Deep Convolutional Generative Adversarial Network

Setup

In [33]:
```
import tensorflow as tf
```

In [34]:
```
tf.__version__
```

Out[34]:
```
'2.17.0'
```

In [35]:
```
# To generate GIFs
!pip install imageio
!pip install git+https://github.com/tensorflow/docs
```

```
Requirement already satisfied: imageio in /opt/anaconda3/envs/ML_AI_ENV/lib/
python3.12/site-packages (2.36.1)
Requirement already satisfied: numpy in /opt/anaconda3/envs/ML_AI_ENV/lib/py
thon3.12/site-packages (from imageio) (1.26.4)
Requirement already satisfied: pillow>=8.3.2 in /opt/anaconda3/envs/ML_AI_EN
V/lib/python3.12/site-packages (from imageio) (11.0.0)
Collecting git+https://github.com/tensorflow/docs
  Cloning https://github.com/tensorflow/docs to /private/var/folders/6q/h812
b4x57vl9tkkrtb9c5w0r0000gn/T/pip-req-build-n7cjezdy
  Running command git clone --filter=blob:none --quiet https://github.com/te
nsorflow/docs /private/var/folders/6q/h812b4x57vl9tkkrtb9c5w0r0000gn/T/pip-r
eq-build-n7cjezdy
  Resolved https://github.com/tensorflow/docs to commit 0c634f4f3bd7ee661a92
bf6f3f753931bc511192
  Preparing metadata (setup.py) ... done
Requirement already satisfied: astor in /opt/anaconda3/envs/ML_AI_ENV/lib/py
thon3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (0.8.1)
Requirement already satisfied: absl-py in /opt/anaconda3/envs/ML_AI_ENV/lib/
python3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (2.1.0)
Requirement already satisfied: jinja2 in /opt/anaconda3/envs/ML_AI_ENV/lib/p
ython3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (3.1.4)
Requirement already satisfied: nbformat in /opt/anaconda3/envs/ML_AI_ENV/li
b/python3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (5.10.4)
Requirement already satisfied: protobuf>=3.12 in /opt/anaconda3/envs/ML_AI_E
NV/lib/python3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (4.2
5.3)
Requirement already satisfied: pyyaml in /opt/anaconda3/envs/ML_AI_ENV/lib/p
ython3.12/site-packages (from tensorflow-docs==2025.2.12.60881) (6.0.2)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/anaconda3/envs/ML_AI_
ENV/lib/python3.12/site-packages (from jinja2->tensorflow-docs==2025.2.12.60
881) (2.1.3)
Requirement already satisfied: fastjsonschema>=2.15 in /opt/anaconda3/envs/M
L_AI_ENV/lib/python3.12/site-packages (from nbformat->tensorflow-docs==2025.
2.12.60881) (2.20.0)
Requirement already satisfied: jsonschema>=2.6 in /opt/anaconda3/envs/ML_AI_
ENV/lib/python3.12/site-packages (from nbformat->tensorflow-docs==2025.2.12.
60881) (4.23.0)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in /opt/anaconda3/
envs/ML_AI_ENV/lib/python3.12/site-packages (from nbformat->tensorflow-docs=
=2025.2.12.60881) (5.7.2)
Requirement already satisfied: traitlets>=5.1 in /opt/anaconda3/envs/ML_AI_E
NV/lib/python3.12/site-packages (from nbformat->tensorflow-docs==2025.2.12.6
0881) (5.14.3)
Requirement already satisfied: attrs>=22.2.0 in /opt/anaconda3/envs/ML_AI_EN
V/lib/python3.12/site-packages (from jsonschema>=2.6->nbformat->tensorflow-d
ocs==2025.2.12.60881) (24.3.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /opt/
anaconda3/envs/ML_AI_ENV/lib/python3.12/site-packages (from jsonschema>=2.6-
>nbformat->tensorflow-docs==2025.2.12.60881) (2023.7.1)
Requirement already satisfied: referencing>=0.28.4 in /opt/anaconda3/envs/ML
_AI_ENV/lib/python3.12/site-packages (from jsonschema>=2.6->nbformat->tensor
flow-docs==2025.2.12.60881) (0.30.2)
Requirement already satisfied: rpds-py>=0.7.1 in /opt/anaconda3/envs/ML_AI_E
NV/lib/python3.12/site-packages (from jsonschema>=2.6->nbformat->tensorflow-
docs==2025.2.12.60881) (0.10.6)
Requirement already satisfied: platformdirs>=2.5 in /opt/anaconda3/envs/ML_A
```

```
I_ENV/lib/python3.12/site-packages (from jupyter-core!=5.0.*,>=4.12->nbforma
t->tensorflow-docs==2025.2.12.60881) (3.10.0)
```

In [36]:
```
import glob
import imageio
import matplotlib.pyplot as plt
import numpy as np
import os
import PIL
import tensorflow as tf
layers = tf.keras.layers
import time

from IPython import display
```

Load and prepare the dataset

You will use the MNIST dataset to train the generator and the discriminator. The generator will generate handwritten digits resembling the MNIST data.

