DataLab Cup 3: Reverse Image Caption

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Text to Image

Platform: Kaggle

Overview

In this work, we are interested in translating text in the form of single-sentence human-written descriptions directly into image pixels. For example, "**this flower has petals that are yellow and has a ruffled stamen**" and "**this pink and yellow flower has a beautiful yellow center with many stamens**". You have to develop a novel deep architecture and GAN formulation to effectively translate visual concepts from characters to pixels.

More specifically, given a set of texts, your task is to generate reasonable images with size 64x64x3 to illustrate the corresponding texts. Here we use Oxford-102 flower dataset and its paired texts as our training dataset.

this flower has petals that are yellow and has a ruffled stamen

this pink and yellow flower has a beautiful yellow center with many stamens

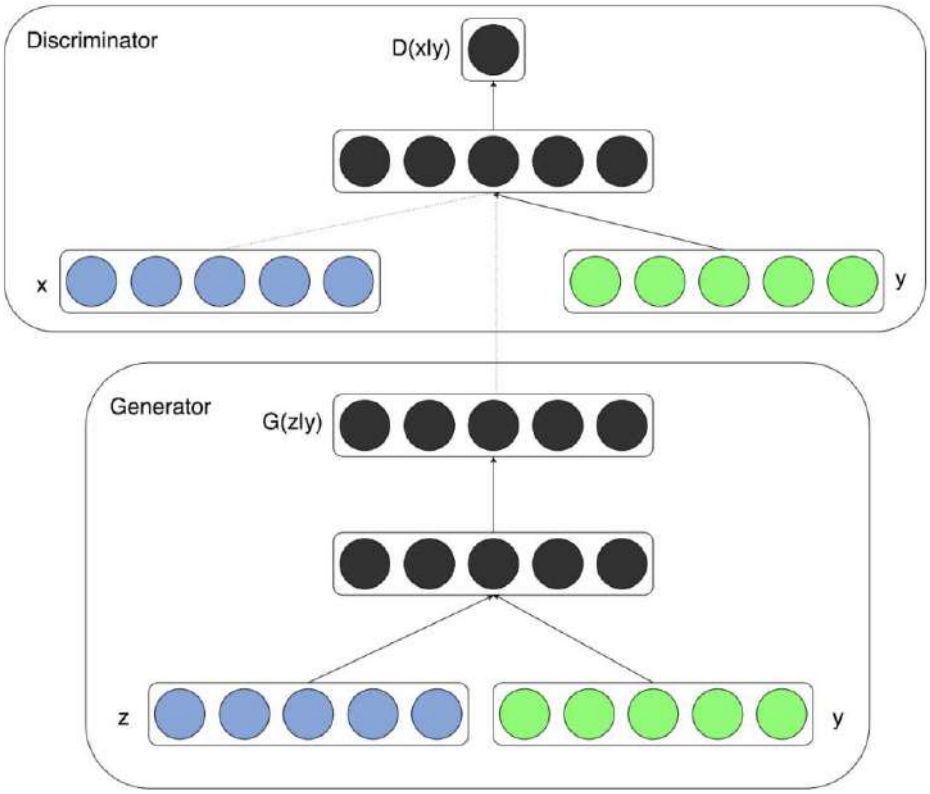
- 7370 images as training set, where each images is annotated with at most 10 texts.
- 819 texts for testing. You must generate 1 64x64x3 image for each text.

Conditional GAN

Given a text, in order to generate the image which can illustrate it, our model must meet several requirements:

1. Our model should have ability to understand and extract the meaning of given texts.
    - Use RNN or other language model, such as BERT, ELMo or XLNet, to capture the meaning of text.
2. Our model should be able to generate image.
    - Use GAN to generate high quality image.
3. GAN-generated image should illustrate the text.
    - Use conditional-GAN to generate image conditioned on given text.

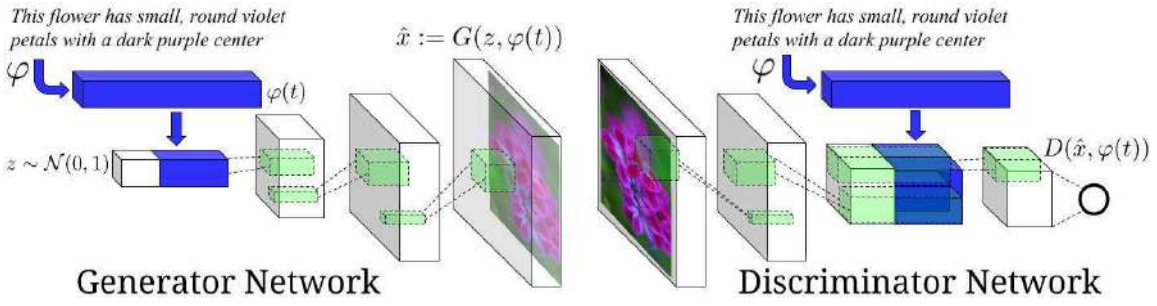
Generative adversarial nets can be extended to a conditional model if both the generator and discriminator are conditioned on some extra information y. We can perform the conditioning by feeding y into both the discriminator and generator as additional input layer.



There are two motivations for using some extra information in a GAN model:

1. Improve GAN.
2. Generate targeted image.

Additional information that is correlated with the input images, such as class labels, can be used to improve the GAN. This improvement may come in the form of more stable training, faster training, and/or generated images that have better quality.



In [ ]:
```
from __future__ import absolute_import, division, print_function, unicode_literals
import tensorflow as tf
from tensorflow.keras import layers
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
import string
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import PIL
import random
import time
from pathlib import Path

import re
from IPython import display
```

In [ ]:
```
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    try:
        # Restrict TensorFlow to only use the first GPU
        tf.config.experimental.set_visible_devices(gpus[0], 'GPU')

        # Currently, memory growth needs to be the same across GPUs
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        logical_gpus = tf.config.experimental.list_logical_devices('GPU')
        print(len(gpus), "Physical GPUs,", len(logical_gpus), "Logical GPUs")
    except RuntimeError as e:
        # Memory growth must be set before GPUs have been initialized
        print(e)
```

Preprocess Text

Since dealing with raw string is inefficient, we have done some data preprocessing for you:

- Delete text over `MAX_SEQ_LENGTH (20)`.
- Delete all puntuation in the texts.
- Encode each vocabulary in `dictionary/vocab.npy`.
- Represent texts by a sequence of integer IDs.
- Replace rare words by `<RARE>` token to reduce vocabulary size for more efficient training.
- Add padding as `<PAD>` to each text to make sure all of them have equal length to `MAX_SEQ_LENGTH (20)`.

It is worth knowing that there is no necessary to append `<ST>` and `<ED>` to each text because we don't need to generate any sequence in this task.

To make sure correctness of encoding of the original text, we can decode sequence vocabulary IDs by looking up the vocabulary dictionary:

- `dictionary/word2Id.npy` is a numpy array mapping word to id.
- `dictionary/id2Word.npy` is a numpy array mapping id back to word.

In [3]:
```
dictionary_path = './dictionary'
vocab = np.load(dictionary_path + '/vocab.npy')
print('there are {} vocabularies in total'.format(len(vocab)))

word2Id_dict = dict(np.load(dictionary_path + '/word2Id.npy'))
id2word_dict = dict(np.load(dictionary_path + '/id2Word.npy'))
print('Word to id mapping, for example: %s -> %s' % ('flower', word2Id_dict['flower
print('Id to word mapping, for example: %s -> %s' % ('1', id2word_dict['1']))
print('Tokens: <PAD>: %s; <RARE>: %s' % (word2Id_dict['<PAD>'], word2Id_dict['<RARE
```

```
there are 5427 vocabularies in total
Word to id mapping, for example: flower -> 1
Id to word mapping, for example: 1 -> flower
Tokens: <PAD>: 5427; <RARE>: 5428
```

In [4]:
```
def sent2IdList(line, MAX_SEQ_LENGTH=20):
    MAX_SEQ_LIMIT = MAX_SEQ_LENGTH
    padding = 0

    # data preprocessing, remove all puntuation in the texts
    prep_line = re.sub('[%s]' % re.escape(string.punctuation), ' ', line.rstrip())
    prep_line = prep_line.replace('-', ' ')
    prep_line = prep_line.replace('-', ' ')
    prep_line = prep_line.replace('  ', ' ')
    prep_line = prep_line.replace('.', '')
    tokens = prep_line.split(' ')
    tokens = [
        tokens[i] for i in range(len(tokens))
        if tokens[i] != ' ' and tokens[i] != ''
    ]
    l = len(tokens)
    padding = MAX_SEQ_LIMIT - l

    # make sure length of each text is equal to MAX_SEQ_LENGTH, and replace the les
    for i in range(padding):
        tokens.append('<PAD>')
    line = [
        word2Id_dict[tokens[k]]
        if tokens[k] in word2Id_dict else word2Id_dict['<RARE>']
        for k in range(len(tokens))
    ]

    return line

text = "the flower shown has yellow anther red pistil and bright red petals."
print(text)
print(sent2IdList(text))
```

```
the flower shown has yellow anther red pistil and bright red petals.
['9', '1', '82', '5', '11', '70', '20', '31', '3', '29', '20', '2', '5427', '542
7', '5427', '5427', '5427', '5427', '5427', '5427']
```

Dataset

For training, the following files are in dataset folder:

- `./dataset/text2ImgData.pkl` is a pandas dataframe with attribute 'Captions' and 'ImagePath'.
  - 'Captions' : A list of text id list contain 1 to 10 captions.
  - 'ImagePath': Image path that store paired image.
- `./102flowers/` is the directory containing all training images.
- `./dataset/testData.pkl` is a pandas a dataframe with attribute 'ID' and 'Captions', which contains testing data.

In [5]:
```
data_path = './dataset'
df = pd.read_pickle(data_path + '/text2ImgData.pkl')
num_training_sample = len(df)
n_images_train = num_training_sample
print('There are %d image in training data' % (n_images_train))
```

```
There are 7370 image in training data
```

In [6]:
```
df.head(5)
```

Out[6]:

ID	Captions	ImagePath
6734	[[9, 2, 17, 9, 1, 6, 14, 13, 18, 3, 41, 8, 11,...	./102flowers/image_06734.jpg
6736	[[4, 1, 5, 12, 2, 3, 11, 31, 28, 68, 106, 132,...	./102flowers/image_06736.jpg
6737	[[9, 2, 27, 4, 1, 6, 14, 7, 12, 19, 5427, 5427...	./102flowers/image_06737.jpg
6738	[[9, 1, 5, 8, 54, 16, 38, 7, 12, 116, 325, 3, ...	./102flowers/image_06738.jpg
6739	[[4, 12, 1, 5, 29, 11, 19, 7, 26, 70, 5427, 54...	./102flowers/image_06739.jpg

Create Dataset by Dataset API

In [7]:
```
# in this competition, you have to generate image in size 64x64x3
IMAGE_HEIGHT = 64
IMAGE_WIDTH = 64
IMAGE_CHANNEL = 3

def training_data_generator(caption, image_path):
    # load in the image according to image path
    img = tf.io.read_file(image_path)
    img = tf.image.decode_image(img, channels=3)
    img = tf.image.convert_image_dtype(img, tf.float32)
    img.set_shape([None, None, 3])
    img = tf.image.resize(img, size=[IMAGE_HEIGHT, IMAGE_WIDTH])
    img.set_shape([IMAGE_HEIGHT, IMAGE_WIDTH, IMAGE_CHANNEL])
    caption = tf.cast(caption, tf.int32)

    return img, caption

def dataset_generator(filenames, batch_size, data_generator):
    # load the training data into two NumPy arrays
    df = pd.read_pickle(filenames)
    captions = df['Captions'].values
    caption = []
    # each image has 1 to 10 corresponding captions
    # we choose one of them randomly for training
    for i in range(len(captions)):
        caption.append(random.choice(captions[i]))
```

```
    caption = np.asarray(caption)
    caption = caption.astype(np.int)
    image_path = df['ImagePath'].values

    # assume that each row of `features` corresponds to the same row as `labels`.
    assert caption.shape[0] == image_path.shape[0]

    dataset = tf.data.Dataset.from_tensor_slices((caption, image_path))
    dataset = dataset.map(data_generator, num_parallel_calls=tf.data.experimental.A
    dataset = dataset.shuffle(len(caption)).batch(batch_size, drop_remainder=True)
    dataset = dataset.prefetch(buffer_size=tf.data.experimental.AUTOTUNE)

    return dataset
```

In [8]:
```
BATCH_SIZE = 64
dataset = dataset_generator(data_path + '/text2ImgData.pkl', BATCH_SIZE, training_d
```

```
/tmp/ipykernel_29626/3313815207.py:28: DeprecationWarning: `np.int` is a deprecate
d alias for the builtin `int`. To silence this warning, use `int` by itself. Doing
this will not modify any behavior and is safe. When replacing `np.int`, you may wi
sh to use e.g. `np.int64` or `np.int32` to specify the precision. If you wish to r
eview your current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdoc
s/release/1.20.0-notes.html#deprecations
  caption = caption.astype(np.int)
```

Conditional GAN Model

As mentioned above, there are three models in this task, text encoder, generator and discriminator.

Text Encoder

A RNN encoder that captures the meaning of input text.

- Input: text, which is a list of ids.
- Output: embedding, or hidden representation of input text.

In [9]:
```
class TextEncoder(tf.keras.Model):
    """
    Encode text (a caption) into hidden representation
    input: text, which is a list of ids
    output: embedding, or hidden representation of input text in dimension of RNN_H
    """
    def __init__(self, hparas):
        super(TextEncoder, self).__init__()
        self.hparas = hparas
        self.batch_size = self.hparas['BATCH_SIZE']

        # embedding with tensorflow API
        self.embedding = layers.Embedding(self.hparas['VOCAB_SIZE'], self.hparas['E
        # RNN, here we use GRU cell, another common RNN cell similar to LSTM
        self.gru = layers.GRU(self.hparas['RNN_HIDDEN_SIZE'],
                              return_sequences=True,
                              return_state=True,
                              recurrent_initializer='glorot_uniform')

    def call(self, text, hidden):
        text = self.embedding(text)
```

```
        output, state = self.gru(text, initial_state = hidden)
        return output[:, -1, :], state

    def initialize_hidden_state(self):
        return tf.zeros((self.hparas['BATCH_SIZE'], self.hparas['RNN_HIDDEN_SIZE']))
```

Generator

A image generator which generates the target image illustrating the input text.

