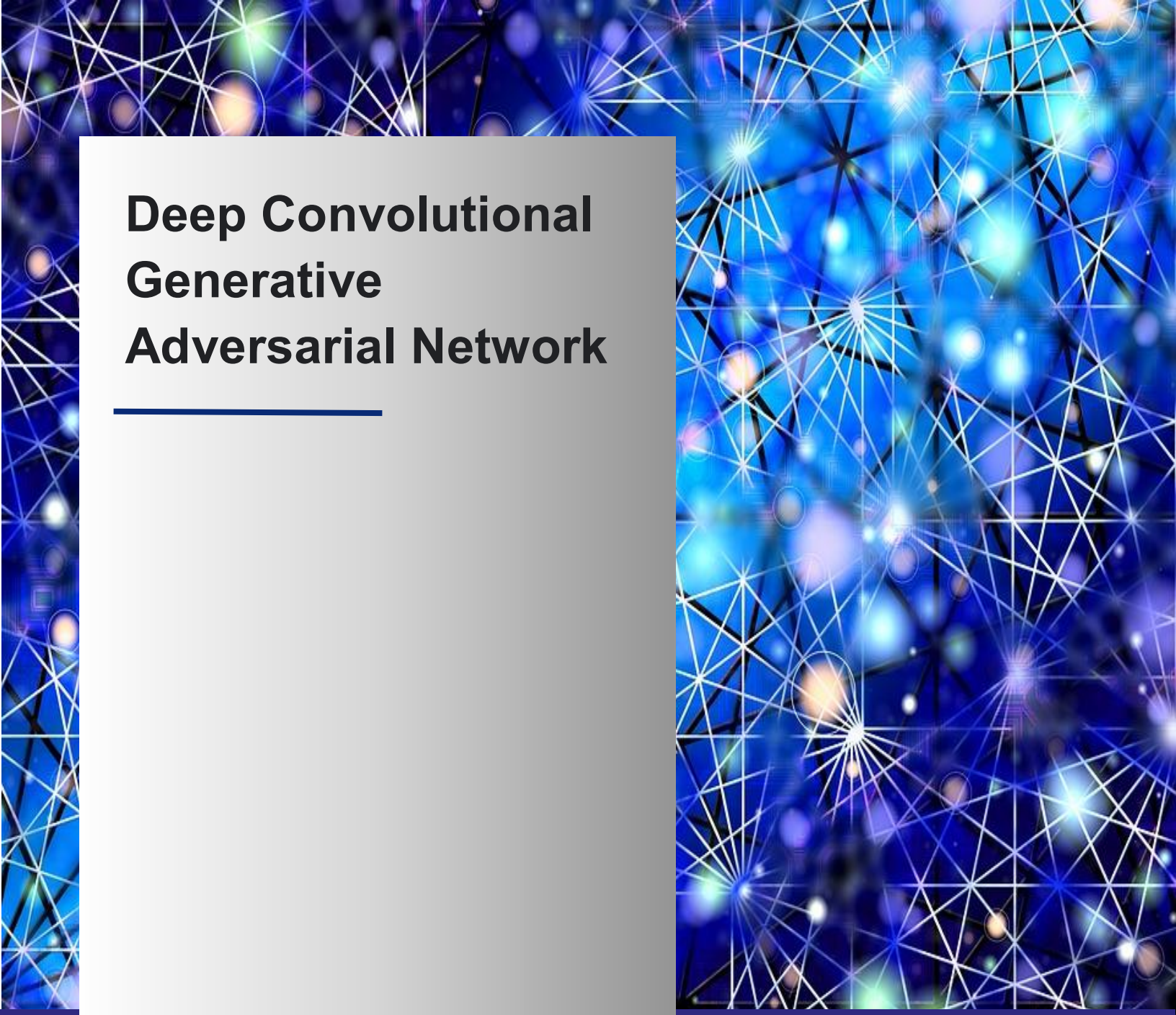

Deep Convolutional Generative Adversarial Network

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GOOGLE COLAB

“DCGAN”