In [37]:
```
!pip install medmnist
```

```
Requirement already satisfied: medmnist in /opt/anaconda3/envs/ML_AI_ENV/li
b/python3.12/site-packages (3.0.2)
Requirement already satisfied: numpy in /opt/anaconda3/envs/ML_AI_ENV/lib/py
thon3.12/site-packages (from medmnist) (1.26.4)
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hon3.12/site-packages (from medmnist) (4.67.1)
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ython3.12/site-packages (from medmnist) (11.0.0)
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hon3.12/site-packages (from medmnist) (0.7.0)
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thon3.12/site-packages (from medmnist) (2.6.0)
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lib/python3.12/site-packages (from medmnist) (0.21.0)
Requirement already satisfied: termcolor in /opt/anaconda3/envs/ML_AI_ENV/li
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Requirement already satisfied: python-dateutil>=2.8.2 in /opt/anaconda3/env
s/ML_AI_ENV/lib/python3.12/site-packages (from pandas->medmnist) (2.9.0.post
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V/lib/python3.12/site-packages (from scikit-image->medmnist) (1.14.1)
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V/lib/python3.12/site-packages (from scikit-image->medmnist) (3.4.2)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /opt/anaconda3/env
s/ML_AI_ENV/lib/python3.12/site-packages (from scikit-image->medmnist) (2.3
6.1)
Requirement already satisfied: tifffile>=2022.8.12 in /opt/anaconda3/envs/ML
_AI_ENV/lib/python3.12/site-packages (from scikit-image->medmnist) (2025.1.1
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Requirement already satisfied: packaging>=21 in /opt/anaconda3/envs/ML_AI_EN
V/lib/python3.12/site-packages (from scikit-image->medmnist) (24.2)
Requirement already satisfied: lazy-loader>=0.4 in /opt/anaconda3/envs/ML_AI
_ENV/lib/python3.12/site-packages (from scikit-image->medmnist) (0.4)
Requirement already satisfied: joblib>=1.2.0 in /opt/anaconda3/envs/ML_AI_EN
V/lib/python3.12/site-packages (from scikit-learn->medmnist) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /opt/anaconda3/envs/M
L_AI_ENV/lib/python3.12/site-packages (from scikit-learn->medmnist) (3.5.0)
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b/python3.12/site-packages (from torch->medmnist) (3.16.1)
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nvs/ML_AI_ENV/lib/python3.12/site-packages (from torch->medmnist) (4.12.2)
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```
ib/python3.12/site-packages (from torch->medmnist) (75.1.0)
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V/lib/python3.12/site-packages (from torch->medmnist) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /opt/anaconda3/envs/ML_
AI_ENV/lib/python3.12/site-packages (from sympy==1.13.1->torch->medmnist)
(1.3.0)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/envs/ML_AI_ENV/li
b/python3.12/site-packages (from python-dateutil>=2.8.2->pandas->medmnist)
(1.16.0)
Requirement already satisfied: MarkupSafe>=2.0 in /opt/anaconda3/envs/ML_AI_
ENV/lib/python3.12/site-packages (from jinja2->torch->medmnist) (2.1.3)
```

In [38]:

```python
import numpy as np
from medmnist import ChestMNIST
```

In [39]:

```python
# Load training data
train_dataset = ChestMNIST(split='train', download=True)
train_images = train_dataset.imgs
train_labels = train_dataset.labels

# Load test data
test_dataset = ChestMNIST(split='test', download=True)
test_images = test_dataset.imgs
test_labels = test_dataset.labels
```

In [40]:

```python
(train_images, train_labels), (_, _) = tf.keras.datasets.mnist.load_data()
```

In [41]:

```python
# Normalize images to [0, 1]
train_images = train_images.astype(np.float32) / 255.0
test_images = test_images.astype(np.float32) / 255.0
```

