fashionGAN

April 4, 2023

**

A basics Generative Adversarial Network (GAN) model created to generate new fashion line. The model is trained with the fashion_mnist datasets using Tensorflow Machine Learning Library

**

0.0.1 Here are two models are created,

0.0.2 - *A Generative model*

0.0.3 - *A Discriminative model*

The generative model is setup so as to be rewarded for creating images that are not easily recognizable by the discriminative model as **FAKE** and the discriminative model is setup so as to be rewarded for recognizing **FAKE** images generated, from **REAL** ones. A custom training loop is setup to have the two model go against each other back and forth so as to make the generative model created more accurate and hard to detect images through more training.

[ ]:
```
!pip install tensorflow matplotlib tensorflow-datasets ipywidgets
```

[ ]:
```
! nvidia-smi
```

```
Tue Apr  4 05:25:53 2023
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 525.85.12    Driver Version: 525.85.12    CUDA Version: 12.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0 |
| N/A   64C    P8    10W /  70W |      3MiB / 15360MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
```

```
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

[ ]:
```python
# importing the tensorflow datasets api

import tensorflow as tf
import tensorflow_datasets as tfds
import matplotlib.pyplot as plt
```

[ ]:
```python
# loading the fashion_mnist dataset by calling the tensorflow dataset api

ds = tfds.load('fashion_mnist', split='train')
```

```
Downloading and preparing dataset Unknown size (download: Unknown size,
generated: Unknown size, total: Unknown size) to
/root/tensorflow_datasets/fashion_mnist/3.0.1…

Dl Completed…: 0 url [00:00, ? url/s]

Dl Size…: 0 MiB [00:00, ? MiB/s]

Extraction completed…: 0 file [00:00, ? file/s]

Generating splits…:   0%|          | 0/2 [00:00<?, ? splits/s]

Generating train examples…: 0 examples [00:00, ? examples/s]

Shuffling /root/tensorflow_datasets/fashion_mnist/3.0.1.incompleteKUYG37/
↪fashion_mnist-train.tfrecord*…:   0…

Generating test examples…: 0 examples [00:00, ? examples/s]

Shuffling /root/tensorflow_datasets/fashion_mnist/3.0.1.incompleteKUYG37/
↪fashion_mnist-test.tfrecord*…:   0%…

Dataset fashion_mnist downloaded and prepared to
/root/tensorflow_datasets/fashion_mnist/3.0.1. Subsequent calls will reuse this
data.
```

[ ]:
```python
# printing the feature names for the dataset

ds.as_numpy_iterator().next().keys()
```

[ ]:
```
dict_keys(['image', 'label'])
```

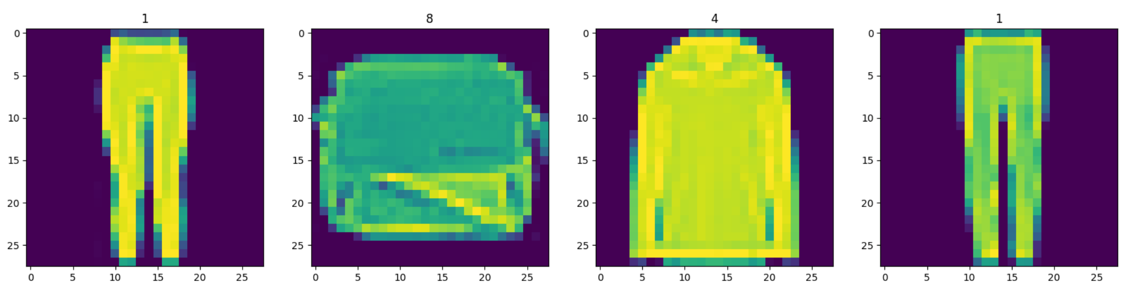
[ ]:
```python
ds.as_numpy_iterator().next()['label']
```

[ ]:
```
2
```

1 2. Visualization of Data & Building the Dataset

[ ]:
```
# data transformation

import numpy as np

# setup connection aka iterator

data_iterator = ds.as_numpy_iterator()

# getting data out of the pipline
data_iterator.next()
```

[ ]:
```
# plotting the images

fig, ax = plt.subplots(ncols=4, figsize=(20, 20))