Deep Convolutional Generative Adversarial Network

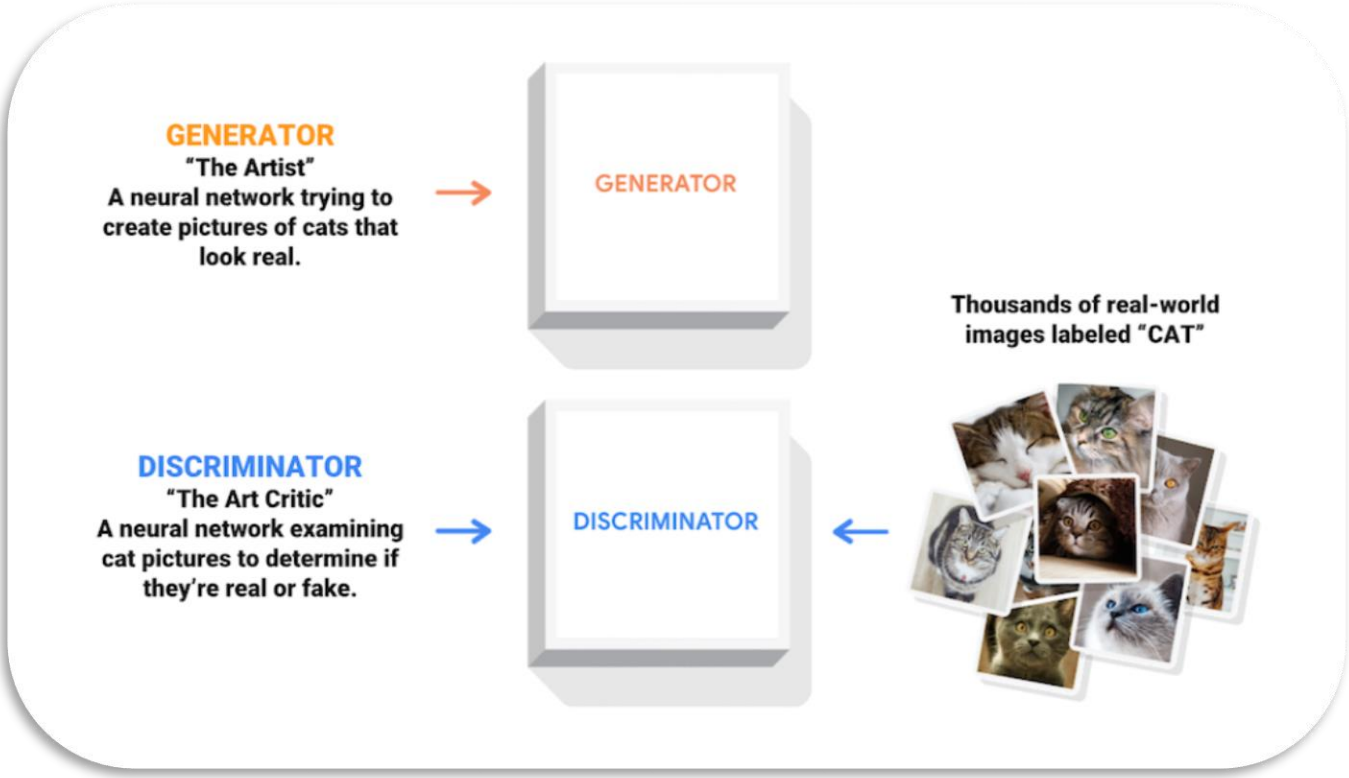
We will use the potential of deep learning to generate real-like images and create a DCGAN Model MNIST Dataset. Our model will be able to generate images of handwritten digits using TensorFlow.