In [42]:

```python
# Expand dimensions to include channel information if necessary
if train_images.ndim == 3:
    train_images = np.expand_dims(train_images, axis=-1)
    test_images = np.expand_dims(test_images, axis=-1)
```

In [43]:

```python
import numpy as np

# Path to your ChestMNIST .npz file
data_path = "/Users/darshilshah/.medmnist/chestmnist.npz"

# Load the .npz file
data = np.load(data_path)

# List the keys stored in the file
print("Keys in the .npz file:", data.files)

# For example, if the file contains training images and labels:
train_images = data['train_images']  # Adjust key names as appropriate
train_labels = data['train_labels']

print("Train images shape:", train_images.shape)
print("Train labels shape:", train_labels.shape)
```

```
Keys in the .npz file: ['train_images', 'val_images', 'test_images', 'train_
labels', 'val_labels', 'test_labels']
Train images shape: (78468, 28, 28)
Train labels shape: (78468, 14)
```

In [44]:

```
import numpy as np

# Set the fraction you want to keep (e.g., 10% of the data)
fraction = 0.1

def sample_subset(images, labels, fraction):
    """
    Randomly samples a fraction of the images and labels.

    Args:
        images (np.ndarray): Array of images.
        labels (np.ndarray): Array of corresponding labels.
        fraction (float): Fraction of the dataset to keep (0.0 - 1.0).

    Returns:
        tuple: (subset_images, subset_labels)
    """
    num_samples = int(len(images) * fraction)
    # Get a random permutation of indices
    indices = np.random.permutation(len(images))[:num_samples]
    return images[indices], labels[indices]

# Assuming you've already loaded your ChestMNIST dataset from the .npz file:
data_path = "/Users/darshilshah/.medmnist/chestmnist.npz"
data = np.load(data_path)

# Full datasets
train_images_full = data['train_images']
train_labels_full = data['train_labels']
val_images_full = data['val_images']
val_labels_full = data['val_labels']
test_images_full = data['test_images']
test_labels_full = data['test_labels']

# Sample reduced subsets from each split
train_images, train_labels = sample_subset(train_images_full, train_labels_f
val_images, val_labels = sample_subset(val_images_full, val_labels_full, fra
test_images, test_labels = sample_subset(test_images_full, test_labels_full,

# Display new shapes to verify the reduction
print("Reduced Train images shape:", train_images.shape)
print("Reduced Train labels shape:", train_labels.shape)
print("Reduced Val images shape:", val_images.shape)
print("Reduced Val labels shape:", val_labels.shape)
print("Reduced Test images shape:", test_images.shape)
print("Reduced Test labels shape:", test_labels.shape)
```

```
Reduced Train images shape: (7846, 28, 28)
Reduced Train labels shape: (7846, 14)
Reduced Val images shape: (1121, 28, 28)
Reduced Val labels shape: (1121, 14)
Reduced Test images shape: (2243, 28, 28)
Reduced Test labels shape: (2243, 14)
```

In [45]:
```
train_images = train_images.reshape(train_images.shape[0], 28, 28, 1).astype
train_images = (train_images - 127.5) / 127.5  # Normalize the images to [-1
```

In [46]:
```
BATCH_SIZE = 64
BUFFER_SIZE = 60000
```

In [47]:
```
train_dataset = tf.data.Dataset.from_tensor_slices((train_images, train_labe
train_dataset = train_dataset.shuffle(buffer_size=1024).batch(BATCH_SIZE)

test_dataset = tf.data.Dataset.from_tensor_slices((test_images, test_labels)
test_dataset = test_dataset.batch(BATCH_SIZE)
```

In [48]:
```
# Batch and shuffle the data
train_dataset = tf.data.Dataset.from_tensor_slices(train_images).shuffle(BUF
```

Create the models

Both the generator and discriminator are defined using the Keras Sequential API.

The Generator

The generator uses `tf.keras.layers.Conv2DTranspose` (upsampling) layers to produce an image from a seed (random noise). Start with a `Dense` layer that takes this seed as input, then upsample several times until you reach the desired image size of 28x28x1. Notice the `tf.keras.layers.LeakyReLU` activation for each layer, except the output layer which uses tanh.