# loop four times and get images
for idx in range(4):

  # grabbing an image and label

  batch = data_iterator.next()

  # plot the image using a specific subplot

  ax[idx].imshow(np.squeeze(batch['image']))

  ax[idx].title.set_text(batch['label'])
```



[ ]:
```
# Scale and return images only
def scale_images(data):
  image = data['image']
  return image / 255
```

```
[ ]: # building a tensorflow datapipeline

     # reloading the dataset from scratch
     ds = tfds.load('fashion_mnist', split='train')
     # running the dataset through the scale_images preprocessing step
     ds = ds.map(scale_images)
     # cache the dataset for that batch
     ds = ds.cache()
     # shuffle
     ds = ds.shuffle(60000)
     # batch into 128 images per sample
     ds = ds.batch(128)
     # step to reduce possible bottlenecking
     ds = ds.prefetch(64)
```

```
[ ]: ds.as_numpy_iterator().next().shape
```

```
[ ]: (128, 28, 28, 1)
```

2 3. Building the Neural Network

####**3.1 Import Modelling Components**

```
[ ]: # importing the Sequential api for the generator and discriminator
     from tensorflow.keras.models import Sequential
     # importing the layers for the neural network
     from tensorflow.keras.layers import Conv2D, Dense, Flatten, Reshape, LeakyReLU,␣
      ↪Dropout, UpSampling2D
```

3.2 Build the Generator Model

```
[ ]: def build_generator():
       model = Sequential()

       # Takes in random values and reshape it to 7x7x128
       model.add(Dense(7*7*128, input_dim=128))
       model.add(LeakyReLU(0.2))
       model.add(Reshape((7, 7, 128)))

       # upsampling block 1
       model.add(UpSampling2D())
       model.add(Conv2D(128, 5, padding='same'))
       model.add(LeakyReLU(0.2))

       # upsampling block 2
       model.add(UpSampling2D())
       model.add(Conv2D(128, 5, padding='same'))
```

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

    # Convolutional block 1
    model.add(Conv2D(128, 4, padding='same'))
    model.add(LeakyReLU(0.2))

    # Convolutional block 2
    model.add(Conv2D(128, 4, padding='same'))
    model.add(LeakyReLU(0.2))

    # Conv layers to end in a single channel
    model.add(Conv2D(1, 4, padding='same', activation='sigmoid'))

    return model
```

[ ]:
```
generator = build_generator()
```

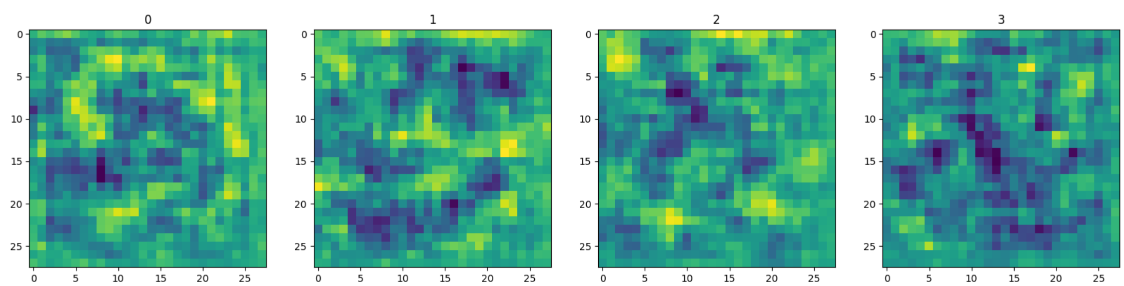
[ ]:
```
generator.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 6272)              809088

 leaky_re_lu (LeakyReLU)     (None, 6272)              0

 reshape (Reshape)           (None, 7, 7, 128)         0

 up_sampling2d (UpSampling2D  (None, 14, 14, 128)      0
 )

 conv2d (Conv2D)             (None, 14, 14, 128)       409728

 leaky_re_lu_1 (LeakyReLU)   (None, 14, 14, 128)       0

 up_sampling2d_1 (UpSampling  (None, 28, 28, 128)      0
 2D)

 conv2d_1 (Conv2D)           (None, 28, 28, 128)       409728

 leaky_re_lu_2 (LeakyReLU)   (None, 28, 28, 128)       0

 conv2d_2 (Conv2D)           (None, 28, 28, 128)       262272

 leaky_re_lu_3 (LeakyReLU)   (None, 28, 28, 128)       0
```

```
 conv2d_3 (Conv2D)           (None, 28, 28, 128)       262272

 leaky_re_lu_4 (LeakyReLU)   (None, 28, 28, 128)       0

 conv2d_4 (Conv2D)           (None, 28, 28, 1)         2049

=================================================================
Total params: 2,155,137
Trainable params: 2,155,137
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```python
# Generating images through randomly generated number sample to test the
 ↪working of the model

img = generator.predict(np.random.randn(4, 128, 1))

# subplot configuration for the images

fig, ax = plt.subplots(ncols=4, figsize=(20, 20))

# loop through an enumerated images
for idx, image in enumerate(img):

  # plot the image using a specific subplot

  ax[idx].imshow(np.squeeze(image))

  ax[idx].title.set_text(idx)
```

```
1/1 [==============================] - 7s 7s/step
```