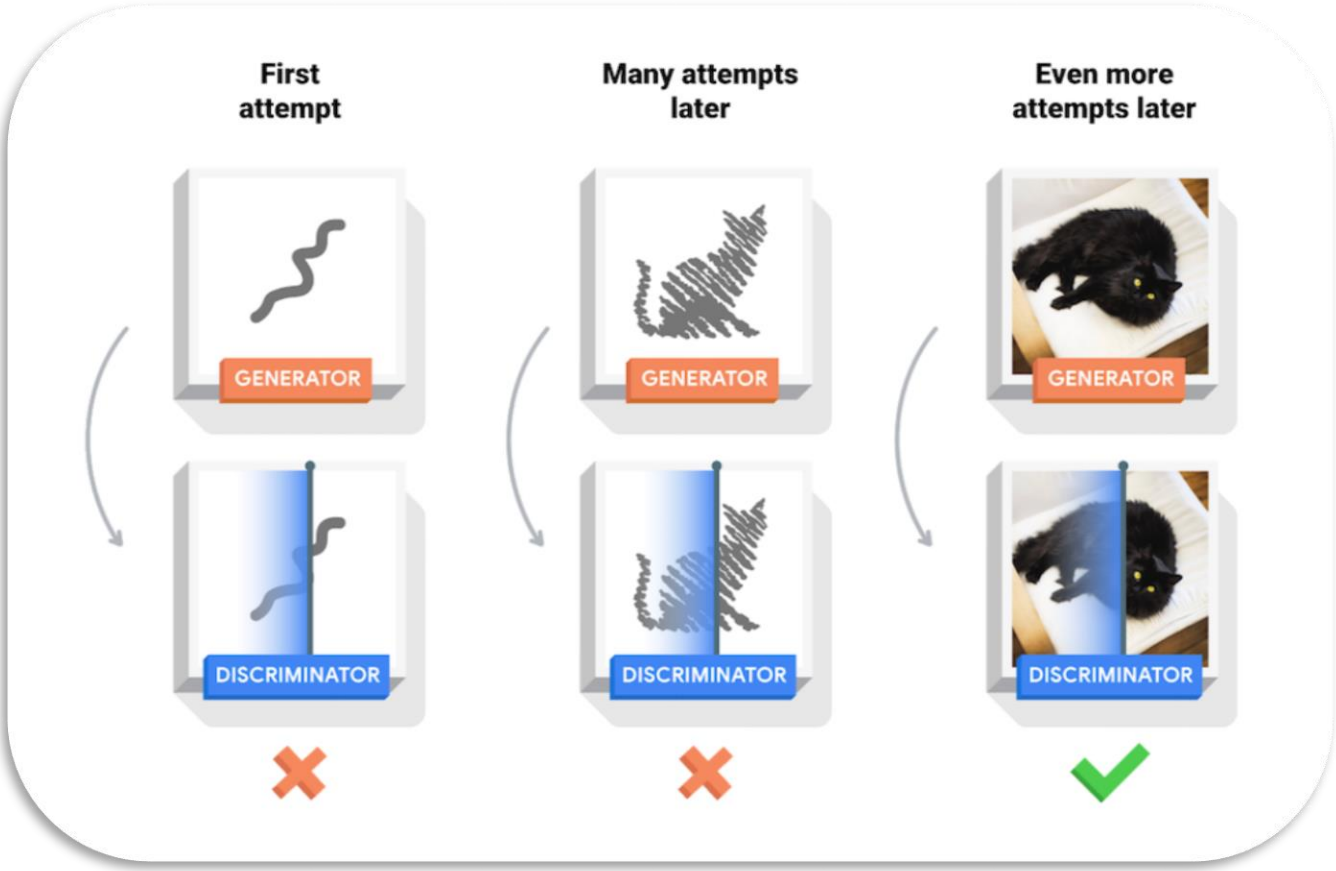
Before we begin, let’s have a quick introduction to GANs:

What are GANs?

The concept of generative adversarial networks (GANs) was introduced by Ian Goodfellow. Goodfellow uses the metaphor of an art critic and an artist to describe the two models—discriminators and generators—that make up GANs.
An art critic (the discriminator) looks at an image and tries to determine if its real or a forgery.
An artist (the generator) who wants to fool the art critic tries to make a forged image that looks as realistic as possible.
These two models “battle” each other; the discriminator uses the output of the generator as training data, and the generator gets feedback from the discriminator.
Each model becomes stronger in the process.
In this way, GANs are able to generate new complex data, based on some amount of known input data, in this case, images.

For example, Generating an image of cat:


GENERATOR
"The Artist"
A neural network trying to create pictures of cats that look real.
GENERATOR
DISCRIMINATOR
"The Art Critic"
A neural network examining cat pictures to determine if they're real or fake.
DISCRIMINATOR
Thousands of real-world images labeled "CAT"


First attempt
Many attempts later
Even more attempts later
GENERATOR
DISCRIMINATOR
GENERATOR
DISCRIMINATOR
GENERATOR
DISCRIMINATOR

GANs have proven to be really successful in modeling and generating high dimensional data, which is why they've become so popular. But they've their own pros and cons. Some are listed below:

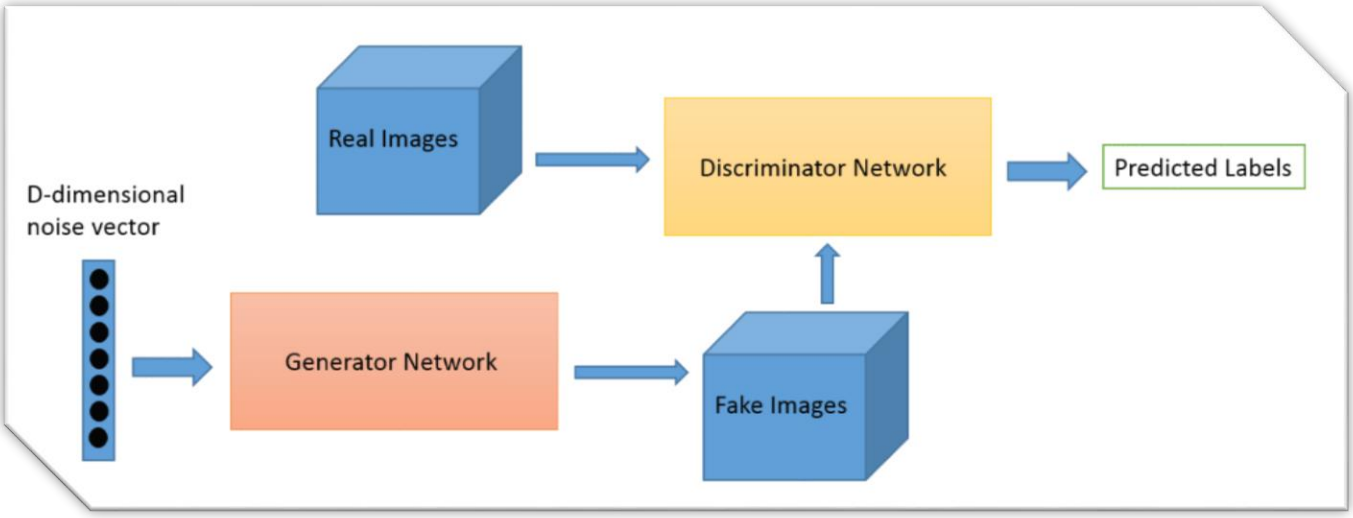
- They currently generate the sharpest images
- They are easy to train (since no statistical inference is required), and only back-propagation is needed to obtain gradients
- GANs are difficult to optimize due to unstable training dynamics.
- No statistical inference can be done with them