- Input: hidden representation of input text and random noise z with random seed.
- Output: target image, which is conditioned on the given text, in size 64x64x3.

In [10]:
```
class Generator(tf.keras.Model):
    """
    Generate fake image based on given text(hidden representation) and noise z
    input: text and noise
    output: fake image with size 64*64*3
    """
    def __init__(self, hparas):
        super(Generator, self).__init__()
        self.hparas = hparas
        self.flatten = tf.keras.layers.Flatten()
        self.d1 = tf.keras.layers.Dense(self.hparas['DENSE_DIM'])
        self.d2 = tf.keras.layers.Dense(64*64*3)

    def call(self, text, noise_z):
        text = self.flatten(text)
        text = self.d1(text)
        text = tf.nn.leaky_relu(text)

        # concatenate input text and random noise
        text_concat = tf.concat([noise_z, text], axis=1)
        text_concat = self.d2(text_concat)

        logits = tf.reshape(text_concat, [-1, 64, 64, 3])
        output = tf.nn.tanh(logits)

        return logits, output
```

Discriminator

A binary classifier which can discriminate the real and fake image:

1. Real image
   - Input: real image and the paired text
   - Output: a floating number representing the result, which is expected to be 1.
2. Fake Image
   - Input: generated image and paired text
   - Output: a floating number representing the result, which is expected to be 0.

In [11]:
```
class Discriminator(tf.keras.Model):
    """
    Differentiate the real and fake image
    input: image and corresponding text
    output: labels, the real image should be 1, while the fake should be 0
    """
```

```
    def __init__(self, hparas):
        super(Discriminator, self).__init__()
        self.hparas = hparas
        self.flatten = tf.keras.layers.Flatten()
        self.d_text = tf.keras.layers.Dense(self.hparas['DENSE_DIM'])
        self.d_img = tf.keras.layers.Dense(self.hparas['DENSE_DIM'])
        self.d = tf.keras.layers.Dense(1)

    def call(self, img, text):
        text = self.flatten(text)
        text = self.d_text(text)
        text = tf.nn.leaky_relu(text)

        img = self.flatten(img)
        img = self.d_img(img)
        img = tf.nn.leaky_relu(img)

        # concatenate image with paired text
        img_text = tf.concat([text, img], axis=1)

        logits = self.d(img_text)
        output = tf.nn.sigmoid(logits)

        return logits, output
```

In [12]:
```
hparas = {
    'MAX_SEQ_LENGTH': 20,                       # maximum sequence length
    'EMBED_DIM': 256,                           # word embedding dimension
    'VOCAB_SIZE': len(word2Id_dict),            # size of dictionary of captions
    'RNN_HIDDEN_SIZE': 128,                     # number of RNN neurons
    'Z_DIM': 512,                               # random noise z dimension
    'DENSE_DIM': 128,                           # number of neurons in dense layer
    'IMAGE_SIZE': [64, 64, 3],                  # render image size
    'BATCH_SIZE': 64,
    'LR': 1e-4,
    'LR_DECAY': 0.5,
    'BETA_1': 0.5,
    'N_EPOCH': 600,
    'N_SAMPLE': num_training_sample,            # size of training data
    'CHECKPOINTS_DIR': './checkpoints/demo',    # checkpoint path
    'PRINT_FREQ': 1                             # printing frequency of loss
}
```

In [13]:
```
text_encoder = TextEncoder(hparas)
generator = Generator(hparas)
discriminator = Discriminator(hparas)
```

Loss Function and Optimization

Although the conditional GAN model is quite complex, the loss function used to optimize the network is relatively simple. Actually, it is simply a binary classification task, thus we use cross entropy as our loss.

In [14]:
```
# This method returns a helper function to compute cross entropy loss
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
```

In [15]:
```
def discriminator_loss(real_logits, fake_logits):
    # output value of real image should be 1
    real_loss = cross_entropy(tf.ones_like(real_logits), real_logits)
    # output value of fake image should be 0
```

```
    fake_loss = cross_entropy(tf.zeros_like(fake_logits), fake_logits)
    total_loss = real_loss + fake_loss
    return total_loss

def generator_loss(fake_output):
    # output value of fake image should be 0
    return cross_entropy(tf.ones_like(fake_output), fake_output)
```

In [16]:
```
# we use seperated optimizers for training generator and discriminator
generator_optimizer = tf.keras.optimizers.Adam(hparas['LR'])
discriminator_optimizer = tf.keras.optimizers.Adam(hparas['LR'])
```

In [17]:
```
# one benefit of tf.train.Checkpoint() API is we can save everything seperately
checkpoint_dir = hparas['CHECKPOINTS_DIR']
checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optimizer,
                                 text_encoder=text_encoder,
                                 generator=generator,
                                 discriminator=discriminator)
```

In [18]:
```
@tf.function
def train_step(real_image, caption, hidden):
    # random noise for generator
    noise = tf.random.normal(shape=[hparas['BATCH_SIZE'], hparas['Z_DIM']], mean=0.

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        text_embed, hidden = text_encoder(caption, hidden)
        _, fake_image = generator(text_embed, noise)
        real_logits, real_output = discriminator(real_image, text_embed)
        fake_logits, fake_output = discriminator(fake_image, text_embed)

        g_loss = generator_loss(fake_logits)
        d_loss = discriminator_loss(real_logits, fake_logits)

    grad_g = gen_tape.gradient(g_loss, generator.trainable_variables)
    grad_d = disc_tape.gradient(d_loss, discriminator.trainable_variables)

    generator_optimizer.apply_gradients(zip(grad_g, generator.trainable_variables))
    discriminator_optimizer.apply_gradients(zip(grad_d, discriminator.trainable_var

    return g_loss, d_loss
```

In [19]:
```
@tf.function
def test_step(caption, noise, hidden):
    text_embed, hidden = text_encoder(caption, hidden)
    _, fake_image = generator(text_embed, noise)
    return fake_image
```

Visualiztion

During training, we can visualize the generated image to evaluate the quality of generator.
The followings are some functions helping visualization.

In [20]:
```
def merge(images, size):
    h, w = images.shape[1], images.shape[2]
    img = np.zeros((h * size[0], w * size[1], 3))
    for idx, image in enumerate(images):
        i = idx % size[1]
        j = idx // size[1]
```

```
        img[j*h:j*h+h, i*w:i*w+w, :] = image
    return img

def imsave(images, size, path):
    # getting the pixel values between [0, 1] to save it
    return plt.imsave(path, merge(images, size)*0.5 + 0.5)

def save_images(images, size, image_path):
    return imsave(images, size, image_path)
```

In [21]:
```
def sample_generator(caption, batch_size):
    caption = np.asarray(caption)
    caption = caption.astype(np.int)
    dataset = tf.data.Dataset.from_tensor_slices(caption)
    dataset = dataset.batch(batch_size)
    return dataset
```

We always use same random seed and same senteces during training, which is more convenient for us to evaluate the quality of generated image.

In [22]:
```
ni = int(np.ceil(np.sqrt(hparas['BATCH_SIZE'])))
sample_size = hparas['BATCH_SIZE']
sample_seed = np.random.normal(loc=0.0, scale=1.0, size=(sample_size, hparas['Z_DIM
sample_sentence = ["the flower shown has yellow anther red pistil and bright red pe
                   ["this flower has petals that are yellow, white and purple and ha
                   ["the petals on this flower are white with a yellow center"] * ir
                   ["this flower has a lot of small round pink petals."] * int(sampl
                   ["this flower is orange in color, and has petals that are ruffled
                   ["the flower has yellow petals and the center of it is brown."] *
                   ["this flower has petals that are blue and white."] * int(sample_
                   ["these white flowers have petals that start off white in color a

for i, sent in enumerate(sample_sentence):
    sample_sentence[i] = sent2IdList(sent)
sample_sentence = sample_generator(sample_sentence, hparas['BATCH_SIZE'])
```

```
/tmp/ipykernel_29626/646496249.py:3: DeprecationWarning: `np.int` is a deprecated
alias for the builtin `int`. To silence this warning, use `int` by itself. Doing t
his will not modify any behavior and is safe. When replacing `np.int`, you may wis
h to use e.g. `np.int64` or `np.int32` to specify the precision. If you wish to re
view your current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdoc
s/release/1.20.0-notes.html#deprecations
  caption = caption.astype(np.int)
```

Training

In [23]:
```
if not os.path.exists('samples/demo'):
    os.makedirs('samples/demo')
```

In [24]:
```
def train(dataset, epochs):
    # hidden state of RNN
    hidden = text_encoder.initialize_hidden_state()
    steps_per_epoch = int(hparas['N_SAMPLE']/hparas['BATCH_SIZE'])

    for epoch in range(hparas['N_EPOCH']):
        g_total_loss = 0
        d_total_loss = 0
        start = time.time()
```

```
        for image, caption in dataset:
            g_loss, d_loss = train_step(image, caption, hidden)
            g_total_loss += g_loss
            d_total_loss += d_loss

        time_tuple = time.localtime()
        time_string = time.strftime("%m/%d/%Y, %H:%M:%S", time_tuple)

        print("Epoch {}, gen_loss: {:.4f}, disc_loss: {:.4f}".format(epoch+1,
                                                                     g_total_loss/s
                                                                     d_total_loss/s
        print('Time for epoch {} is {:.4f} sec'.format(epoch+1, time.time()-start))

        # save the model
        if (epoch + 1) % 50 == 0:
            checkpoint.save(file_prefix = checkpoint_prefix)

        # visualization
        if (epoch + 1) % hparas['PRINT_FREQ'] == 0:
            for caption in sample_sentence:
                fake_image = test_step(caption, sample_seed, hidden)
            save_images(fake_image, [ni, ni], 'samples/demo/train_{:02d}.jpg'.forma
```