3.3 Building the Discriminator model

The Discriminator model is created to classify whether a given image is authentic or generated with GAN we created

[ ]:
```python
def build_discriminator():
  model = Sequential()

  # first Covolutional layer
  model.add(Conv2D(32, 5, input_shape = (28, 28, 1)))
  model.add(LeakyReLU(0.2)) # LeakyReLU is more prefered as the activation␣
↪function for GANs in general.
  model.add(Dropout(0.4)) # Regularization

  # second Convolutional layer
  model.add(Conv2D(64, 5))
  model.add(LeakyReLU(0.2))
  model.add(Dropout(0.4))

  # third Convolutional layer
  model.add(Conv2D(128, 5))
  model.add(LeakyReLU(0.2))
  model.add(Dropout(0.4))

  # fourth Convolutional layer
  model.add(Conv2D(256, 5))
  model.add(LeakyReLU(0.2))
  model.add(Dropout(0.4))

  # Flatten then pass to Dense layer

  model.add(Flatten())
  model.add(Dropout(0.4))
  model.add(Dense(1, activation='sigmoid'))

  return model
```

[ ]:
```python
discriminator = build_discriminator()

discriminator.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_5 (Conv2D)           (None, 24, 24, 32)        832

 leaky_re_lu_5 (LeakyReLU)   (None, 24, 24, 32)        0

 dropout (Dropout)           (None, 24, 24, 32)        0

 conv2d_6 (Conv2D)           (None, 20, 20, 64)        51264
```

```
 leaky_re_lu_6 (LeakyReLU)   (None, 20, 20, 64)        0

 dropout_1 (Dropout)         (None, 20, 20, 64)        0

 conv2d_7 (Conv2D)           (None, 16, 16, 128)       204928

 leaky_re_lu_7 (LeakyReLU)   (None, 16, 16, 128)       0

 dropout_2 (Dropout)         (None, 16, 16, 128)       0

 conv2d_8 (Conv2D)           (None, 12, 12, 256)       819456

 leaky_re_lu_8 (LeakyReLU)   (None, 12, 12, 256)       0

 dropout_3 (Dropout)         (None, 12, 12, 256)       0

 flatten (Flatten)           (None, 36864)             0

 dropout_4 (Dropout)         (None, 36864)             0

 dense_1 (Dense)             (None, 1)                 36865

=================================================================
Total params: 1,113,345
Trainable params: 1,113,345
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
img = img[0]
```

[ ]:
```
img.shape
```

[ ]:
```
(28, 28, 1)
```

3 4. Constructing Custom Training Loops

4.1 Setup Losses and Optimizers

[ ]:
```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
```

[ ]:
```
g_opt = Adam(learning_rate=0.0001)
d_opt = Adam(learning_rate=(0.00001))
g_loss = BinaryCrossentropy()
d_loss = BinaryCrossentropy()
```

4.2 Build Subclassed model

[ ]:
```
# importing the base model class to subclass out training step
from tensorflow.keras.models import Model
```