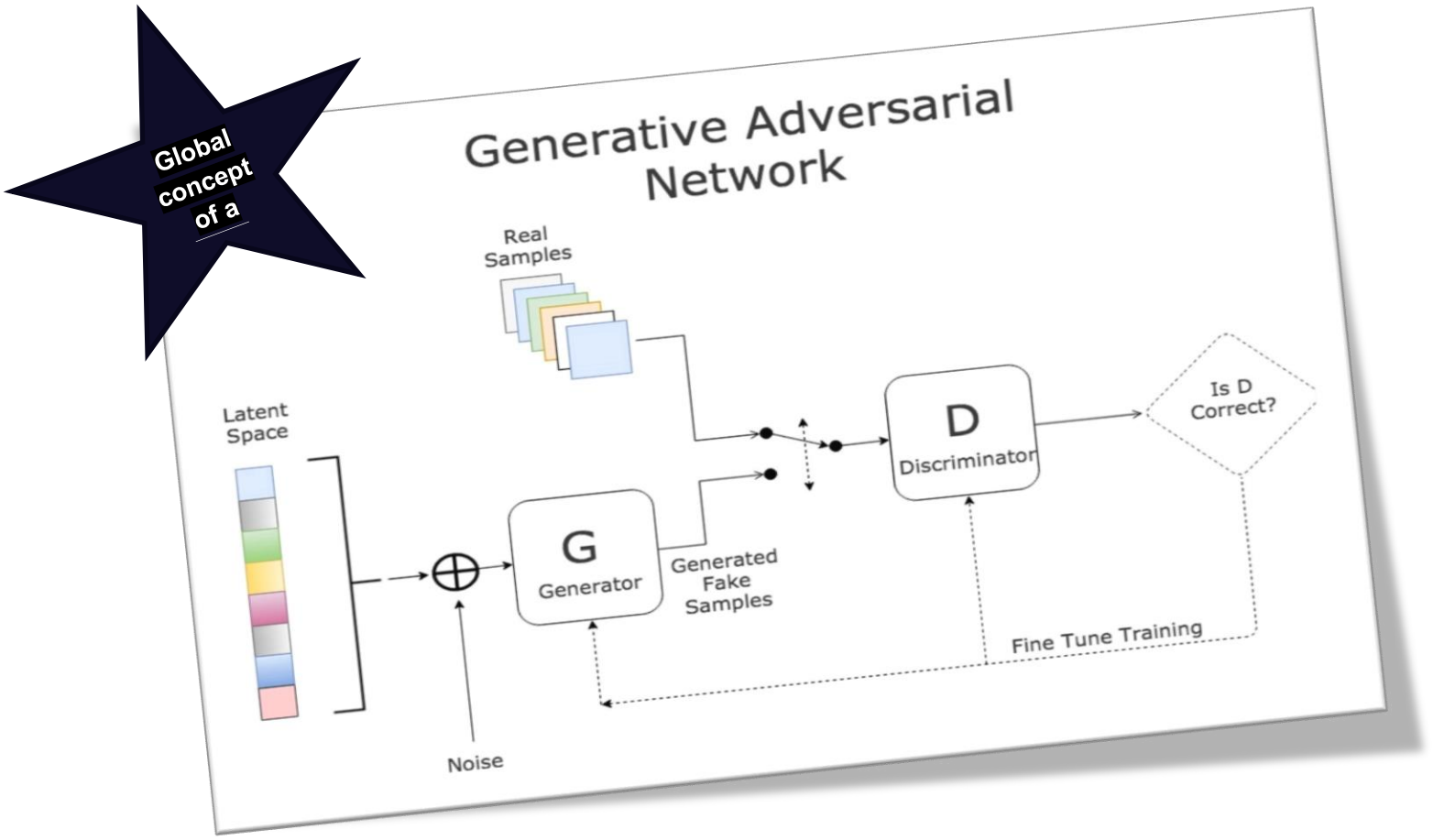
Now we begin with our Model:

Architecture of our DCGAN

Here, we are not trying to mimic simple numerical data—we are trying to mimic an image, which should even be able to fool a human. The generator takes a randomly generated noise vector as input data and then uses a technique called deconvolution to transform the data into an image.

The discriminator is a classical convolutional neural network, which classifies real and fake images.




Global concept of a
Generative Adversarial Network
Real Samples
Latent Space
G
Generator
Generated Fake Samples
D
Discriminator
Is D Correct?
Fine Tune Training
Noise

CODE:

1. Importing the required Libraries:

```
import tensorflow as tf
```

```
[ ]  tf.__version__
```

```
'2.4.1'
```

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

```
  Building wheel for tensorflow-docs (setup.py) ... done
```

```
[ ]  import glob
     import imageio
     import matplotlib.pyplot as plt
     import numpy as np
     import os
     import PIL
     from tensorflow.keras import layers
     import time

     from IPython import display
```

2. Loading the dataset:

MNIST Dataset:

It is a dataset containing `hand-written digits` from 0 to 9.

Our generator will generate handwritten digits resembling the MNIST data.

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

```
[ ]  train_images = train_images.reshape(train_images.shape[0], 28, 28, 1).astype('float32')
     train_images = (train_images - 127.5) / 127.5  # Normalize the images to [-1, 1]
```

```
[ ]  BUFFER_SIZE = 60000
     BATCH_SIZE = 256
```

```
[ ]  # Batch and shuffle the data
     train_dataset = tf.data.Dataset.from_tensor_slices(train_images).shuffle(BUFFER_SIZE).batch(BATCH_SIZE)
```

3. Creating the Model:

GENERATOR

It is a generative network, which generates the images, from the input of a `vector of noise`. We will use the following layers in our model:

- *`Dense:`* The noise layer of our generator.
- *`Conv2DTranspose:`* Upscaling and convolving the image at the same time.
- *`LeakyReLU:`* We use it to avoid gradient vanish.
- *`BatchNormalization:`* Normalizing the result of a convolution to get better results.

`Basic Idea`: From the random noise, we will convolve the data until we generate an image.