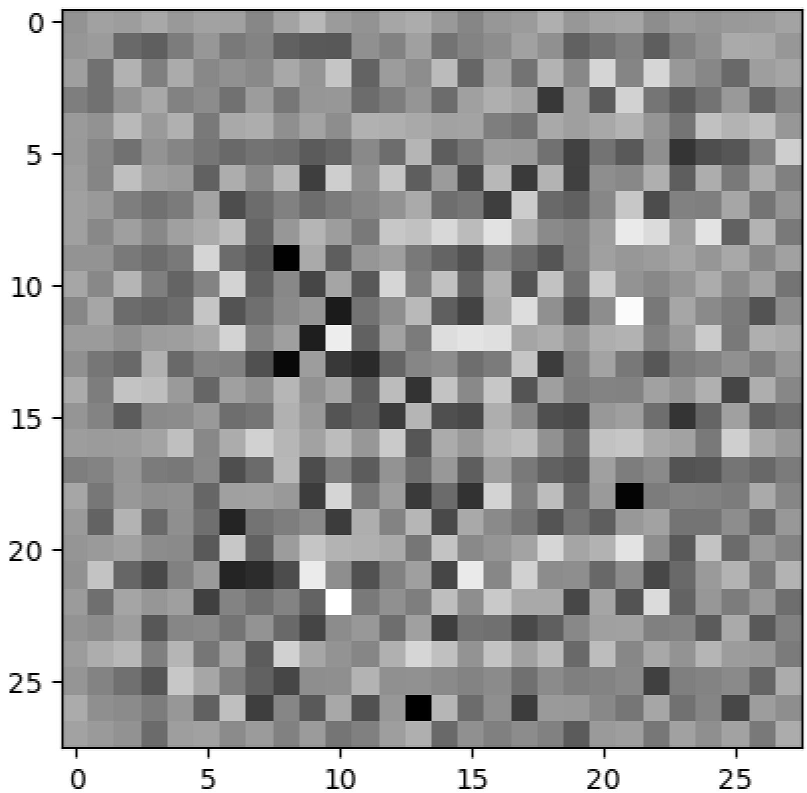
In [49]:
```
def make_generator_model():
    model = tf.keras.Sequential()
    model.add(layers.Dense(7*7*256, use_bias=False, input_shape=(100,)))
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())

    model.add(layers.Reshape((7, 7, 256)))
    assert model.output_shape == (None, 7, 7, 256)  # Note: None is the batc

    model.add(layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='s
    assert model.output_shape == (None, 7, 7, 128)
    model.add(layers.BatchNormalization())
    model.add(layers.LeakyReLU())

    model.add(layers.Conv2DTranspose(64, (5, 5), strides=(2, 2), padding='sa
    assert model.output_shape == (None, 14, 14, 64)
    model.add(layers.BatchNormalization())
```

```
    model.add(layers.LeakyReLU())

    model.add(layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='sam
    assert model.output_shape == (None, 28, 28, 1)

    return model
```

Use the (as yet untrained) generator to create an image.

In [50]:
```
generator = make_generator_model()

noise = tf.random.normal([1, 100])
generated_image = generator(noise, training=False)

plt.imshow(generated_image[0, :, :, 0], cmap='gray')
```

Out[50]: <matplotlib.image.AxesImage at 0x365f35730>



The Discriminator

The discriminator is a CNN-based image classifier.

In [51]:
```
def make_discriminator_model():
    model = tf.keras.Sequential()
    model.add(layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same',
                                     input_shape=[28, 28, 1]))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))
```

```
    model.add(layers.Conv2D(128, (5, 5), strides=(2, 2), padding='same'))
    model.add(layers.LeakyReLU())
    model.add(layers.Dropout(0.3))

    model.add(layers.Flatten())
    model.add(layers.Dense(1))

    return model
```

Use the (as yet untrained) discriminator to classify the generated images as real or fake. The model will be trained to output positive values for real images, and negative values for fake images.

In [52]:
```
discriminator = make_discriminator_model()
decision = discriminator(generated_image)
print (decision)
```

```
tf.Tensor([[-0.0002986]], shape=(1, 1), dtype=float32)
```

Define the loss and optimizers

Define loss functions and optimizers for both models.

In [53]:
```
# This method returns a helper function to compute cross entropy loss
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
```

Discriminator loss

This method quantifies how well the discriminator is able to distinguish real images from fakes. It compares the discriminator's predictions on real images to an array of 1s, and the discriminator's predictions on fake (generated) images to an array of 0s.

In [54]:
```
def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss
```

Generator loss

The generator's loss quantifies how well it was able to trick the discriminator. Intuitively, if the generator is performing well, the discriminator will classify the fake images as real (or 1). Here, compare the discriminators decisions on the generated images to an array of 1s.

In [55]:
```
def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)
```

The discriminator and the generator optimizers are different since you will train two networks separately.