In [25]:
```
train(dataset, hparas['N_EPOCH'])
```

```
2022-11-23 10:51:06.854118: I tensorflow/stream_executor/cuda/cuda_dnn.cc:384] Loa
ded cuDNN version 8201
```

```
Epoch 1, gen_loss: 0.4364, disc_loss: 1.1589
Time for epoch 1 is 6.4657 sec
Epoch 2, gen_loss: 0.4609, disc_loss: 1.1169
Time for epoch 2 is 2.8109 sec
Epoch 3, gen_loss: 0.7003, disc_loss: 0.8476
Time for epoch 3 is 2.8191 sec
Epoch 4, gen_loss: 1.1180, disc_loss: 0.5337
Time for epoch 4 is 2.9703 sec
Epoch 5, gen_loss: 2.1168, disc_loss: 0.1785
Time for epoch 5 is 2.8329 sec
Epoch 6, gen_loss: 1.9798, disc_loss: 0.2144
Time for epoch 6 is 2.8044 sec
Epoch 7, gen_loss: 2.2416, disc_loss: 0.1638
Time for epoch 7 is 2.7629 sec
Epoch 8, gen_loss: 2.6708, disc_loss: 0.1144
Time for epoch 8 is 2.7492 sec
Epoch 9, gen_loss: 2.7469, disc_loss: 0.1200
Time for epoch 9 is 2.7638 sec
Epoch 10, gen_loss: 3.0936, disc_loss: 0.1244
Time for epoch 10 is 2.5924 sec
Epoch 11, gen_loss: 3.5398, disc_loss: 0.1227
Time for epoch 11 is 2.5874 sec
Epoch 12, gen_loss: 3.2764, disc_loss: 0.2010
Time for epoch 12 is 2.8076 sec
Epoch 13, gen_loss: 3.7002, disc_loss: 0.2672
Time for epoch 13 is 2.7153 sec
Epoch 14, gen_loss: 3.8901, disc_loss: 0.3380
Time for epoch 14 is 2.6933 sec
Epoch 15, gen_loss: 3.3203, disc_loss: 0.4580
Time for epoch 15 is 2.7301 sec
Epoch 16, gen_loss: 3.2107, disc_loss: 0.5796
Time for epoch 16 is 2.7159 sec
Epoch 17, gen_loss: 3.3180, disc_loss: 0.5807
Time for epoch 17 is 2.8851 sec
Epoch 18, gen_loss: 3.2794, disc_loss: 0.5899
Time for epoch 18 is 2.8288 sec
Epoch 19, gen_loss: 2.9915, disc_loss: 0.6637
Time for epoch 19 is 2.6269 sec
Epoch 20, gen_loss: 2.8574, disc_loss: 0.7690
Time for epoch 20 is 2.9169 sec
Epoch 21, gen_loss: 2.7805, disc_loss: 0.6750
Time for epoch 21 is 2.7499 sec
Epoch 22, gen_loss: 2.4794, disc_loss: 0.7101
Time for epoch 22 is 2.7760 sec
Epoch 23, gen_loss: 2.5188, disc_loss: 0.6775
Time for epoch 23 is 2.8413 sec
Epoch 24, gen_loss: 2.2181, disc_loss: 0.7694
Time for epoch 24 is 2.8376 sec
Epoch 25, gen_loss: 2.0179, disc_loss: 0.8207
Time for epoch 25 is 2.7066 sec
Epoch 26, gen_loss: 1.9934, disc_loss: 0.8338
Time for epoch 26 is 2.7065 sec
Epoch 27, gen_loss: 2.2491, disc_loss: 0.8071
Time for epoch 27 is 2.7918 sec
Epoch 28, gen_loss: 2.2550, disc_loss: 0.7524
Time for epoch 28 is 2.7575 sec
Epoch 29, gen_loss: 2.4824, disc_loss: 0.5772
Time for epoch 29 is 2.8193 sec
Epoch 30, gen_loss: 2.4119, disc_loss: 0.5899
Time for epoch 30 is 2.7940 sec
Epoch 31, gen_loss: 2.2011, disc_loss: 0.6949
Time for epoch 31 is 2.7396 sec
Epoch 32, gen_loss: 2.4667, disc_loss: 0.5465
Time for epoch 32 is 2.8088 sec
```

```
Epoch 33, gen_loss: 2.2277, disc_loss: 0.5884
Time for epoch 33 is 2.8558 sec
Epoch 34, gen_loss: 1.8392, disc_loss: 0.7087
Time for epoch 34 is 2.6343 sec
Epoch 35, gen_loss: 1.6541, disc_loss: 0.8404
Time for epoch 35 is 2.6432 sec
Epoch 36, gen_loss: 1.7993, disc_loss: 0.7966
Time for epoch 36 is 2.8168 sec
Epoch 37, gen_loss: 1.5980, disc_loss: 0.8697
Time for epoch 37 is 2.8117 sec
Epoch 38, gen_loss: 1.5760, disc_loss: 0.8208
Time for epoch 38 is 2.7579 sec
Epoch 39, gen_loss: 1.5320, disc_loss: 0.7401
Time for epoch 39 is 2.9055 sec
Epoch 40, gen_loss: 1.3264, disc_loss: 0.8475
Time for epoch 40 is 2.8203 sec
Epoch 41, gen_loss: 1.3784, disc_loss: 0.8276
Time for epoch 41 is 2.6340 sec
Epoch 42, gen_loss: 1.2372, disc_loss: 0.9461
Time for epoch 42 is 2.6340 sec
Epoch 43, gen_loss: 1.1619, disc_loss: 1.0563
Time for epoch 43 is 2.6973 sec
Epoch 44, gen_loss: 1.2657, disc_loss: 0.9792
Time for epoch 44 is 2.5737 sec
Epoch 45, gen_loss: 1.3325, disc_loss: 0.9950
Time for epoch 45 is 2.6825 sec
Epoch 46, gen_loss: 1.1811, disc_loss: 1.1596
Time for epoch 46 is 2.6573 sec
Epoch 47, gen_loss: 1.2318, disc_loss: 1.1932
Time for epoch 47 is 2.6589 sec
Epoch 48, gen_loss: 1.3921, disc_loss: 1.1612
Time for epoch 48 is 2.8030 sec
Epoch 49, gen_loss: 1.8097, disc_loss: 0.8338
Time for epoch 49 is 2.6953 sec
Epoch 50, gen_loss: 1.9475, disc_loss: 0.8069
Time for epoch 50 is 2.8073 sec
Epoch 51, gen_loss: 2.0441, disc_loss: 0.7018
Time for epoch 51 is 2.8398 sec
Epoch 52, gen_loss: 1.7792, disc_loss: 0.7774
Time for epoch 52 is 2.6281 sec
Epoch 53, gen_loss: 1.8446, disc_loss: 0.6930
Time for epoch 53 is 2.6442 sec
Epoch 54, gen_loss: 1.3656, disc_loss: 0.9966
Time for epoch 54 is 2.9931 sec
Epoch 55, gen_loss: 1.3377, disc_loss: 1.0219
Time for epoch 55 is 2.9101 sec
Epoch 56, gen_loss: 1.3888, disc_loss: 0.9737
Time for epoch 56 is 2.9658 sec
Epoch 57, gen_loss: 1.4115, disc_loss: 1.0109
Time for epoch 57 is 2.6824 sec
Epoch 58, gen_loss: 1.5952, disc_loss: 0.9119
Time for epoch 58 is 2.6289 sec
Epoch 59, gen_loss: 1.4854, disc_loss: 0.9072
Time for epoch 59 is 2.7560 sec
Epoch 60, gen_loss: 1.5935, disc_loss: 0.8635
Time for epoch 60 is 2.7365 sec
Epoch 61, gen_loss: 1.7238, disc_loss: 0.8577
Time for epoch 61 is 2.6844 sec
Epoch 62, gen_loss: 1.5285, disc_loss: 0.9000
Time for epoch 62 is 2.5478 sec
Epoch 63, gen_loss: 2.0553, disc_loss: 0.6168
Time for epoch 63 is 2.6852 sec
Epoch 64, gen_loss: 1.5557, disc_loss: 0.8291
Time for epoch 64 is 2.7248 sec
```

```
Epoch 65, gen_loss: 1.4671, disc_loss: 0.8832
Time for epoch 65 is 2.7288 sec
Epoch 66, gen_loss: 1.4583, disc_loss: 0.9236
Time for epoch 66 is 2.8655 sec
Epoch 67, gen_loss: 1.2149, disc_loss: 1.1991
Time for epoch 67 is 2.8211 sec
Epoch 68, gen_loss: 1.4782, disc_loss: 0.9738
Time for epoch 68 is 2.6730 sec
Epoch 69, gen_loss: 1.5135, disc_loss: 0.9301
Time for epoch 69 is 2.6890 sec
Epoch 70, gen_loss: 1.6259, disc_loss: 0.9133
Time for epoch 70 is 2.7414 sec
Epoch 71, gen_loss: 1.6113, disc_loss: 0.8651
Time for epoch 71 is 2.8060 sec
Epoch 72, gen_loss: 1.5670, disc_loss: 0.9376
Time for epoch 72 is 2.7964 sec
Epoch 73, gen_loss: 1.6260, disc_loss: 0.7706
Time for epoch 73 is 2.7392 sec
Epoch 74, gen_loss: 1.5159, disc_loss: 0.8097
Time for epoch 74 is 2.7193 sec
Epoch 75, gen_loss: 1.4416, disc_loss: 0.9139
Time for epoch 75 is 2.6357 sec
Epoch 76, gen_loss: 1.3253, disc_loss: 1.0042
Time for epoch 76 is 2.7168 sec
Epoch 77, gen_loss: 1.4751, disc_loss: 0.9114
Time for epoch 77 is 2.9280 sec
Epoch 78, gen_loss: 1.1866, disc_loss: 1.1838
Time for epoch 78 is 2.7866 sec
Epoch 79, gen_loss: 1.4802, disc_loss: 0.9979
Time for epoch 79 is 2.8527 sec
Epoch 80, gen_loss: 1.3509, disc_loss: 1.1450
Time for epoch 80 is 2.8522 sec
Epoch 81, gen_loss: 1.5979, disc_loss: 0.9789
Time for epoch 81 is 2.7772 sec
Epoch 82, gen_loss: 1.6496, disc_loss: 0.8433
Time for epoch 82 is 2.7292 sec
Epoch 83, gen_loss: 1.8771, disc_loss: 0.7104
Time for epoch 83 is 2.7698 sec
Epoch 84, gen_loss: 1.5543, disc_loss: 0.9779
Time for epoch 84 is 2.8987 sec
Epoch 85, gen_loss: 1.6199, disc_loss: 0.8222
Time for epoch 85 is 2.6661 sec
Epoch 86, gen_loss: 1.3985, disc_loss: 0.9203
Time for epoch 86 is 2.7393 sec
Epoch 87, gen_loss: 1.3435, disc_loss: 0.9956
Time for epoch 87 is 2.8992 sec
Epoch 88, gen_loss: 1.3395, disc_loss: 1.0460
Time for epoch 88 is 2.6905 sec
Epoch 89, gen_loss: 1.1854, disc_loss: 1.1986
Time for epoch 89 is 2.7423 sec
Epoch 90, gen_loss: 1.2187, disc_loss: 1.2287
Time for epoch 90 is 2.7155 sec
Epoch 91, gen_loss: 1.6799, disc_loss: 0.9987
Time for epoch 91 is 2.6935 sec
Epoch 92, gen_loss: 1.5032, disc_loss: 1.0959
Time for epoch 92 is 2.6835 sec
Epoch 93, gen_loss: 1.8747, disc_loss: 0.7749
Time for epoch 93 is 2.6922 sec
Epoch 94, gen_loss: 1.8685, disc_loss: 0.7463
Time for epoch 94 is 2.8375 sec
Epoch 95, gen_loss: 1.5439, disc_loss: 0.9151
Time for epoch 95 is 2.5907 sec
Epoch 96, gen_loss: 1.6795, disc_loss: 0.9026
Time for epoch 96 is 2.6272 sec
```

```
Epoch 97, gen_loss: 1.6810, disc_loss: 0.8357
Time for epoch 97 is 2.8076 sec
Epoch 98, gen_loss: 1.2692, disc_loss: 1.1110
Time for epoch 98 is 2.7257 sec
Epoch 99, gen_loss: 1.5281, disc_loss: 0.9534
Time for epoch 99 is 2.7764 sec
Epoch 100, gen_loss: 1.3780, disc_loss: 1.0605
Time for epoch 100 is 2.7014 sec
Epoch 101, gen_loss: 1.2994, disc_loss: 1.0896
Time for epoch 101 is 2.7676 sec
Epoch 102, gen_loss: 1.3778, disc_loss: 1.0861
Time for epoch 102 is 2.5861 sec
Epoch 103, gen_loss: 1.4424, disc_loss: 1.0795
Time for epoch 103 is 2.7135 sec
Epoch 104, gen_loss: 1.6152, disc_loss: 0.9349
Time for epoch 104 is 2.6470 sec
Epoch 105, gen_loss: 1.5634, disc_loss: 0.8363
Time for epoch 105 is 2.6651 sec
Epoch 106, gen_loss: 1.5207, disc_loss: 0.8634
Time for epoch 106 is 2.5486 sec
Epoch 107, gen_loss: 1.4024, disc_loss: 1.0777
Time for epoch 107 is 2.7026 sec
Epoch 108, gen_loss: 1.4811, disc_loss: 1.0022
Time for epoch 108 is 2.7292 sec
Epoch 109, gen_loss: 1.3014, disc_loss: 1.1267
Time for epoch 109 is 2.7041 sec
Epoch 110, gen_loss: 1.7332, disc_loss: 0.9028
Time for epoch 110 is 2.5589 sec
Epoch 111, gen_loss: 1.6340, disc_loss: 0.9368
Time for epoch 111 is 2.6403 sec
Epoch 112, gen_loss: 1.7182, disc_loss: 0.8618
Time for epoch 112 is 2.6824 sec
Epoch 113, gen_loss: 1.7934, disc_loss: 0.8071
Time for epoch 113 is 2.6463 sec
Epoch 114, gen_loss: 1.6865, disc_loss: 0.9140
Time for epoch 114 is 2.8104 sec
Epoch 115, gen_loss: 1.5720, disc_loss: 0.8998
Time for epoch 115 is 2.7755 sec
Epoch 116, gen_loss: 1.4464, disc_loss: 0.9584
Time for epoch 116 is 2.7589 sec
Epoch 117, gen_loss: 1.4378, disc_loss: 1.0738
Time for epoch 117 is 2.7641 sec
Epoch 118, gen_loss: 1.4586, disc_loss: 0.9319
Time for epoch 118 is 2.7699 sec
Epoch 119, gen_loss: 1.2176, disc_loss: 1.0874
Time for epoch 119 is 2.7896 sec
Epoch 120, gen_loss: 1.3419, disc_loss: 1.0732
Time for epoch 120 is 2.6355 sec
Epoch 121, gen_loss: 1.3132, disc_loss: 1.0574
Time for epoch 121 is 2.7735 sec
Epoch 122, gen_loss: 1.1665, disc_loss: 1.2653
Time for epoch 122 is 2.8039 sec
Epoch 123, gen_loss: 1.2515, disc_loss: 1.1753
Time for epoch 123 is 2.7389 sec
Epoch 124, gen_loss: 1.4718, disc_loss: 1.0452
Time for epoch 124 is 2.6802 sec
Epoch 125, gen_loss: 1.5014, disc_loss: 1.0212
Time for epoch 125 is 2.6490 sec
Epoch 126, gen_loss: 1.6835, disc_loss: 0.8953
Time for epoch 126 is 2.7503 sec
Epoch 127, gen_loss: 1.7121, disc_loss: 0.9067
Time for epoch 127 is 2.7326 sec
Epoch 128, gen_loss: 1.7355, disc_loss: 0.9228
Time for epoch 128 is 2.6401 sec
```

```
Epoch 129, gen_loss: 1.4000, disc_loss: 1.0729
Time for epoch 129 is 2.6908 sec
Epoch 130, gen_loss: 1.5924, disc_loss: 0.9089
Time for epoch 130 is 2.7549 sec
Epoch 131, gen_loss: 1.3808, disc_loss: 1.0266
Time for epoch 131 is 2.7874 sec
Epoch 132, gen_loss: 1.3226, disc_loss: 1.0729
Time for epoch 132 is 2.6691 sec
Epoch 133, gen_loss: 1.4847, disc_loss: 1.0205
Time for epoch 133 is 2.7808 sec
Epoch 134, gen_loss: 1.3367, disc_loss: 1.1488
Time for epoch 134 is 2.6593 sec
Epoch 135, gen_loss: 1.3471, disc_loss: 1.1402
Time for epoch 135 is 2.6591 sec
Epoch 136, gen_loss: 1.3646, disc_loss: 1.0708
Time for epoch 136 is 2.6642 sec
Epoch 137, gen_loss: 1.4698, disc_loss: 0.9890
Time for epoch 137 is 2.6439 sec
Epoch 138, gen_loss: 1.4207, disc_loss: 1.1021
Time for epoch 138 is 2.6299 sec
Epoch 139, gen_loss: 1.5090, disc_loss: 0.9443
Time for epoch 139 is 2.8363 sec
Epoch 140, gen_loss: 1.6061, disc_loss: 0.9085
Time for epoch 140 is 2.7644 sec
Epoch 141, gen_loss: 1.4787, disc_loss: 1.0390
Time for epoch 141 is 2.7733 sec
Epoch 142, gen_loss: 1.5669, disc_loss: 0.9498
Time for epoch 142 is 2.8179 sec
Epoch 143, gen_loss: 1.4865, disc_loss: 1.0280
Time for epoch 143 is 2.8063 sec
Epoch 144, gen_loss: 1.3309, disc_loss: 1.1425
Time for epoch 144 is 2.7698 sec
Epoch 145, gen_loss: 1.6407, disc_loss: 0.9441
Time for epoch 145 is 2.7685 sec
Epoch 146, gen_loss: 1.6000, disc_loss: 1.0913
Time for epoch 146 is 2.6512 sec
Epoch 147, gen_loss: 1.5675, disc_loss: 1.0543
Time for epoch 147 is 2.7228 sec
Epoch 148, gen_loss: 1.9242, disc_loss: 0.7131
Time for epoch 148 is 2.5541 sec
Epoch 149, gen_loss: 1.4638, disc_loss: 0.9551
Time for epoch 149 is 2.6536 sec
Epoch 150, gen_loss: 1.4844, disc_loss: 0.9487
Time for epoch 150 is 2.5515 sec
Epoch 151, gen_loss: 1.3229, disc_loss: 1.0601
Time for epoch 151 is 2.8130 sec
Epoch 152, gen_loss: 1.4318, disc_loss: 0.9633
Time for epoch 152 is 2.7064 sec
Epoch 153, gen_loss: 1.4065, disc_loss: 0.9805
Time for epoch 153 is 2.7590 sec
Epoch 154, gen_loss: 1.3065, disc_loss: 1.1302
Time for epoch 154 is 2.7382 sec
Epoch 155, gen_loss: 1.3249, disc_loss: 1.1022
Time for epoch 155 is 2.7275 sec
Epoch 156, gen_loss: 1.5262, disc_loss: 1.0262
Time for epoch 156 is 2.6433 sec
Epoch 157, gen_loss: 1.1472, disc_loss: 1.3655
Time for epoch 157 is 2.6548 sec
Epoch 158, gen_loss: 1.3324, disc_loss: 1.1970
Time for epoch 158 is 2.7177 sec
Epoch 159, gen_loss: 1.8308, disc_loss: 0.9318
Time for epoch 159 is 2.7238 sec
Epoch 160, gen_loss: 1.2781, disc_loss: 1.2044
Time for epoch 160 is 2.7112 sec
```