The generator goes the other way: It is the artist who is trying to fool the discriminator. This network consists of 3 convolutional layers. Each convolutional layer performs a convolution and then performs batch normalization and a leaky ReLu as well. Then, we return the tanh activation function.

```
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 batch size

    model.add(layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same', use_bias=False))
    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='same', use_bias=False))
    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='same', use_bias=False, activation='tanh'))
    assert model.output_shape == (None, 28, 28, 1)

    return model
```

Checking our generator works fine:

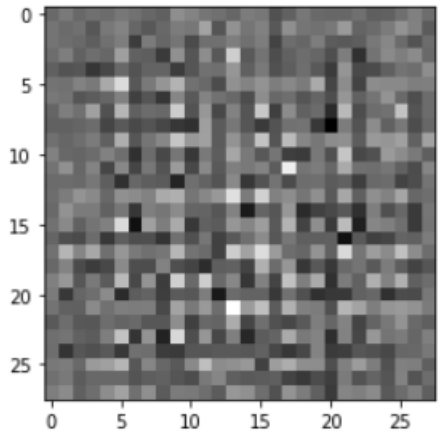
Our network is not trained yet so, it should generate only noise.

```
generator = make_generator_model()

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

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

```
<matplotlib.image.AxesImage at 0x7f06acce0850>
```



DISCRIMINATOR

Our discriminator network is a normal convolutional neural network. It will take an image as input and as output will return a binary value.

For every layer of the network, we are going to perform a convolution, then we use LeakyRelu to avoid gradient vanish, followed by a dropout layers to avoid overfitting. We complete the structure of discriminator with Flatten and Dense layers.

```
[ ]  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
```

Our model, yet untrained so, the discriminator should 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.

```
[ ]  discriminator = make_discriminator_model()
     decision = discriminator(generated_image)
     print (decision)

     tf.Tensor([[-2.54669e-05]], shape=(1, 1), dtype=float32)
```

4. Define the loss and optimizers:

We need to define three loss functions:

- The loss of the generator,
- The loss of the discriminator when using real images, and
- The loss of the discriminator when using fake images.

The sum of the fake image and real image loss is the overall discriminator loss.

```
[ ]  # 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

First, we define our loss for the real images. For that, we pass the output of the discriminator when dealing with real images and compare it with the labels, which are all 1, which means true.

Then, we define the loss for our fake images. This time we pass in the output of the discriminator when dealing with fake images and compare it to our labels, which are all 0, which means they are fake.

Lastly, our total discriminator loss is sum of the above two losses.

```
[ ]  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.

For the generator loss, we do the same like we did for fake loss, but instead of comparing the output with all 0s, we compare it with 1s, since we want to fool the discriminator.

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

We optimize the generator and discriminator individually, since we wnat to train both the networks separately.

```
generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)
```

5. Saving the Checkpoints

We need to save checkpoints to reload our model back, if we accidently get disconnected.

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

6. Training the GAN model:

Training is the hardest part and since a GAN contains two separately trained networks, its training algorithm must address two complications:

- GANs must juggle two different kinds of training (generator and discriminator).
- GAN convergence is hard to identify.

As the generator improves with training, the discriminator performance gets worse because the discriminator can't easily tell the difference between real and fake. If the generator succeeds perfectly, then the discriminator has a 50% accuracy. In effect, the discriminator flips a coin to make its prediction.

This progression poses a problem for convergence of the GAN as a whole: the discriminator feedback gets less meaningful over time. If the GAN continues training past the point when

the discriminator is giving completely random feedback, then the generator starts to train on junk feedback, and its quality may collapse.

```
[ ]  EPOCHS = 70
     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 random noise as input, which is then used to produce an image. The discriminator then classifies 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.

```
[ ]  # 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_variables)
         gradients_of_discriminator = disc_tape.gradient(disc_loss, discriminator.trainable_variables)

         generator_optimizer.apply_gradients(zip(gradients_of_generator, generator.trainable_variables))
         discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator, discriminator.trainable_variables))
```

```
[ ]  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)
```

7. Generate and Save Images:

```
[ ]  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()
```

We 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.

```
train(train_dataset, EPOCHS)
```

Restore the latest checkpoint

```
[ ]  checkpoint.restore(tf.train.latest_checkpoint(checkpoint_dir))

     <tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7f0660177c10>
```

8. Create GIF:

```
# 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))
```

```
[ ]  display_image(EPOCHS)
```

```
[ ]  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)
```

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

REFERENCES:

- Code is taken from [https://www.tensorflow.org/tutorials/generative/dcgan]