In [56]:
```
generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)
```

Save checkpoints

This notebook also demonstrates how to save and restore models, which can be helpful in case a long running training task is interrupted.

In [57]:
```
checkpoint_dir = './training_checkpoints'
checkpoint_prefix = os.path.join(checkpoint_dir, "ckpt")
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optim
                                 generator=generator,
                                 discriminator=discriminator)
```

Define the training loop

In [58]:
```
EPOCHS = 20
noise_dim = 100
num_examples_to_generate = 16

# You will reuse this seed overtime (so it's easier)
# to visualize progress in the animated GIF)
seed = tf.random.normal([num_examples_to_generate, noise_dim])
```

The training loop begins with generator receiving a random seed as input. That seed is used to produce an image. The discriminator is then used to classify real images (drawn from the training set) and fakes images (produced by the generator). The loss is calculated for each of these models, and the gradients are used to update the generator and discriminator.

In [59]:
```
# Notice the use of `tf.function`
# This annotation causes the function to be "compiled".
@tf.function
def train_step(images):
    noise = tf.random.normal([BATCH_SIZE, noise_dim])

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
      generated_images = generator(noise, training=True)

      real_output = discriminator(images, training=True)
      fake_output = discriminator(generated_images, training=True)

      gen_loss = generator_loss(fake_output)
      disc_loss = discriminator_loss(real_output, fake_output)
```

```
    gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable
    gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator

    generator_optimizer.apply_gradients(zip(gradients_of_generator, generato
    discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator,
```

In [60]:
```
def generate_and_save_images(model, epoch, test_input):
  # Notice `training` is set to False.
  # This is so all layers run in inference mode (batchnorm).
  predictions = model(test_input, training=False)

  fig = plt.figure(figsize=(4, 4))

  for i in range(predictions.shape[0]):
      plt.subplot(4, 4, i+1)
      plt.imshow(predictions[i, :, :, 0] * 127.5 + 127.5, cmap='gray')
      plt.axis('off')

  plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
  plt.show()
```

In [61]:
```
import tensorflow as tf
import time
from IPython import display



# Optionally initialize checkpoints if you're using them
checkpoint = tf.train.Checkpoint(generator_optimizer=generator_optimizer,
                                 discriminator_optimizer=discriminator_optim
                                 generator=generator,
                                 discriminator=discriminator)
checkpoint_prefix = './training_checkpoints/cp.ckpt'

@tf.function
def train_step(image_batch):
    noise = tf.random.normal([BATCH_SIZE, noise_dim])

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        # Forward pass through the generator and discriminator
        generated_images = generator(noise, training=True)
        real_output = discriminator(image_batch, training=True)
        fake_output = discriminator(generated_images, training=True)

        # Compute the loss and gradients
        gen_loss = generator_loss(fake_output)
        disc_loss = discriminator_loss(real_output, fake_output)

    # Calculate gradients and update the models
    gradients_of_generator = gen_tape.gradient(gen_loss, generator.trainable
    gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator

    generator_optimizer.apply_gradients(zip(gradients_of_generator, generato
    discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator,
```

```
def train(dataset, epochs):
    for epoch in range(epochs):
        start = time.time()

        for image_batch in dataset:
            train_step(image_batch)

        # Produce images for the GIF as you go
        display.clear_output(wait=True)
        generate_and_save_images(generator, epoch + 1, seed)

        # Save the model every 15 epochs
        if (epoch + 1) % 15 == 0:
            checkpoint.save(file_prefix=checkpoint_prefix)

        print(f'Time for epoch {epoch + 1} is {time.time() - start} sec')

    # Generate after the final epoch
    display.clear_output(wait=True)
    generate_and_save_images(generator, epochs, seed)
```

In [62]:
```
def train(dataset, epochs):
  for epoch in range(epochs):
    start = time.time()

    for image_batch in dataset:
      train_step(image_batch)

    # Produce images for the GIF as you go
    display.clear_output(wait=True)
    generate_and_save_images(generator,
                             epoch + 1,
                             seed)

    # Save the model every 15 epochs
    if (epoch + 1) % 15 == 0:
      checkpoint.save(file_prefix = checkpoint_prefix)

    print ('Time for epoch {} is {} sec'.format(epoch + 1, time.time()-start

  # Generate after the final epoch
  display.clear_output(wait=True)
  generate_and_save_images(generator,
                           epochs,
                           seed)
```