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Epoch 161, gen_loss: 1.6296, disc_loss: 1.0205
Time for epoch 161 is 2.6859 sec
Epoch 162, gen_loss: 1.7293, disc_loss: 0.8931
Time for epoch 162 is 2.8377 sec
Epoch 163, gen_loss: 1.4117, disc_loss: 1.1352
Time for epoch 163 is 2.8510 sec
Epoch 164, gen_loss: 1.5326, disc_loss: 1.0279
Time for epoch 164 is 2.6824 sec
Epoch 165, gen_loss: 1.7529, disc_loss: 0.8632
Time for epoch 165 is 2.6333 sec
Epoch 166, gen_loss: 1.2982, disc_loss: 1.1294
Time for epoch 166 is 2.7312 sec
Epoch 167, gen_loss: 1.4800, disc_loss: 0.9923
Time for epoch 167 is 2.7350 sec
Epoch 168, gen_loss: 1.4480, disc_loss: 1.0499
Time for epoch 168 is 2.6698 sec
Epoch 169, gen_loss: 1.4168, disc_loss: 0.9776
Time for epoch 169 is 2.6832 sec
Epoch 170, gen_loss: 1.2764, disc_loss: 1.1027
Time for epoch 170 is 2.6964 sec
Epoch 171, gen_loss: 1.2168, disc_loss: 1.1893
Time for epoch 171 is 2.7892 sec
Epoch 172, gen_loss: 1.2654, disc_loss: 1.2524
Time for epoch 172 is 2.7115 sec
Epoch 173, gen_loss: 1.4095, disc_loss: 1.1211
Time for epoch 173 is 2.7019 sec
Epoch 174, gen_loss: 1.4555, disc_loss: 1.2201
Time for epoch 174 is 2.7992 sec
Epoch 175, gen_loss: 1.6975, disc_loss: 0.9438
Time for epoch 175 is 2.7630 sec
Epoch 176, gen_loss: 1.4668, disc_loss: 1.0841
Time for epoch 176 is 2.7659 sec
Epoch 177, gen_loss: 1.6393, disc_loss: 0.9737
Time for epoch 177 is 2.9364 sec
Epoch 178, gen_loss: 1.3379, disc_loss: 1.1710
Time for epoch 178 is 2.5878 sec
Epoch 179, gen_loss: 1.5771, disc_loss: 1.0915
Time for epoch 179 is 2.7223 sec
Epoch 180, gen_loss: 1.6919, disc_loss: 0.9597
Time for epoch 180 is 2.6808 sec
Epoch 181, gen_loss: 1.4670, disc_loss: 1.1084
Time for epoch 181 is 2.7678 sec
Epoch 182, gen_loss: 1.6527, disc_loss: 1.0418
Time for epoch 182 is 2.6347 sec
Epoch 183, gen_loss: 1.5148, disc_loss: 1.1753
Time for epoch 183 is 2.7407 sec
Epoch 184, gen_loss: 1.7776, disc_loss: 0.9156
Time for epoch 184 is 2.6605 sec
Epoch 185, gen_loss: 1.6029, disc_loss: 0.9785
Time for epoch 185 is 2.6741 sec
Epoch 186, gen_loss: 1.7658, disc_loss: 0.7776
Time for epoch 186 is 2.7111 sec
Epoch 187, gen_loss: 1.4713, disc_loss: 0.9678
Time for epoch 187 is 2.7466 sec
Epoch 188, gen_loss: 1.5302, disc_loss: 0.9258
Time for epoch 188 is 2.8551 sec
Epoch 189, gen_loss: 1.2274, disc_loss: 1.1876
Time for epoch 189 is 2.6145 sec
Epoch 190, gen_loss: 1.2406, disc_loss: 1.1040
Time for epoch 190 is 2.7718 sec
Epoch 191, gen_loss: 1.2513, disc_loss: 1.2083
Time for epoch 191 is 2.8533 sec
Epoch 192, gen_loss: 1.2350, disc_loss: 1.2202
Time for epoch 192 is 2.7032 sec
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Epoch 193, gen_loss: 1.3220, disc_loss: 1.1078
Time for epoch 193 is 2.8181 sec
Epoch 194, gen_loss: 1.2431, disc_loss: 1.4220
Time for epoch 194 is 2.8269 sec
Epoch 195, gen_loss: 1.1901, disc_loss: 1.3847
Time for epoch 195 is 2.8127 sec
Epoch 196, gen_loss: 1.5008, disc_loss: 1.0429
Time for epoch 196 is 2.7738 sec
Epoch 197, gen_loss: 1.3847, disc_loss: 1.1408
Time for epoch 197 is 2.8744 sec
Epoch 198, gen_loss: 1.5579, disc_loss: 1.1464
Time for epoch 198 is 2.7678 sec
Epoch 199, gen_loss: 1.5096, disc_loss: 1.2377
Time for epoch 199 is 2.8698 sec
Epoch 200, gen_loss: 1.4926, disc_loss: 1.1002
Time for epoch 200 is 2.7252 sec
Epoch 201, gen_loss: 1.8154, disc_loss: 0.9880
Time for epoch 201 is 2.6172 sec
Epoch 202, gen_loss: 1.8034, disc_loss: 0.8771
Time for epoch 202 is 2.6201 sec
Epoch 203, gen_loss: 1.5226, disc_loss: 1.0093
Time for epoch 203 is 2.8317 sec
Epoch 204, gen_loss: 1.4101, disc_loss: 1.0743
Time for epoch 204 is 2.6827 sec
Epoch 205, gen_loss: 1.6045, disc_loss: 0.9989
Time for epoch 205 is 2.7057 sec
Epoch 206, gen_loss: 1.5377, disc_loss: 1.0190
Time for epoch 206 is 2.7033 sec
Epoch 207, gen_loss: 1.5059, disc_loss: 1.0256
Time for epoch 207 is 2.7224 sec
Epoch 208, gen_loss: 1.4472, disc_loss: 1.0772
Time for epoch 208 is 2.7084 sec
Epoch 209, gen_loss: 1.4207, disc_loss: 1.1413
Time for epoch 209 is 2.7778 sec
Epoch 210, gen_loss: 1.3966, disc_loss: 1.1686
Time for epoch 210 is 2.6917 sec
Epoch 211, gen_loss: 1.6718, disc_loss: 0.9500
Time for epoch 211 is 2.6727 sec
Epoch 212, gen_loss: 1.4375, disc_loss: 1.2049
Time for epoch 212 is 2.6813 sec
Epoch 213, gen_loss: 1.5637, disc_loss: 1.1077
Time for epoch 213 is 2.8819 sec
Epoch 214, gen_loss: 1.6571, disc_loss: 1.0925
Time for epoch 214 is 2.9648 sec
Epoch 215, gen_loss: 1.7018, disc_loss: 1.0251
Time for epoch 215 is 2.9791 sec
Epoch 216, gen_loss: 1.8695, disc_loss: 0.8181
Time for epoch 216 is 2.8715 sec
Epoch 217, gen_loss: 1.7698, disc_loss: 0.7700
Time for epoch 217 is 2.8623 sec
Epoch 218, gen_loss: 1.6875, disc_loss: 0.8059
Time for epoch 218 is 2.7885 sec
Epoch 219, gen_loss: 1.5561, disc_loss: 0.9675
Time for epoch 219 is 2.6436 sec
Epoch 220, gen_loss: 1.4371, disc_loss: 1.0898
Time for epoch 220 is 2.6830 sec
Epoch 221, gen_loss: 1.3833, disc_loss: 1.1408
Time for epoch 221 is 2.7298 sec
Epoch 222, gen_loss: 1.4868, disc_loss: 1.1606
Time for epoch 222 is 2.6984 sec
Epoch 223, gen_loss: 1.4988, disc_loss: 1.0247
Time for epoch 223 is 2.6416 sec
Epoch 224, gen_loss: 1.3950, disc_loss: 1.0279
Time for epoch 224 is 2.7603 sec
```

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Epoch 225, gen_loss: 1.2873, disc_loss: 1.1358
Time for epoch 225 is 2.7235 sec
Epoch 226, gen_loss: 1.3522, disc_loss: 1.1329
Time for epoch 226 is 2.7960 sec
Epoch 227, gen_loss: 1.0637, disc_loss: 1.4348
Time for epoch 227 is 2.9057 sec
Epoch 228, gen_loss: 1.4231, disc_loss: 1.1979
Time for epoch 228 is 2.8483 sec
Epoch 229, gen_loss: 1.5613, disc_loss: 1.1716
Time for epoch 229 is 2.6304 sec
Epoch 230, gen_loss: 1.4185, disc_loss: 1.2045
Time for epoch 230 is 2.8518 sec
Epoch 231, gen_loss: 1.6212, disc_loss: 1.0430
Time for epoch 231 is 2.7309 sec
Epoch 232, gen_loss: 1.7648, disc_loss: 1.0391
Time for epoch 232 is 2.6946 sec
Epoch 233, gen_loss: 1.5442, disc_loss: 1.2060
Time for epoch 233 is 2.8439 sec
Epoch 234, gen_loss: 1.8573, disc_loss: 0.9331
Time for epoch 234 is 2.8349 sec
Epoch 235, gen_loss: 2.0443, disc_loss: 0.8022
Time for epoch 235 is 2.9737 sec
Epoch 236, gen_loss: 1.9171, disc_loss: 0.7502
Time for epoch 236 is 2.7987 sec
Epoch 237, gen_loss: 1.9386, disc_loss: 0.7525
Time for epoch 237 is 2.6919 sec
Epoch 238, gen_loss: 1.5386, disc_loss: 0.9561
Time for epoch 238 is 2.7903 sec
Epoch 239, gen_loss: 1.4744, disc_loss: 1.0515
Time for epoch 239 is 2.7831 sec
Epoch 240, gen_loss: 1.4129, disc_loss: 1.1608
Time for epoch 240 is 2.6549 sec
Epoch 241, gen_loss: 1.3050, disc_loss: 1.3024
Time for epoch 241 is 2.9748 sec
Epoch 242, gen_loss: 1.3427, disc_loss: 1.3079
Time for epoch 242 is 2.8496 sec
Epoch 243, gen_loss: 1.3053, disc_loss: 1.3177
Time for epoch 243 is 2.7616 sec
Epoch 244, gen_loss: 1.7363, disc_loss: 0.9112
Time for epoch 244 is 2.7450 sec
Epoch 245, gen_loss: 1.3155, disc_loss: 1.2216
Time for epoch 245 is 2.6733 sec
Epoch 246, gen_loss: 1.4095, disc_loss: 1.1270
Time for epoch 246 is 2.7029 sec
Epoch 247, gen_loss: 1.5622, disc_loss: 1.1004
Time for epoch 247 is 2.7613 sec
Epoch 248, gen_loss: 1.7007, disc_loss: 0.9649
Time for epoch 248 is 2.9177 sec
Epoch 249, gen_loss: 1.3659, disc_loss: 1.2208
Time for epoch 249 is 2.7960 sec
Epoch 250, gen_loss: 1.9298, disc_loss: 0.8285
Time for epoch 250 is 2.7713 sec
Epoch 251, gen_loss: 1.7595, disc_loss: 0.8405
Time for epoch 251 is 2.8186 sec
Epoch 252, gen_loss: 1.5344, disc_loss: 1.0992
Time for epoch 252 is 2.7067 sec
Epoch 253, gen_loss: 1.6915, disc_loss: 0.9595
Time for epoch 253 is 2.7990 sec
Epoch 254, gen_loss: 1.5983, disc_loss: 1.0121
Time for epoch 254 is 2.8418 sec
Epoch 255, gen_loss: 1.3506, disc_loss: 1.1591
Time for epoch 255 is 2.7906 sec
Epoch 256, gen_loss: 1.5117, disc_loss: 1.0851
Time for epoch 256 is 2.7844 sec
```

```
Epoch 257, gen_loss: 1.3142, disc_loss: 1.2615
Time for epoch 257 is 2.8266 sec
Epoch 258, gen_loss: 1.4411, disc_loss: 1.0700
Time for epoch 258 is 2.7264 sec
Epoch 259, gen_loss: 1.1577, disc_loss: 1.2061
Time for epoch 259 is 2.6246 sec
Epoch 260, gen_loss: 1.4220, disc_loss: 1.0851
Time for epoch 260 is 2.7252 sec
Epoch 261, gen_loss: 1.3585, disc_loss: 1.1567
Time for epoch 261 is 2.7612 sec
Epoch 262, gen_loss: 1.2247, disc_loss: 1.3895
Time for epoch 262 is 2.9515 sec
Epoch 263, gen_loss: 1.2732, disc_loss: 1.3774
Time for epoch 263 is 2.7841 sec
Epoch 264, gen_loss: 1.4416, disc_loss: 1.3462
Time for epoch 264 is 2.6572 sec
Epoch 265, gen_loss: 1.3250, disc_loss: 1.3090
Time for epoch 265 is 2.7527 sec
Epoch 266, gen_loss: 1.4844, disc_loss: 1.2132
Time for epoch 266 is 2.5791 sec
Epoch 267, gen_loss: 1.8190, disc_loss: 0.9538
Time for epoch 267 is 2.7806 sec
Epoch 268, gen_loss: 2.0903, disc_loss: 0.7580
Time for epoch 268 is 2.7876 sec
Epoch 269, gen_loss: 1.7547, disc_loss: 0.9348
Time for epoch 269 is 2.7605 sec
Epoch 270, gen_loss: 1.7218, disc_loss: 0.9265
Time for epoch 270 is 2.8252 sec
Epoch 271, gen_loss: 1.8513, disc_loss: 0.9348
Time for epoch 271 is 2.7492 sec
Epoch 272, gen_loss: 1.8183, disc_loss: 1.0588
Time for epoch 272 is 2.6567 sec
Epoch 273, gen_loss: 1.6136, disc_loss: 0.9468
Time for epoch 273 is 2.7929 sec
Epoch 274, gen_loss: 1.4519, disc_loss: 1.0622
Time for epoch 274 is 2.7231 sec
Epoch 275, gen_loss: 1.4036, disc_loss: 1.0936
Time for epoch 275 is 2.8790 sec
Epoch 276, gen_loss: 1.5005, disc_loss: 0.9928
Time for epoch 276 is 2.8418 sec
Epoch 277, gen_loss: 1.5284, disc_loss: 1.1343
Time for epoch 277 is 2.9306 sec
Epoch 278, gen_loss: 1.3337, disc_loss: 1.1566
Time for epoch 278 is 2.7686 sec
Epoch 279, gen_loss: 1.3872, disc_loss: 1.1414
Time for epoch 279 is 2.7699 sec
Epoch 280, gen_loss: 1.5129, disc_loss: 1.0755
Time for epoch 280 is 2.8942 sec
Epoch 281, gen_loss: 1.1406, disc_loss: 1.5051
Time for epoch 281 is 2.6282 sec
Epoch 282, gen_loss: 1.4127, disc_loss: 1.1997
Time for epoch 282 is 2.6639 sec
Epoch 283, gen_loss: 1.6613, disc_loss: 1.1306
Time for epoch 283 is 2.7509 sec
Epoch 284, gen_loss: 1.4131, disc_loss: 1.1062
Time for epoch 284 is 2.8086 sec
Epoch 285, gen_loss: 1.6414, disc_loss: 1.0623
Time for epoch 285 is 2.9261 sec
Epoch 286, gen_loss: 1.4476, disc_loss: 1.1518
Time for epoch 286 is 2.8268 sec
Epoch 287, gen_loss: 1.3745, disc_loss: 1.1608
Time for epoch 287 is 2.8192 sec
Epoch 288, gen_loss: 1.3930, disc_loss: 1.2188
Time for epoch 288 is 2.7996 sec
```

```
Epoch 289, gen_loss: 1.6432, disc_loss: 0.8799
Time for epoch 289 is 2.7188 sec
Epoch 290, gen_loss: 1.5918, disc_loss: 0.9818
Time for epoch 290 is 2.7611 sec
Epoch 291, gen_loss: 1.8098, disc_loss: 0.8682
Time for epoch 291 is 2.8230 sec
Epoch 292, gen_loss: 1.5497, disc_loss: 1.1377
Time for epoch 292 is 2.6379 sec
Epoch 293, gen_loss: 1.4540, disc_loss: 1.1749
Time for epoch 293 is 2.8885 sec
Epoch 294, gen_loss: 1.3085, disc_loss: 1.3871
Time for epoch 294 is 2.7974 sec
Epoch 295, gen_loss: 1.6358, disc_loss: 1.1094
Time for epoch 295 is 2.8617 sec
Epoch 296, gen_loss: 1.6265, disc_loss: 1.0766
Time for epoch 296 is 2.7733 sec
Epoch 297, gen_loss: 1.4983, disc_loss: 1.0836
Time for epoch 297 is 2.8805 sec
Epoch 298, gen_loss: 1.6753, disc_loss: 0.9909
Time for epoch 298 is 2.6323 sec
Epoch 299, gen_loss: 1.9241, disc_loss: 0.7800
Time for epoch 299 is 2.9880 sec
Epoch 300, gen_loss: 1.2872, disc_loss: 1.2479
Time for epoch 300 is 2.9007 sec
Epoch 301, gen_loss: 1.6593, disc_loss: 0.9086
Time for epoch 301 is 2.8858 sec
Epoch 302, gen_loss: 1.6631, disc_loss: 0.9807
Time for epoch 302 is 2.8047 sec
Epoch 303, gen_loss: 1.6169, disc_loss: 0.9004
Time for epoch 303 is 2.9854 sec
Epoch 304, gen_loss: 1.4279, disc_loss: 1.1204
Time for epoch 304 is 2.9919 sec
Epoch 305, gen_loss: 1.4570, disc_loss: 1.2273
Time for epoch 305 is 2.9441 sec
Epoch 306, gen_loss: 1.5632, disc_loss: 1.1381
Time for epoch 306 is 2.7382 sec
Epoch 307, gen_loss: 1.3286, disc_loss: 1.2466
Time for epoch 307 is 2.7870 sec
Epoch 308, gen_loss: 1.4674, disc_loss: 1.2308
Time for epoch 308 is 2.7111 sec
Epoch 309, gen_loss: 1.4283, disc_loss: 1.2386
Time for epoch 309 is 2.7855 sec
Epoch 310, gen_loss: 1.7795, disc_loss: 0.8981
Time for epoch 310 is 2.6546 sec
Epoch 311, gen_loss: 1.4665, disc_loss: 1.0958
Time for epoch 311 is 2.6369 sec
Epoch 312, gen_loss: 1.3966, disc_loss: 1.1400
Time for epoch 312 is 2.6846 sec
Epoch 313, gen_loss: 1.3346, disc_loss: 1.3311
Time for epoch 313 is 2.6534 sec
Epoch 314, gen_loss: 1.6244, disc_loss: 1.0815
Time for epoch 314 is 2.7793 sec
Epoch 315, gen_loss: 1.6190, disc_loss: 1.0886
Time for epoch 315 is 2.7612 sec
Epoch 316, gen_loss: 1.9007, disc_loss: 0.9334
Time for epoch 316 is 2.6074 sec
Epoch 317, gen_loss: 1.5427, disc_loss: 1.0687
Time for epoch 317 is 2.7645 sec
Epoch 318, gen_loss: 1.5660, disc_loss: 1.0877
Time for epoch 318 is 2.7915 sec
Epoch 319, gen_loss: 1.7837, disc_loss: 1.0065
Time for epoch 319 is 2.6891 sec
Epoch 320, gen_loss: 1.3288, disc_loss: 1.2286
Time for epoch 320 is 2.8767 sec
```