[ ]:
```
class FashionGAN(Model):
  def __init__(self, generator, discriminator, *args, **kwargs):
    super().__init__(*args, **kwargs)

    # create attributes for generator and discriminator

    self.generator = generator
    self.discriminator = discriminator

  def compile(self, g_opt, d_opt, g_loss, d_loss, *args, **kwargs):
    # compile with base class
    super().compile(*args, **kwargs)
    # create attributes for losses and optimizers
    self.g_opt = g_opt
    self.d_opt = d_opt
    self.g_loss = g_loss
    self.d_loss = d_loss


  def train_step(self, batch):
    real_images = batch
    fake_images = self.generator(tf.random.normal((128, 128, 1)), training =␣
↪False)

    # Train the discriminator
    with tf.GradientTape() as d_tape:
      # Pass the real and fake images to the discriminator model
      yhat_real = self.discriminator(real_images, training=True)
      yhat_fake = self.discriminator(fake_images, training=True)
      yhat_realfake = tf.concat([yhat_real, yhat_fake], axis = 0)

      # create label for real and fake images
      y_realfake = tf.concat([tf.zeros_like(yhat_real), tf.
↪ones_like(yhat_fake)], axis=0)

      # add some noise to the TRUE outputs
      noise_real = 0.15 * tf.random.uniform(tf.shape(yhat_real))
      noise_fake = 0.15 * tf.random.uniform(tf.shape(yhat_fake))
      y_realfake += tf.concat([noise_real, noise_fake], axis = 0)

      # calulate loss
      total_d_loss = self.d_loss(y_realfake, yhat_realfake)
```

```
    # apply backpropogation - nn learn
    d_grad = d_tape.gradient(total_d_loss, self.discriminator.
 ↪trainable_variables)
    self.d_opt.apply_gradients(zip(d_grad, self.discriminator.
 ↪trainable_variables))

    # Train the generator
    with tf.GradientTape() as g_tape:
      # generate some new images
      gen_images = self.generator(tf.random.normal((128, 128, 1)),␣
 ↪training=True)

      # create the predicted labels
      predicted_labels = self.discriminator(gen_images, training=False)

      # calculate the loss
      total_g_loss = self.g_loss(tf.zeros_like(predicted_labels),␣
 ↪predicted_labels)

    # apply backpropogation
    g_grad = g_tape.gradient(total_g_loss, self.generator.trainable_variables)
    self.g_opt.apply_gradients(zip(g_grad, self.generator.trainable_variables))

    return {"d_loss": total_d_loss, "g_loss": total_g_loss}
```

[ ]:
```
# create a instance of the subclass

f_gan = FashionGAN(generator, discriminator)
```

[ ]:
```
# compile the model

f_gan.compile(g_opt, d_opt, g_loss, d_loss)
```

4.3 Build Callback

[ ]:
```
import os
from tensorflow.keras.preprocessing.image import array_to_img
from tensorflow.keras.callbacks import Callback
```

[ ]:
```
class ModelMonitor(Callback):
  def __init__(self, num_img = 3, latent_dim = 128):
    self.num_img = num_img
    self.latent_dim = latent_dim

  def on_epoch_end(self, epoch, logs = None):
    random_latent_vectors = tf.random.uniform((self.num_img, self.latent_dim,␣
 ↪1))
```

```
    generated_images = self.model.generator(random_latent_vectors)
    generated_images *= 255
    generated_images.numpy()
    for i in range(self.num_img):
      img = array_to_img(generated_images[i])

  # loop through an enumerated images
  for idx, image in enumerate(img):

    # plot the image using a specific subplot

    ax[idx].imshow(np.squeeze(image))

    ax[idx].title.set_text(idx)
```

4.4 Train

[ ]:
```
# Recommended 2000 epoch if you have the time

hist = f_gan.fit(ds, epochs = 20, callbacks = [ModelMonitor()])
```

