9
7	6	1	7	7	8	9	3	1	1
6	9	6	8	9	5	8	7	1	9
9	4	2	6	9	5	9	9	1	9
2	9	8	3	2	2	1	4	2	0
6	6	7	2	5	1	6	2	2	7