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Epoch 321, gen_loss: 1.7182, disc_loss: 0.8514
Time for epoch 321 is 2.8580 sec
Epoch 322, gen_loss: 1.2799, disc_loss: 1.2151
Time for epoch 322 is 2.7880 sec
Epoch 323, gen_loss: 1.3362, disc_loss: 1.2152
Time for epoch 323 is 2.7481 sec
Epoch 324, gen_loss: 1.6702, disc_loss: 0.9521
Time for epoch 324 is 2.7856 sec
Epoch 325, gen_loss: 1.1675, disc_loss: 1.3478
Time for epoch 325 is 2.6974 sec
Epoch 326, gen_loss: 1.4348, disc_loss: 1.2409
Time for epoch 326 is 2.8468 sec
Epoch 327, gen_loss: 1.4106, disc_loss: 1.3255
Time for epoch 327 is 2.7237 sec
Epoch 328, gen_loss: 1.3221, disc_loss: 1.5220
Time for epoch 328 is 2.6975 sec
Epoch 329, gen_loss: 1.2438, disc_loss: 1.5355
Time for epoch 329 is 2.7704 sec
Epoch 330, gen_loss: 1.7441, disc_loss: 1.1445
Time for epoch 330 is 2.6853 sec
Epoch 331, gen_loss: 1.7485, disc_loss: 0.9878
Time for epoch 331 is 2.7803 sec
Epoch 332, gen_loss: 1.7707, disc_loss: 0.9071
Time for epoch 332 is 2.8351 sec
Epoch 333, gen_loss: 1.6581, disc_loss: 0.9851
Time for epoch 333 is 2.7319 sec
Epoch 334, gen_loss: 1.7044, disc_loss: 1.0054
Time for epoch 334 is 2.7197 sec
Epoch 335, gen_loss: 1.5939, disc_loss: 1.1581
Time for epoch 335 is 2.6878 sec
Epoch 336, gen_loss: 1.7731, disc_loss: 0.9612
Time for epoch 336 is 2.7581 sec
Epoch 337, gen_loss: 1.7216, disc_loss: 0.9264
Time for epoch 337 is 2.7563 sec
Epoch 338, gen_loss: 1.5040, disc_loss: 1.1345
Time for epoch 338 is 2.6521 sec
Epoch 339, gen_loss: 1.6214, disc_loss: 0.9291
Time for epoch 339 is 2.6662 sec
Epoch 340, gen_loss: 1.7217, disc_loss: 0.9582
Time for epoch 340 is 2.7671 sec
Epoch 341, gen_loss: 1.5390, disc_loss: 1.0010
Time for epoch 341 is 2.7349 sec
Epoch 342, gen_loss: 1.3240, disc_loss: 1.0776
Time for epoch 342 is 2.7630 sec
Epoch 343, gen_loss: 1.3072, disc_loss: 1.1885
Time for epoch 343 is 2.9502 sec
Epoch 344, gen_loss: 1.3794, disc_loss: 1.1979
Time for epoch 344 is 2.7727 sec
Epoch 345, gen_loss: 1.4357, disc_loss: 1.2087
Time for epoch 345 is 2.8577 sec
Epoch 346, gen_loss: 1.3950, disc_loss: 1.2965
Time for epoch 346 is 2.9441 sec
Epoch 347, gen_loss: 1.1808, disc_loss: 1.5667
Time for epoch 347 is 2.7166 sec
Epoch 348, gen_loss: 1.5733, disc_loss: 1.4118
Time for epoch 348 is 2.8128 sec
Epoch 349, gen_loss: 1.4873, disc_loss: 1.2795
Time for epoch 349 is 2.7518 sec
Epoch 350, gen_loss: 1.4292, disc_loss: 1.4488
Time for epoch 350 is 2.9816 sec
Epoch 351, gen_loss: 1.6256, disc_loss: 1.0396
Time for epoch 351 is 2.8595 sec
Epoch 352, gen_loss: 1.8274, disc_loss: 0.9704
Time for epoch 352 is 2.9678 sec
```

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Epoch 353, gen_loss: 1.4814, disc_loss: 1.1546
Time for epoch 353 is 2.7894 sec
Epoch 354, gen_loss: 1.6868, disc_loss: 0.9467
Time for epoch 354 is 2.9174 sec
Epoch 355, gen_loss: 1.7749, disc_loss: 0.9340
Time for epoch 355 is 2.8553 sec
Epoch 356, gen_loss: 1.4263, disc_loss: 1.0692
Time for epoch 356 is 2.7612 sec
Epoch 357, gen_loss: 1.4434, disc_loss: 1.2290
Time for epoch 357 is 2.8467 sec
Epoch 358, gen_loss: 1.6983, disc_loss: 1.0236
Time for epoch 358 is 2.7407 sec
Epoch 359, gen_loss: 1.6323, disc_loss: 1.1382
Time for epoch 359 is 2.6560 sec
Epoch 360, gen_loss: 1.2418, disc_loss: 1.4237
Time for epoch 360 is 2.7045 sec
Epoch 361, gen_loss: 1.9009, disc_loss: 0.8905
Time for epoch 361 is 2.8315 sec
Epoch 362, gen_loss: 1.4465, disc_loss: 1.2576
Time for epoch 362 is 2.7036 sec
Epoch 363, gen_loss: 1.6023, disc_loss: 1.0113
Time for epoch 363 is 2.7296 sec
Epoch 364, gen_loss: 1.6522, disc_loss: 1.0643
Time for epoch 364 is 2.7128 sec
Epoch 365, gen_loss: 1.4827, disc_loss: 1.1957
Time for epoch 365 is 2.6435 sec
Epoch 366, gen_loss: 1.3175, disc_loss: 1.2713
Time for epoch 366 is 2.7248 sec
Epoch 367, gen_loss: 1.5251, disc_loss: 1.1212
Time for epoch 367 is 2.8105 sec
Epoch 368, gen_loss: 1.4801, disc_loss: 1.1093
Time for epoch 368 is 2.6388 sec
Epoch 369, gen_loss: 1.1733, disc_loss: 1.4442
Time for epoch 369 is 2.6636 sec
Epoch 370, gen_loss: 1.4051, disc_loss: 1.3949
Time for epoch 370 is 2.6614 sec
Epoch 371, gen_loss: 1.2759, disc_loss: 1.4257
Time for epoch 371 is 2.7569 sec
Epoch 372, gen_loss: 1.2629, disc_loss: 1.4058
Time for epoch 372 is 2.7644 sec
Epoch 373, gen_loss: 1.4763, disc_loss: 1.1981
Time for epoch 373 is 2.7033 sec
Epoch 374, gen_loss: 1.7870, disc_loss: 1.0129
Time for epoch 374 is 2.6969 sec
Epoch 375, gen_loss: 1.6267, disc_loss: 1.1171
Time for epoch 375 is 2.7625 sec
Epoch 376, gen_loss: 1.6906, disc_loss: 0.9901
Time for epoch 376 is 2.5614 sec
Epoch 377, gen_loss: 2.1171, disc_loss: 0.7844
Time for epoch 377 is 2.6701 sec
Epoch 378, gen_loss: 1.6431, disc_loss: 1.0625
Time for epoch 378 is 2.7074 sec
Epoch 379, gen_loss: 1.8434, disc_loss: 0.9448
Time for epoch 379 is 2.7283 sec
Epoch 380, gen_loss: 1.7540, disc_loss: 1.0864
Time for epoch 380 is 2.6521 sec
Epoch 381, gen_loss: 1.7315, disc_loss: 0.9845
Time for epoch 381 is 2.6950 sec
Epoch 382, gen_loss: 1.8021, disc_loss: 0.8711
Time for epoch 382 is 2.9052 sec
Epoch 383, gen_loss: 1.3917, disc_loss: 1.0544
Time for epoch 383 is 2.7707 sec
Epoch 384, gen_loss: 1.2276, disc_loss: 1.3515
Time for epoch 384 is 2.7151 sec
```