Generate and save images

In [63]:
```
def generate_and_save_images(model, epoch, test_input):
  # Notice `training` is set to False.
  # This is so all layers run in inference mode (batchnorm).
  predictions = model(test_input, training=False)

  fig = plt.figure(figsize=(4, 4))
```

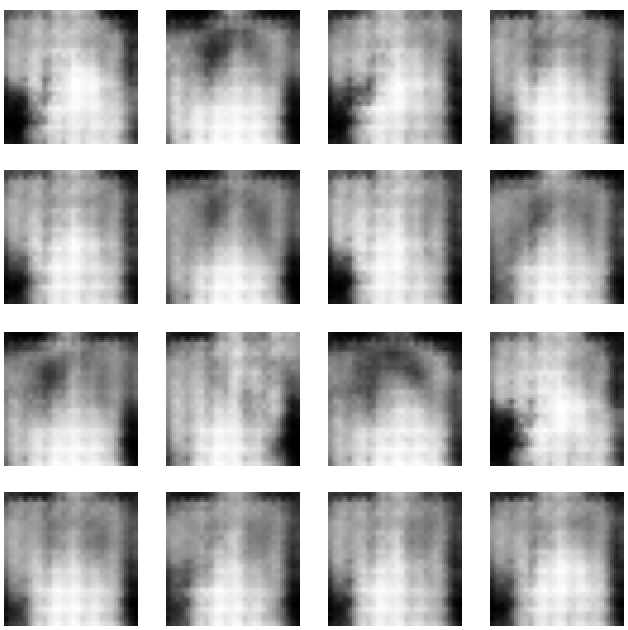
```python
for i in range(predictions.shape[0]):
    plt.subplot(4, 4, i+1)
    plt.imshow(predictions[i, :, :, 0] * 127.5 + 127.5, cmap='gray')
    plt.axis('off')

plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
plt.show()
```

Train the model

Call the `train()` method defined above to train the generator and discriminator simultaneously. Note, training GANs can be tricky. It's important that the generator and discriminator do not overpower each other (e.g., that they train at a similar rate).

At the beginning of the training, the generated images look like random noise. As training progresses, the generated digits will look increasingly real. After about 50 epochs, they resemble MNIST digits. This may take about one minute / epoch with the default settings on Colab.

In [64]:
```python
train(train_dataset, EPOCHS)
```



Restore the latest checkpoint.

In [65]:
```python
checkpoint.restore(tf.train.latest_checkpoint(checkpoint_dir))
```

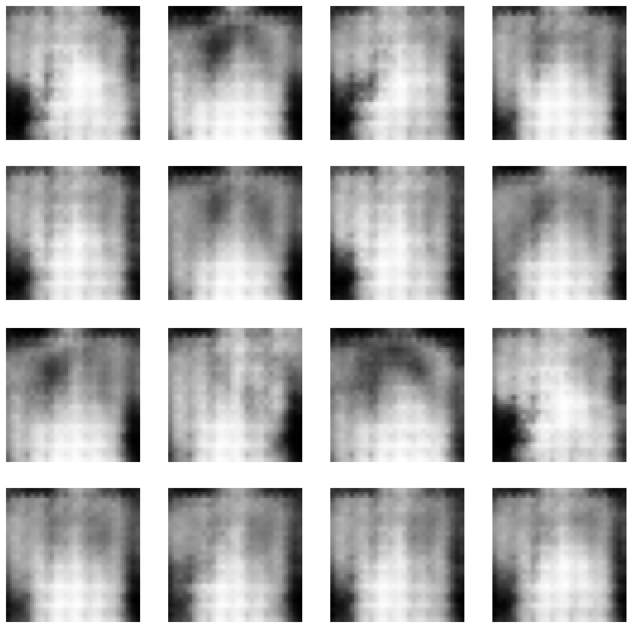
Out[65]:
```
<tensorflow.python.checkpoint.checkpoint.CheckpointLoadStatus at 0x37fe53e6
0>
```

Create a GIF

In [66]:
```
# Display a single image using the epoch number
def display_image(epoch_no):
  return PIL.Image.open('image_at_epoch_{:04d}.png'.format(epoch_no))
```

In [67]:
```
display_image(EPOCHS)
```

Out[67]:



Use `imageio` to create an animated gif using the images saved during training.