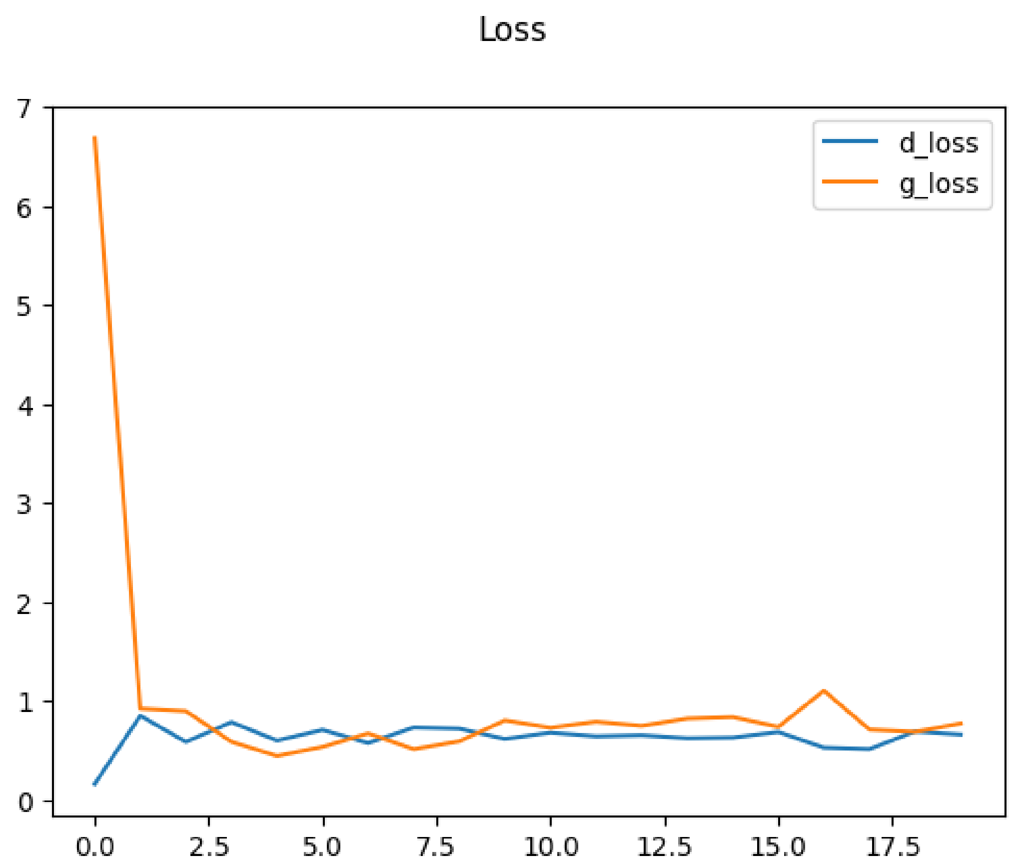
```
Epoch 1/20
  6/469 […] - ETA: 1:17 - d_loss: 0.6906 - g_loss:
0.7039

WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the
batch time (batch time: 0.0707s vs `on_train_batch_end` time: 0.0791s). Check
your callbacks.

469/469 [==============================] - 92s 174ms/step - d_loss: 0.4449 -
g_loss: 1.6962
Epoch 2/20
469/469 [==============================] - 81s 173ms/step - d_loss: -3.5068e-04
- g_loss: 15.6435
Epoch 3/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6383 -
g_loss: 0.8738
Epoch 4/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6546 -
g_loss: 0.6503
Epoch 5/20
469/469 [==============================] - 81s 172ms/step - d_loss: 0.6127 -
g_loss: 0.6475
Epoch 6/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.7012 -
g_loss: 0.5161
Epoch 7/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6453 -
g_loss: 0.6874
```

```
Epoch 8/20
469/469 [==============================] - 81s 172ms/step - d_loss: 0.6690 -
g_loss: 0.5681
Epoch 9/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6896 -
g_loss: 0.6695
Epoch 10/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6845 -
g_loss: 0.7407
Epoch 11/20
469/469 [==============================] - 81s 172ms/step - d_loss: 0.6884 -
g_loss: 0.7263
Epoch 12/20
469/469 [==============================] - 81s 172ms/step - d_loss: 0.6770 -
g_loss: 0.7580
Epoch 13/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6834 -
g_loss: 0.7484
Epoch 14/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6754 -
g_loss: 0.7475
Epoch 15/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6879 -
g_loss: 0.7426
Epoch 16/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6877 -
g_loss: 0.7549
Epoch 17/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6818 -
g_loss: 0.8116
Epoch 18/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6076 -
g_loss: 0.8609
Epoch 19/20
469/469 [==============================] - 81s 173ms/step - d_loss: 0.6840 -
g_loss: 0.6341
Epoch 20/20
469/469 [==============================] - 81s 172ms/step - d_loss: 0.6858 -
g_loss: 0.7131
```