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Epoch 385, gen_loss: 1.2708, disc_loss: 1.2914
Time for epoch 385 is 2.7132 sec
Epoch 386, gen_loss: 1.5658, disc_loss: 1.0703
Time for epoch 386 is 2.7494 sec
Epoch 387, gen_loss: 1.3154, disc_loss: 1.2437
Time for epoch 387 is 3.0056 sec
Epoch 388, gen_loss: 1.5441, disc_loss: 1.0274
Time for epoch 388 is 2.5559 sec
Epoch 389, gen_loss: 1.6212, disc_loss: 0.9835
Time for epoch 389 is 2.6446 sec
Epoch 390, gen_loss: 1.2129, disc_loss: 1.3541
Time for epoch 390 is 2.5817 sec
Epoch 391, gen_loss: 1.3833, disc_loss: 1.2118
Time for epoch 391 is 2.8167 sec
Epoch 392, gen_loss: 1.1538, disc_loss: 1.5138
Time for epoch 392 is 2.7704 sec
Epoch 393, gen_loss: 1.2686, disc_loss: 1.6675
Time for epoch 393 is 2.9392 sec
Epoch 394, gen_loss: 1.5654, disc_loss: 1.1984
Time for epoch 394 is 2.7612 sec
Epoch 395, gen_loss: 1.8232, disc_loss: 0.9601
Time for epoch 395 is 2.7999 sec
Epoch 396, gen_loss: 1.8364, disc_loss: 0.8544
Time for epoch 396 is 2.7923 sec
Epoch 397, gen_loss: 1.7980, disc_loss: 0.9042
Time for epoch 397 is 2.8229 sec
Epoch 398, gen_loss: 1.3374, disc_loss: 1.1641
Time for epoch 398 is 2.7677 sec
Epoch 399, gen_loss: 1.8681, disc_loss: 0.9643
Time for epoch 399 is 2.7539 sec
Epoch 400, gen_loss: 1.5787, disc_loss: 0.9883
Time for epoch 400 is 2.8390 sec
Epoch 401, gen_loss: 1.6181, disc_loss: 1.0654
Time for epoch 401 is 2.6751 sec
Epoch 402, gen_loss: 1.3172, disc_loss: 1.3174
Time for epoch 402 is 2.7015 sec
Epoch 403, gen_loss: 1.7209, disc_loss: 0.9637
Time for epoch 403 is 2.7929 sec
Epoch 404, gen_loss: 1.2229, disc_loss: 1.3733
Time for epoch 404 is 2.7659 sec
Epoch 405, gen_loss: 1.3866, disc_loss: 1.2168
Time for epoch 405 is 2.7028 sec
Epoch 406, gen_loss: 1.2791, disc_loss: 1.3222
Time for epoch 406 is 2.7254 sec
Epoch 407, gen_loss: 1.3150, disc_loss: 1.3072
Time for epoch 407 is 2.7362 sec
Epoch 408, gen_loss: 1.2204, disc_loss: 1.4637
Time for epoch 408 is 2.7454 sec
Epoch 409, gen_loss: 2.0186, disc_loss: 0.8106
Time for epoch 409 is 2.7442 sec
Epoch 410, gen_loss: 1.6033, disc_loss: 1.0769
Time for epoch 410 is 2.7539 sec
Epoch 411, gen_loss: 1.4859, disc_loss: 1.2395
Time for epoch 411 is 2.8115 sec
Epoch 412, gen_loss: 1.4391, disc_loss: 1.1866
Time for epoch 412 is 2.7873 sec
Epoch 413, gen_loss: 1.5675, disc_loss: 1.0501
Time for epoch 413 is 2.7097 sec
Epoch 414, gen_loss: 1.4487, disc_loss: 1.2659
Time for epoch 414 is 2.8515 sec
Epoch 415, gen_loss: 1.2983, disc_loss: 1.3585
Time for epoch 415 is 2.6504 sec
Epoch 416, gen_loss: 1.3784, disc_loss: 1.3412
Time for epoch 416 is 2.6366 sec
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Epoch 417, gen_loss: 1.5210, disc_loss: 1.1293
Time for epoch 417 is 2.6563 sec
Epoch 418, gen_loss: 1.6260, disc_loss: 1.0689
Time for epoch 418 is 2.6230 sec
Epoch 419, gen_loss: 1.6314, disc_loss: 1.1181
Time for epoch 419 is 2.7198 sec
Epoch 420, gen_loss: 1.5543, disc_loss: 1.1009
Time for epoch 420 is 2.7455 sec
Epoch 421, gen_loss: 1.3679, disc_loss: 1.2846
Time for epoch 421 is 2.6184 sec
Epoch 422, gen_loss: 1.9187, disc_loss: 1.0367
Time for epoch 422 is 2.6684 sec
Epoch 423, gen_loss: 1.5627, disc_loss: 1.1382
Time for epoch 423 is 2.6449 sec
Epoch 424, gen_loss: 1.6289, disc_loss: 1.1250
Time for epoch 424 is 2.6629 sec
Epoch 425, gen_loss: 2.0070, disc_loss: 0.8487
Time for epoch 425 is 2.6019 sec
Epoch 426, gen_loss: 1.5220, disc_loss: 1.1775
Time for epoch 426 is 2.6972 sec
Epoch 427, gen_loss: 1.7632, disc_loss: 0.8631
Time for epoch 427 is 2.6447 sec
Epoch 428, gen_loss: 1.5201, disc_loss: 1.0043
Time for epoch 428 is 2.8476 sec
Epoch 429, gen_loss: 1.4938, disc_loss: 1.0774
Time for epoch 429 is 2.6557 sec
Epoch 430, gen_loss: 1.3933, disc_loss: 1.2085
Time for epoch 430 is 2.7787 sec
Epoch 431, gen_loss: 1.2867, disc_loss: 1.2714
Time for epoch 431 is 2.7234 sec
Epoch 432, gen_loss: 1.4389, disc_loss: 1.2660
Time for epoch 432 is 2.8022 sec
Epoch 433, gen_loss: 1.5362, disc_loss: 1.0666
Time for epoch 433 is 2.8580 sec
Epoch 434, gen_loss: 1.2960, disc_loss: 1.3087
Time for epoch 434 is 2.9488 sec
Epoch 435, gen_loss: 1.4256, disc_loss: 1.0963
Time for epoch 435 is 2.8921 sec
Epoch 436, gen_loss: 1.5434, disc_loss: 0.9924
Time for epoch 436 is 2.8644 sec
Epoch 437, gen_loss: 1.2536, disc_loss: 1.3110
Time for epoch 437 is 2.7915 sec
Epoch 438, gen_loss: 1.0823, disc_loss: 1.5584
Time for epoch 438 is 2.9781 sec
Epoch 439, gen_loss: 1.3536, disc_loss: 1.2896
Time for epoch 439 is 2.6991 sec
Epoch 440, gen_loss: 1.6026, disc_loss: 1.2936
Time for epoch 440 is 2.7059 sec
Epoch 441, gen_loss: 1.5154, disc_loss: 1.1366
Time for epoch 441 is 2.7734 sec
Epoch 442, gen_loss: 1.5212, disc_loss: 1.0960
Time for epoch 442 is 2.7291 sec
Epoch 443, gen_loss: 1.3036, disc_loss: 1.3351
Time for epoch 443 is 2.5449 sec
Epoch 444, gen_loss: 1.4602, disc_loss: 1.4262
Time for epoch 444 is 2.7202 sec
Epoch 445, gen_loss: 1.5130, disc_loss: 1.3583
Time for epoch 445 is 2.8305 sec
Epoch 446, gen_loss: 1.4605, disc_loss: 1.3482
Time for epoch 446 is 2.6786 sec
Epoch 447, gen_loss: 1.6412, disc_loss: 1.0524
Time for epoch 447 is 2.7903 sec
Epoch 448, gen_loss: 1.8714, disc_loss: 0.8906
Time for epoch 448 is 2.8496 sec
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Epoch 449, gen_loss: 1.8497, disc_loss: 0.9716
Time for epoch 449 is 2.9732 sec
Epoch 450, gen_loss: 1.7351, disc_loss: 0.9426
Time for epoch 450 is 2.8633 sec
Epoch 451, gen_loss: 1.5395, disc_loss: 1.1873
Time for epoch 451 is 2.7796 sec
Epoch 452, gen_loss: 1.6101, disc_loss: 1.0879
Time for epoch 452 is 2.7569 sec
Epoch 453, gen_loss: 1.7661, disc_loss: 1.0346
Time for epoch 453 is 2.8468 sec
Epoch 454, gen_loss: 1.4266, disc_loss: 1.1831
Time for epoch 454 is 2.5675 sec
Epoch 455, gen_loss: 1.6030, disc_loss: 1.1439
Time for epoch 455 is 2.8151 sec
Epoch 456, gen_loss: 1.4727, disc_loss: 1.0945
Time for epoch 456 is 2.7031 sec
Epoch 457, gen_loss: 1.7364, disc_loss: 0.9952
Time for epoch 457 is 2.7427 sec
Epoch 458, gen_loss: 1.7599, disc_loss: 0.9355
Time for epoch 458 is 2.6672 sec
Epoch 459, gen_loss: 1.4262, disc_loss: 1.3085
Time for epoch 459 is 2.8015 sec
Epoch 460, gen_loss: 1.5590, disc_loss: 1.1239
Time for epoch 460 is 2.6729 sec
Epoch 461, gen_loss: 1.5915, disc_loss: 1.1408
Time for epoch 461 is 2.6674 sec
Epoch 462, gen_loss: 1.5240, disc_loss: 1.3077
Time for epoch 462 is 2.8612 sec
Epoch 463, gen_loss: 2.2941, disc_loss: 0.7807
Time for epoch 463 is 2.8878 sec
Epoch 464, gen_loss: 1.4038, disc_loss: 1.2953
Time for epoch 464 is 2.6226 sec
Epoch 465, gen_loss: 1.5378, disc_loss: 1.0863
Time for epoch 465 is 2.7499 sec
Epoch 466, gen_loss: 1.9171, disc_loss: 0.8427
Time for epoch 466 is 2.6729 sec
Epoch 467, gen_loss: 1.5662, disc_loss: 1.0975
Time for epoch 467 is 2.6927 sec
Epoch 468, gen_loss: 1.2825, disc_loss: 1.3178
Time for epoch 468 is 2.6455 sec
Epoch 469, gen_loss: 1.4879, disc_loss: 1.1401
Time for epoch 469 is 2.6707 sec
Epoch 470, gen_loss: 1.4572, disc_loss: 1.1605
Time for epoch 470 is 2.7070 sec
Epoch 471, gen_loss: 1.5924, disc_loss: 1.0746
Time for epoch 471 is 2.7430 sec
Epoch 472, gen_loss: 1.5058, disc_loss: 1.0792
Time for epoch 472 is 2.8028 sec
Epoch 473, gen_loss: 1.2779, disc_loss: 1.1645
Time for epoch 473 is 2.7782 sec
Epoch 474, gen_loss: 1.4913, disc_loss: 1.1427
Time for epoch 474 is 2.7103 sec
Epoch 475, gen_loss: 1.3261, disc_loss: 1.3336
Time for epoch 475 is 2.6980 sec
Epoch 476, gen_loss: 1.0999, disc_loss: 1.6573
Time for epoch 476 is 2.7192 sec
Epoch 477, gen_loss: 1.4050, disc_loss: 1.3802
Time for epoch 477 is 2.7733 sec
Epoch 478, gen_loss: 1.2912, disc_loss: 1.4844
Time for epoch 478 is 2.8197 sec
Epoch 479, gen_loss: 1.6490, disc_loss: 1.1076
Time for epoch 479 is 2.8114 sec
Epoch 480, gen_loss: 1.4154, disc_loss: 1.2301
Time for epoch 480 is 2.6944 sec
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Epoch 481, gen_loss: 1.5465, disc_loss: 1.1103
Time for epoch 481 is 2.6894 sec
Epoch 482, gen_loss: 1.3327, disc_loss: 1.2531
Time for epoch 482 is 2.6376 sec
Epoch 483, gen_loss: 1.4315, disc_loss: 1.1828
Time for epoch 483 is 2.6310 sec
Epoch 484, gen_loss: 1.6578, disc_loss: 1.1946
Time for epoch 484 is 2.6974 sec
Epoch 485, gen_loss: 1.5816, disc_loss: 1.2462
Time for epoch 485 is 2.6284 sec
Epoch 486, gen_loss: 1.5966, disc_loss: 1.0815
Time for epoch 486 is 2.8203 sec
Epoch 487, gen_loss: 1.6828, disc_loss: 1.0564
Time for epoch 487 is 2.7773 sec
Epoch 488, gen_loss: 1.7555, disc_loss: 1.0164
Time for epoch 488 is 2.8441 sec
Epoch 489, gen_loss: 1.9055, disc_loss: 0.8449
Time for epoch 489 is 2.9597 sec
Epoch 490, gen_loss: 1.4928, disc_loss: 1.0706
Time for epoch 490 is 2.8854 sec
Epoch 491, gen_loss: 1.2476, disc_loss: 1.2289
Time for epoch 491 is 2.8749 sec
Epoch 492, gen_loss: 1.3137, disc_loss: 1.2651
Time for epoch 492 is 3.0401 sec
Epoch 493, gen_loss: 1.3372, disc_loss: 1.2935
Time for epoch 493 is 2.7728 sec
Epoch 494, gen_loss: 1.2992, disc_loss: 1.3009
Time for epoch 494 is 2.7506 sec
Epoch 495, gen_loss: 1.2431, disc_loss: 1.4563
Time for epoch 495 is 2.7109 sec
Epoch 496, gen_loss: 1.4048, disc_loss: 1.2899
Time for epoch 496 is 2.8585 sec
Epoch 497, gen_loss: 1.5306, disc_loss: 1.2232
Time for epoch 497 is 2.8410 sec
Epoch 498, gen_loss: 1.7924, disc_loss: 0.9876
Time for epoch 498 is 2.9499 sec
Epoch 499, gen_loss: 1.6207, disc_loss: 1.1187
Time for epoch 499 is 2.6812 sec
Epoch 500, gen_loss: 1.4136, disc_loss: 1.2424
Time for epoch 500 is 2.8371 sec
Epoch 501, gen_loss: 2.1174, disc_loss: 0.7992
Time for epoch 501 is 2.7750 sec
Epoch 502, gen_loss: 1.4939, disc_loss: 1.1240
Time for epoch 502 is 2.8081 sec
Epoch 503, gen_loss: 1.2996, disc_loss: 1.2645
Time for epoch 503 is 2.6079 sec
Epoch 504, gen_loss: 1.7164, disc_loss: 1.1071
Time for epoch 504 is 2.7863 sec
Epoch 505, gen_loss: 1.6398, disc_loss: 1.0651
Time for epoch 505 is 2.8250 sec
Epoch 506, gen_loss: 1.5029, disc_loss: 1.1538
Time for epoch 506 is 2.9609 sec
Epoch 507, gen_loss: 1.7585, disc_loss: 1.0341
Time for epoch 507 is 2.8943 sec
Epoch 508, gen_loss: 1.9368, disc_loss: 0.8680
Time for epoch 508 is 2.8941 sec
Epoch 509, gen_loss: 1.4061, disc_loss: 1.1411
Time for epoch 509 is 2.8259 sec
Epoch 510, gen_loss: 1.5924, disc_loss: 1.0409
Time for epoch 510 is 2.6853 sec
Epoch 511, gen_loss: 1.6224, disc_loss: 0.9173
Time for epoch 511 is 2.7522 sec
Epoch 512, gen_loss: 1.4257, disc_loss: 1.0282
Time for epoch 512 is 2.7143 sec
```