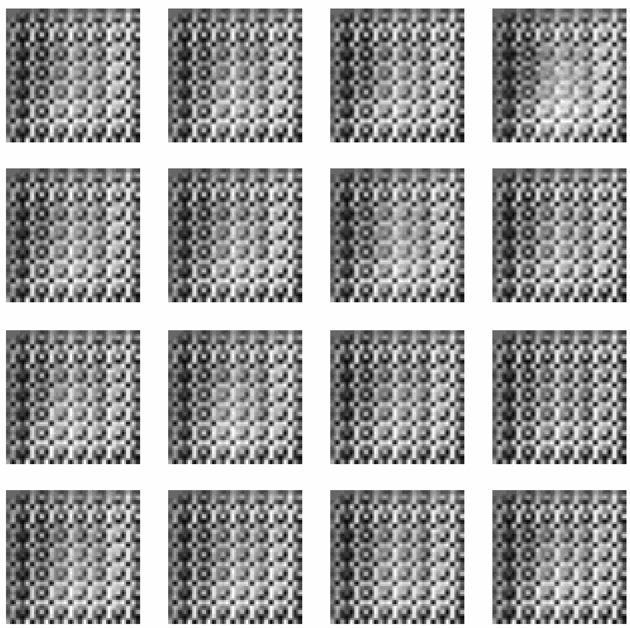
In [68]:
```
anim_file = 'dcgan.gif'

with imageio.get_writer(anim_file, mode='I') as writer:
  filenames = glob.glob('image*.png')
  filenames = sorted(filenames)
  for filename in filenames:
    image = imageio.imread(filename)
    writer.append_data(image)
  image = imageio.imread(filename)
  writer.append_data(image)
```

```
/var/folders/6q/h812b4x57vl9tkkrtb9c5w0r0000gn/T/ipykernel_28079/1982054950.
py:7: DeprecationWarning: Starting with ImageIO v3 the behavior of this func
tion will switch to that of iio.v3.imread. To keep the current behavior (and
make this warning disappear) use `import imageio.v2 as imageio` or call `ima
geio.v2.imread` directly.
  image = imageio.imread(filename)
/var/folders/6q/h812b4x57vl9tkkrtb9c5w0r0000gn/T/ipykernel_28079/1982054950.
py:9: DeprecationWarning: Starting with ImageIO v3 the behavior of this func
tion will switch to that of iio.v3.imread. To keep the current behavior (and
make this warning disappear) use `import imageio.v2 as imageio` or call `ima
geio.v2.imread` directly.
  image = imageio.imread(filename)
```

In [69]:

```
import tensorflow_docs.vis.embed as embed
embed.embed_file(anim_file)
```

Out[69]:



In [ ]:

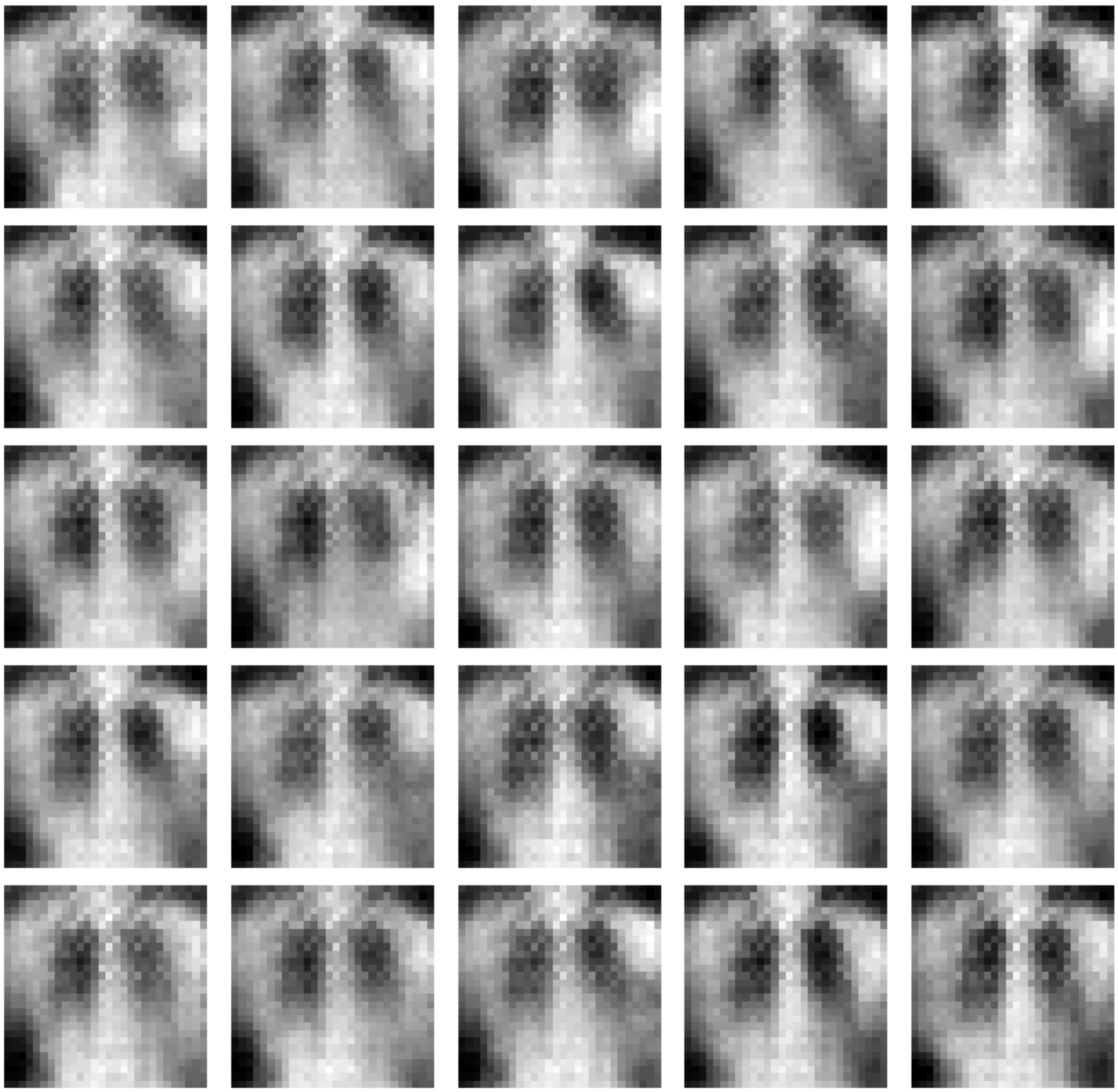
```
import torch
import numpy as np
import matplotlib.pyplot as plt

# ----------------------------
# Set up the device
# ----------------------------
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

# ----------------------------
# Helper functions for Part 2
# ----------------------------

def evaluate_generator(generator, device, noise_dim, num_samples=100):
```

```
    """
    Generate synthetic images using the trained Generator model.

    Args:
        generator (torch.nn.Sequential): The trained Generator (Sequential m
        device (torch.device): Device to run the generation.
        noise_dim (int): Dimensionality of the noise vector.
        num_samples (int): Number of synthetic images to generate.

    Returns:
        np.ndarray: Generated synthetic images.
    """
    with torch.no_grad():  # Ensure no gradients are computed
        # Generate random noise vectors
        noise = torch.randn(num_samples, noise_dim, device=device)
        # Produce synthetic images
        fake_images = generator(noise).cpu().numpy()  # Convert to NumPy
    return fake_images


def plot_generated_images(images, grid_size=5, title="Generated Images"):
    """
    Plot a grid of images.

    Args:
        images (np.ndarray): Array of images to plot.
        grid_size (int): Number of images per row/column.
        title (str): Title of the plot.
    """
    plt.figure(figsize=(10, 10))
    total = grid_size * grid_size
    for i in range(total):
        plt.subplot(grid_size, grid_size, i + 1)
        img = np.squeeze(images[i])  # Remove extra dimensions if necessary
        plt.imshow(img, cmap='gray')
        plt.axis('off')
    plt.suptitle(title)
    plt.tight_layout()
    plt.show()




# Generate synthetic images using your trained generator.
synthetic_images = evaluate_generator(generator, device, noise_dim, num_samp

# Display a grid of synthetic images.
plot_generated_images(synthetic_images, grid_size=5, title="Synthetic ChestM

# For visual comparison, also display a grid of real images.
plot_generated_images(train_images, grid_size=5, title="Real ChestMNIST Imag
```

```
Using device: cpu
WARNING:tensorflow:From /var/folders/6q/h812b4x57vl9tkkrtb9c5w0r0000gn/T/ipy
kernel_28079/552029103.py:32: _EagerTensorBase.cpu (from tensorflow.python.f
ramework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.identity with explicit device placement instead.
```


```
WARNING:tensorflow:From /var/folders/6q/h812b4x57vl9tkkrtb9c5w0r0000gn/T/ipy
kernel_28079/552029103.py:32: _EagerTensorBase.cpu (from tensorflow.python.f
ramework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.identity with explicit device placement instead.
```


Synthetic ChestMNIST Images



Real ChestMNIST Images