```
Epoch 513, gen_loss: 1.3125, disc_loss: 1.1940
Time for epoch 513 is 2.5786 sec
Epoch 514, gen_loss: 1.3834, disc_loss: 1.2133
Time for epoch 514 is 2.7398 sec
Epoch 515, gen_loss: 1.1962, disc_loss: 1.5243
Time for epoch 515 is 2.8060 sec
Epoch 516, gen_loss: 1.2929, disc_loss: 1.4014
Time for epoch 516 is 2.9010 sec
Epoch 517, gen_loss: 1.4878, disc_loss: 1.2858
Time for epoch 517 is 2.8596 sec
Epoch 518, gen_loss: 1.1814, disc_loss: 1.6164
Time for epoch 518 is 2.7642 sec
Epoch 519, gen_loss: 1.4546, disc_loss: 1.2266
Time for epoch 519 is 2.6708 sec
Epoch 520, gen_loss: 1.6875, disc_loss: 1.0968
Time for epoch 520 is 2.7628 sec
Epoch 521, gen_loss: 1.3046, disc_loss: 1.2740
Time for epoch 521 is 2.6423 sec
Epoch 522, gen_loss: 1.4252, disc_loss: 1.2737
Time for epoch 522 is 2.7360 sec
Epoch 523, gen_loss: 1.4886, disc_loss: 1.2958
Time for epoch 523 is 2.7144 sec
Epoch 524, gen_loss: 1.6100, disc_loss: 1.1328
Time for epoch 524 is 2.7411 sec
Epoch 525, gen_loss: 1.5873, disc_loss: 1.1115
Time for epoch 525 is 2.7918 sec
Epoch 526, gen_loss: 1.6348, disc_loss: 0.9571
Time for epoch 526 is 2.7395 sec
Epoch 527, gen_loss: 1.7451, disc_loss: 0.9149
Time for epoch 527 is 2.7273 sec
Epoch 528, gen_loss: 1.7042, disc_loss: 1.0534
Time for epoch 528 is 2.7114 sec
Epoch 529, gen_loss: 1.5268, disc_loss: 1.1351
Time for epoch 529 is 2.6077 sec
Epoch 530, gen_loss: 1.4707, disc_loss: 1.1536
Time for epoch 530 is 2.7618 sec
Epoch 531, gen_loss: 1.7358, disc_loss: 0.9980
Time for epoch 531 is 2.7217 sec
Epoch 532, gen_loss: 1.6163, disc_loss: 1.0855
Time for epoch 532 is 2.6190 sec
Epoch 533, gen_loss: 1.5931, disc_loss: 1.1077
Time for epoch 533 is 2.6307 sec
Epoch 534, gen_loss: 1.3834, disc_loss: 1.2589
Time for epoch 534 is 2.6582 sec
Epoch 535, gen_loss: 1.6760, disc_loss: 1.0114
Time for epoch 535 is 2.5883 sec
Epoch 536, gen_loss: 1.5303, disc_loss: 1.1686
Time for epoch 536 is 2.8013 sec
Epoch 537, gen_loss: 1.3518, disc_loss: 1.3193
Time for epoch 537 is 2.6143 sec
Epoch 538, gen_loss: 1.5777, disc_loss: 1.1940
Time for epoch 538 is 2.6405 sec
Epoch 539, gen_loss: 1.3867, disc_loss: 1.5501
Time for epoch 539 is 2.5839 sec
Epoch 540, gen_loss: 1.5092, disc_loss: 1.3023
Time for epoch 540 is 2.8567 sec
Epoch 541, gen_loss: 1.4207, disc_loss: 1.3526
Time for epoch 541 is 2.8238 sec
Epoch 542, gen_loss: 1.6522, disc_loss: 1.1371
Time for epoch 542 is 2.6856 sec
Epoch 543, gen_loss: 1.8273, disc_loss: 0.9875
Time for epoch 543 is 2.7811 sec
Epoch 544, gen_loss: 1.4701, disc_loss: 1.1248
Time for epoch 544 is 2.7667 sec
```

```
Epoch 545, gen_loss: 1.7753, disc_loss: 1.0201
Time for epoch 545 is 2.9215 sec
Epoch 546, gen_loss: 1.5912, disc_loss: 1.1389
Time for epoch 546 is 2.8773 sec
Epoch 547, gen_loss: 1.3136, disc_loss: 1.3174
Time for epoch 547 is 2.7584 sec
Epoch 548, gen_loss: 1.9351, disc_loss: 0.9570
Time for epoch 548 is 2.8885 sec
Epoch 549, gen_loss: 1.5576, disc_loss: 1.1265
Time for epoch 549 is 2.8406 sec
Epoch 550, gen_loss: 1.4023, disc_loss: 1.1809
Time for epoch 550 is 2.8195 sec
Epoch 551, gen_loss: 1.5920, disc_loss: 1.1071
Time for epoch 551 is 2.6180 sec
Epoch 552, gen_loss: 1.6358, disc_loss: 1.1785
Time for epoch 552 is 2.6449 sec
Epoch 553, gen_loss: 1.3750, disc_loss: 1.1346
Time for epoch 553 is 2.6846 sec
Epoch 554, gen_loss: 1.3347, disc_loss: 1.2719
Time for epoch 554 is 2.6199 sec
Epoch 555, gen_loss: 1.4284, disc_loss: 1.2857
Time for epoch 555 is 2.7669 sec
Epoch 556, gen_loss: 1.5654, disc_loss: 1.1866
Time for epoch 556 is 2.5750 sec
Epoch 557, gen_loss: 1.8400, disc_loss: 1.0466
Time for epoch 557 is 2.7649 sec
Epoch 558, gen_loss: 1.5340, disc_loss: 1.1476
Time for epoch 558 is 2.6049 sec
Epoch 559, gen_loss: 1.4575, disc_loss: 1.1819
Time for epoch 559 is 2.6871 sec
Epoch 560, gen_loss: 1.5891, disc_loss: 1.0939
Time for epoch 560 is 2.7941 sec
Epoch 561, gen_loss: 1.5378, disc_loss: 1.0439
Time for epoch 561 is 2.6607 sec
Epoch 562, gen_loss: 1.6763, disc_loss: 1.0366
Time for epoch 562 is 2.7165 sec
Epoch 563, gen_loss: 1.2656, disc_loss: 1.3536
Time for epoch 563 is 2.6650 sec
Epoch 564, gen_loss: 1.4976, disc_loss: 1.0266
Time for epoch 564 is 2.7758 sec
Epoch 565, gen_loss: 1.5531, disc_loss: 1.1300
Time for epoch 565 is 2.6458 sec
Epoch 566, gen_loss: 1.2524, disc_loss: 1.5051
Time for epoch 566 is 2.7671 sec
Epoch 567, gen_loss: 1.5045, disc_loss: 1.3402
Time for epoch 567 is 2.8564 sec
Epoch 568, gen_loss: 1.7216, disc_loss: 1.2275
Time for epoch 568 is 2.7879 sec
Epoch 569, gen_loss: 1.1315, disc_loss: 1.4727
Time for epoch 569 is 2.6206 sec
Epoch 570, gen_loss: 1.2762, disc_loss: 1.4192
Time for epoch 570 is 2.7381 sec
Epoch 571, gen_loss: 1.8761, disc_loss: 1.0647
Time for epoch 571 is 2.7208 sec
Epoch 572, gen_loss: 1.5518, disc_loss: 1.1672
Time for epoch 572 is 2.7640 sec
Epoch 573, gen_loss: 1.5545, disc_loss: 1.0629
Time for epoch 573 is 2.8095 sec
Epoch 574, gen_loss: 1.4991, disc_loss: 1.1363
Time for epoch 574 is 2.8818 sec
Epoch 575, gen_loss: 1.8073, disc_loss: 0.9132
Time for epoch 575 is 2.6395 sec
Epoch 576, gen_loss: 1.9095, disc_loss: 0.8053
Time for epoch 576 is 2.8770 sec
```

```
Epoch 577, gen_loss: 1.6568, disc_loss: 0.8860
Time for epoch 577 is 2.7472 sec
Epoch 578, gen_loss: 1.1618, disc_loss: 1.3050
Time for epoch 578 is 2.6350 sec
Epoch 579, gen_loss: 1.5038, disc_loss: 1.0389
Time for epoch 579 is 2.6233 sec
Epoch 580, gen_loss: 1.0898, disc_loss: 1.5164
Time for epoch 580 is 2.9061 sec
Epoch 581, gen_loss: 1.2877, disc_loss: 1.3794
Time for epoch 581 is 2.7541 sec
Epoch 582, gen_loss: 1.1556, disc_loss: 1.4464
Time for epoch 582 is 2.8219 sec
Epoch 583, gen_loss: 1.5210, disc_loss: 1.2693
Time for epoch 583 is 2.8192 sec
Epoch 584, gen_loss: 1.1246, disc_loss: 1.5835
Time for epoch 584 is 2.7571 sec
Epoch 585, gen_loss: 1.5627, disc_loss: 1.2289
Time for epoch 585 is 2.8443 sec
Epoch 586, gen_loss: 1.2672, disc_loss: 1.5386
Time for epoch 586 is 2.7702 sec
Epoch 587, gen_loss: 1.4507, disc_loss: 1.3906
Time for epoch 587 is 2.7806 sec
Epoch 588, gen_loss: 1.7697, disc_loss: 1.1264
Time for epoch 588 is 2.7343 sec
Epoch 589, gen_loss: 1.4761, disc_loss: 1.2017
Time for epoch 589 is 2.6996 sec
Epoch 590, gen_loss: 1.7790, disc_loss: 0.9650
Time for epoch 590 is 2.7334 sec
Epoch 591, gen_loss: 1.2539, disc_loss: 1.3430
Time for epoch 591 is 2.7755 sec
Epoch 592, gen_loss: 1.6775, disc_loss: 0.9512
Time for epoch 592 is 2.8040 sec
Epoch 593, gen_loss: 1.8180, disc_loss: 0.8583
Time for epoch 593 is 2.7300 sec
Epoch 594, gen_loss: 1.6375, disc_loss: 0.9610
Time for epoch 594 is 2.7661 sec
Epoch 595, gen_loss: 1.6283, disc_loss: 0.9444
Time for epoch 595 is 2.7414 sec
Epoch 596, gen_loss: 1.3661, disc_loss: 1.1386
Time for epoch 596 is 2.6704 sec
Epoch 597, gen_loss: 1.3053, disc_loss: 1.2511
Time for epoch 597 is 2.7331 sec
Epoch 598, gen_loss: 1.5153, disc_loss: 1.2351
Time for epoch 598 is 2.8413 sec
Epoch 599, gen_loss: 1.6095, disc_loss: 1.1348
Time for epoch 599 is 2.7835 sec
Epoch 600, gen_loss: 1.2252, disc_loss: 1.5143
Time for epoch 600 is 2.7972 sec
```

Evaluation

`dataset/testData.pkl` is a pandas dataframe containing testing text with attributes 'ID' and 'Captions'.

- 'ID': text ID used to name generated image.
- 'Captions': text used as condition to generate image.

For each captions, you need to generate **inference_ID.png** to evaluate quality of generated image. You must name the generated image in this format, otherwise we cannot evaluate your images.

Testing Dataset

If you change anything during preprocessing of training dataset, you must make sure same operations have be done in testing dataset.

In [26]:
```
def testing_data_generator(caption, index):
    caption = tf.cast(caption, tf.float32)
    return caption, index

def testing_dataset_generator(batch_size, data_generator):
    data = pd.read_pickle('./dataset/testData.pkl')
    captions = data['Captions'].values
    caption = []
    for i in range(len(captions)):
        caption.append(captions[i])
    caption = np.asarray(caption)
    caption = caption.astype(np.int)
    index = data['ID'].values
    index = np.asarray(index)

    dataset = tf.data.Dataset.from_tensor_slices((caption, index))
    dataset = dataset.map(data_generator, num_parallel_calls=tf.data.experimental.A
    dataset = dataset.repeat().batch(batch_size)

    return dataset
```

In [27]:
```
testing_dataset = testing_dataset_generator(hparas['BATCH_SIZE'], testing_data_gene
```

```
/tmp/ipykernel_29626/466323065.py:12: DeprecationWarning: `np.int` is a deprecated
alias for the builtin `int`. To silence this warning, use `int` by itself. Doing t
his will not modify any behavior and is safe. When replacing `np.int`, you may wis
h to use e.g. `np.int64` or `np.int32` to specify the precision. If you wish to re
view your current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdoc
s/release/1.20.0-notes.html#deprecations
  caption = caption.astype(np.int)
```

In [28]:
```
data = pd.read_pickle('./dataset/testData.pkl')
captions = data['Captions'].values

NUM_TEST = len(captions)
EPOCH_TEST = int(NUM_TEST / hparas['BATCH_SIZE'])
```

Inferece

In [32]:
```
if not os.path.exists('./inference/demo'):
    os.makedirs('./inference/demo')
```

In [33]:
```
def inference(dataset):
    hidden = text_encoder.initialize_hidden_state()
    sample_size = hparas['BATCH_SIZE']
    sample_seed = np.random.normal(loc=0.0, scale=1.0, size=(sample_size, hparas['Z

    step = 0
    start = time.time()
    for captions, idx in dataset:
        if step > EPOCH_TEST:
            break
```

```
        fake_image = test_step(captions, sample_seed, hidden)
        step += 1
        for i in range(hparas['BATCH_SIZE']):
            plt.imsave('./inference/demo/inference_{:04d}.jpg'.format(idx[i]), fake

    print('Time for inference is {:.4f} sec'.format(time.time()-start))
```

In [34]:
```
checkpoint.restore(checkpoint_dir + '/ckpt-1')
```

Out[34]:
```
<tensorflow.python.checkpoint.checkpoint.CheckpointLoadStatus at 0x7f640c349430>
```

In [35]:
```
inference(testing_dataset)
```

```
Time for inference is 1.5614 sec
```

Inception Score & Cosine Similarity

In this competition, we use both inception score and cosine distance as our final score to evaluate quality and diversity of generated images. You can find more details about inception score in this article. The final score is based on:

- Similarity of images and the given contents. How similar are the generated images and the given texts?
- KL divergence of generated images. Are the generated images very diverse?

After generating images with given testing texts, you have to run evaluation script to generate `score.csv` file, and then upload it to Kaggle to get the final score.

1. Run evaluation script to generate score.csv

1. Open terminal and move to the folder containing `inception_score.py`. Otherwise you have to modify the path used in the file.
2. Run **`python ./inception_score.py [argv1] [argv2] [argv3]`**
   - argv1: directory of generated image (inference).
   - argv2: directory of output file and its name.
   - argv3: batch size. Please set batch size to 1, 2, 3, 7, 9, 21, 39 to avoid remainder.

For exmaple, run following comment **`python inception_score.py ../inference/demo ../score_demo.csv 39`**.

It is better for you to know that evaluation needs to run on GPUs, please make sure the GPU resource is available.

2. Submit

Submit `score.csv` to DataLabCup: Reverse Image Caption

Precautions

Competition timeline

- 2023/11/30(Thur) competition announced.
- 2023/12/22(Thur) 08:00(TW) competition deadline.
- 2023/12/24(Sun) 23:59(TW) report deadline.
- 2023/12/28(Thur) winner team share.

Scoring

- Ranking of **private** leaderboard of competition. **(50%)**
  - team name should be exactly matched with google sheet or you will get zero in this part
- Inference images. **(30%)**
  - Use subjective human evaluation of the generated images in order to evaluate the quality of generated images thoroughly. Basically, the default score is based on private leaderboard of competition. We will modify the score only if quality of generated images are much better or worse than the score. Therefore, instead of being the winner in the competition, you have to make sure the generated images have reasonable quality.
- Report. **(20%)**

The final report should contain following points:

1. Pick 5 descriptions from testing data and generate 5 images with different noise z respectively.
2. Models you tried during competition. Briefly describe the main idea of the model and the reason you chose that model.
3. List the experiment you did. For example, data augmentation, hyper-parameters tuning, architecture tuning, optimizer tuning, and so on.
4. Anything worth mentioning. For example, how to pre-train the model.

Report and inference images

Submit the link of Google Drive containing report, model and 819 inference images. Please name the report as `DL_comp3_{Your Team name}_report.ipynb.` and code of trainable model as `DL_comp3_{Your Team name}_model.ipynb.` . Moreover, please place inference images under the folder called `inference` , compress that folder with the other two notebook, and then upload to Google Drive. The compressed file should be named as `DL_comp3_{Your Team name}.zip` .

```
└── DL_comp3_{Your Team Name}.zip
    ├── DL_comp3_{Your Team Name}_report.ipynb
    ├── DL_comp3_{Your Team Name}_model.ipynb
    └── inference
        ├── inference_0023.jpg
        ├── inference_0041.jpg
        ├── inference_0057.jpg
        ├── ...
        ├── ...
```

What you can do

- Pre-train text encoder on other dataset.
- Use pre-trained text encoder, like general purpose word embedding, pre-trained RNN or other language model, such as BERT, ELMo and XLNet. But you are **not allowed** to use any text encoder pre-trained on 102 flowers dataset.
- Reuse the data and model from previous competitions and labs.
- Use any package under tensorflow. You **cannot** implement your model by `tensorlayer` API.

What you should NOT do

- Use categorical labels from flower dataset in any part of model.
- Use official Oxford-102 flower dataset and other image dataset to train your GAN. Pre-trained GAN and transfer learning are prohibited as well.
- Clone others' project or use pre-trained model from other resouces(you can only use general purpose word embedding or pretrained RNN, not pretrained GAN).
- Use text encoder pre-trained on 102 flowers dataset.
- Access data or backpropagation signals from testing model in `inception_score.py` and `eval_metrics.pkl`.
- Plagiarism other teams' work.

Hints

- You can find details about text to image in Generative Adversarial Text to Image Synthesis. This competition is based on this paper.
- **Data augmentation** might improve performance a lot.
- Use more complicated **loss function** to increase training stability and efficiency.
- **Pretrained RNN** might have better hidden representation for input text. Additionally, it might accelerate the training process, and also make training more stable.
  - Learning Deep Representations of Fine-Grained Visual Descriptions model proposes a better RNN architecture and corresponding loss function for text to image task. This architecture can encode text into image-like hidden representation.
- **Different architecture of conditional GAN** might generate the image with better quality or higher resolution
  - You can try with simple GAN and DCGAN first.
  - Generative Adversarial Text to Image Synthesis proposes another RNN architecture for text to image task. The author also propose another architecture of conditional GAN to generate the images with better quality.
  - StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks proposes two-stage architecture to generate more impressive images.
  - Improved Training of Wasserstein GANs improves WGAN loss on conditional GAN can improve training stability.
  - You can find other architecture of GAN in The GAN Zoo.

- Check **GAN training tips** to obtain some GAN training tricks, including how to generate diverse images and to prevent mode collapsing. It is worth knowing that GAN is not easy to train, and those tricks are quite helpful.

Last but not least, there are plenty of papers related to text-to-image task. Here has more information about them.

Demo

We demonstrate the capability of our model (TA80) to generate plausible images of flowers from detailed text descriptions.

In [36]:
```
def visualize(idx):
    fig = plt.figure(figsize=(14, 14))

    for count, i in enumerate(idx):
        loc = np.where(i==index)[0][0]
        text = ''
        for word in captions[loc]:
            if id2word_dict[word] != '<PAD>':
                text += id2word_dict[word]
                text += ' '
        print(text)

        path = './inference/TA80/inference_{:04d}.jpg'.format(i)
        fake_iamge = plt.imread(path)

        plt.subplot(7, 7, count+1)
        plt.imshow(fake_iamge)
        plt.axis('off')
```

In [37]:
```
data = pd.read_pickle('./dataset/testData.pkl')
captions = data['Captions'].values
index = data['ID'].values
random_idx = [23, 216, 224, 413, 713, 859, 876, 974, 1177, 1179, 1241, 2169, 2196,
              2356, 2611, 2621, 2786, 2951, 2962, 3145, 3255, 3327, 3639, 3654, 392
              4321, 4517, 5067, 5147, 5955, 6167, 6216, 6410, 6413, 6579, 6584, 680
              7049, 7160]

visualize(random_idx)
```

flower with white long white petals and very long purple stamen
this medium white flower has rows of thin blue petals and thick stamen
this flower is white and purple in color with petals that are oval shaped
this flower is pink and yellow in color with petals that are oval shaped
the flower has a large bright orange petal with pink anther
the flower shown has a smooth white petal with patches of yellow as well
white petals that become yellow as they go to the center where there is an orange stamen
this flower has bright red petals with green pedicel as its main features
this flower has the overlapping yellow petals arranged closely toward the center
this flower has green sepals surrounding several layers of slightly ruffled pink petals
the pedicel on this flower is purple with a green sepal and rose colored petals
this white flower has connected circular petals with yellow stamen
the flower has yellow petals overlapping each other and are yellow in color
this flower has numerous stamen ringed by multiple layers of thin pink petals
the petals are broad but thin at the edges with purple tints at the edges and white in the middle
the yellow flower has petals that are soft smooth and arranged in two layers below the bunch of stamen
this flower has petals that are pink and yellow with yellow stamen
red stacked petals surround yellow stamen and a black pistil
the petals of the flower are in multiple layers and are pink in yellow in color
this flower has a yellow center and layers of peach colored petals with pointed tips
this bright pink flower has several fluttery petals and a tubular center
this flower is white and yellow in color with petals that are rounded at the endges
the flower has a several pieces of yellow colored petals that looks similar to its leaves
this flower has several light pink petals and yellow anthers
this flower is yellow and white in color with petals that are star shaped near the cener
lavender and white pedal and yellow small flower in the middle of the pedals
this flower has lavender petals with maroon stripes and brown anther filaments
this flower has six plain pale yellow petals that alternate with three dark yellow speckled petals
this flower has petals that are yellow with orange lines
the flower has petals that are orange with yellow stamen
this flower has a brown center surrounded by layers of long yellow petals with rounded tips
this flower is lavender in color with petals that are ruffled and wavy
this flower is blue in color with petals that have veins
the petals on this flower are white with yellow stamen
this flower has petals that are cone shaped and dark purple
this flower is purple and white in color and has petals that are multi colored
a large group of bells that are blue on this flower
this flower is bright purple with many pedals that are roundish whth pale white outer petals
this flower has large yellow petals and long yellow stamen on it
this flower has spiky blue petals and a spiky black stigma on it
this flower is purple and yellow in color with petals that are oval shaped
the flower has petals that are large and pink with yellow anther

Unfortunately, it is not perfect. The following figure illustrates images chosen randomly, without cherry picking.

In [38]:
```
DATA_PATH = './inference/TA80/'
img_path = Path(DATA_PATH).glob('*.jpg')
img_path = [str(path.resolve()) for path in img_path]
img_path = np.asarray(img_path)

idx = np.random.randint(len(captions), size=42)
idx.sort()

random_idx = []
for each in idx:
    path = img_path[each].split("/")
    path = path[-1].replace('inference_', '')
    random_idx.append(int(path.replace('.jpg', '')))

visualize(random_idx)
```

this flower has big yellow petals and yellow stamen along with a green pedicel
this flower has thin pink petals as its main feature
this flower has petals that are pink with white edges
this flower is white in color with petals that are ruffled on the edges
small oval shaped petals arranged in a circular manner having white shades in the bottom of the petals
this droopy white flower has a trumpet shaped blossom surrounded by several large wide slightly pointed white petals
the flower has bright orange petals with a yellow inner ring
this flower has pointy faded pink petals that are white around their edges and have deep green veins
this pretty flower has yellow and orange petals with a white center
this flower has bright yellow petals and green pedicel and sepal
the petals on this flower are white with yellow stamen
this flower is yellow in color with petals that are bunched closely together
the flower shown has white petals with green lines on the inside of each petal
the flower is disc shaped and has soft smooth and thin petals and has stamens in the centre
this flower has yellow petals with a tad of orange and a green pedicel
this flower has petals that are red with yellow stamen
this flower has small white and peach petals as its main feature
the petals of the flower are red and yellow in color and have a large green leaf
the flower has peach and yellow petals with yellow stamen
this flower has many yellow and light pink petals with dark yellow anthers
this flower has petals that are white with a small stigma
this flower is white in color with petals that are oval shaped
this flower has a yellow petal and green sepal and pedicel
this water lily has a ton of yellow stamen and white petals that stand up
this flower is pink and white in color with petals that are closely wrapped around the ovule
this flower has the overlapping yellow petals arranged closely toward the center
this flower has white curved petals with pink and brown spots with pink speckled stamen come out of the ovule
this is a flower with thin wide pink petals and a white pollen tube
a bright white and yellow flower with a dark yellow stigma
this flower is white and pink in color with petals that are pink near the tips
this flower is white and pink in color with petals that are pink near the tips
this flower is pink and white in color with petals that have a pink stripe in the center
this flower has petals that are pink with a yellow center
this flower has a very tall pistol and pink petals that have white streaks through them
this flower is yellow and white in color with petals that are oval shaped
a flower with purple petals and dark purple pistils and anther filaments
flower petals are rounde in shape they are light pink in color
this flower is orange in color with petals that are ruffled and darker near the center
petals are rounded in shape they are orange in color
the flower has purple petals with white spots and green sepal
this flower is purple in color with petals that are ruffled
5 angled petals creating a unique star shape with two tones fading into each other