4.5 Review Performance

[ ]:

```
plt.suptitle('Loss')
plt.plot(hist.history['d_loss'], label='d_loss')
plt.plot(hist.history['g_loss'], label='g_loss')
plt.legend()
plt.show()
```

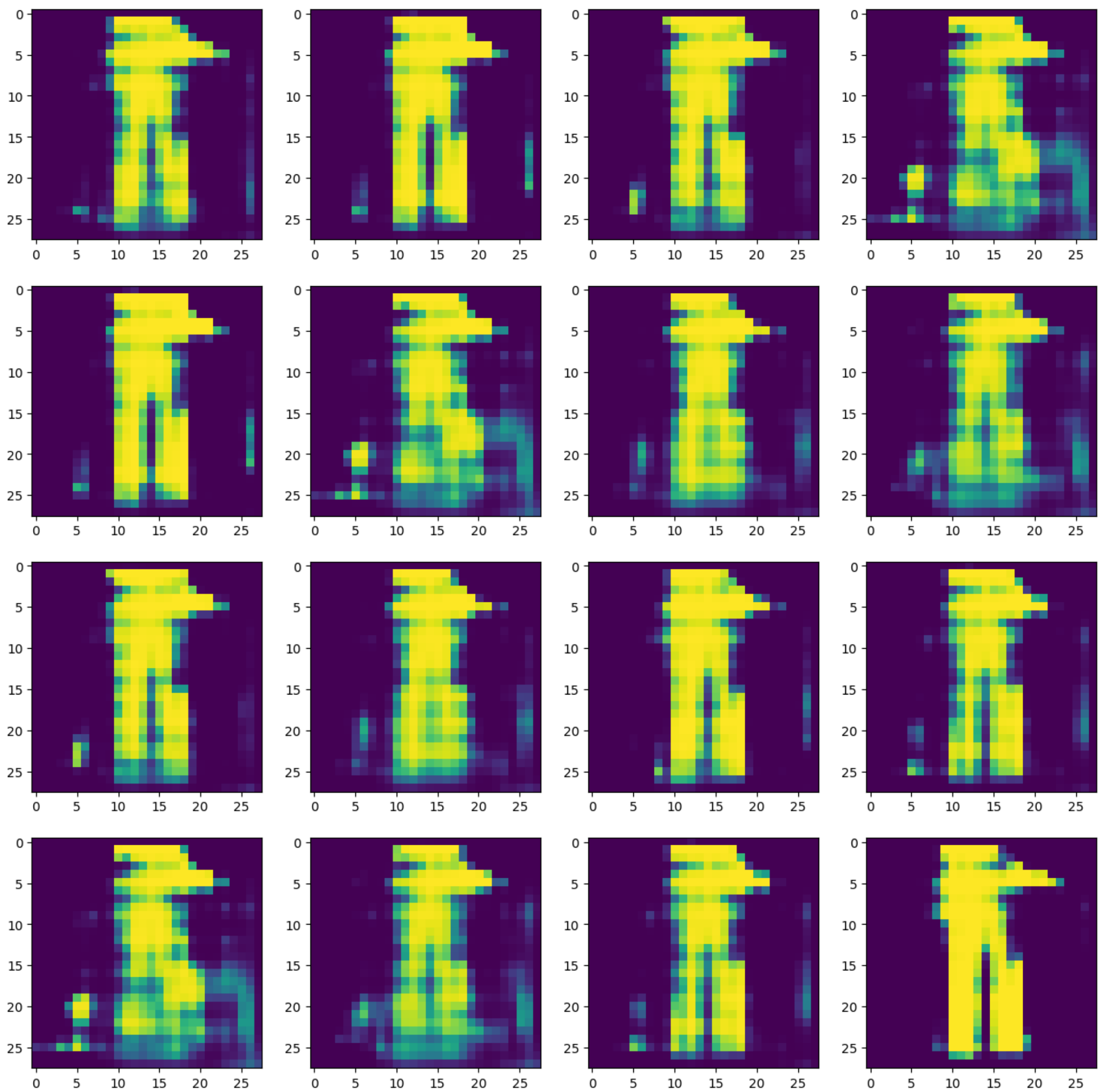


4 5. Testing the Generator

5.1 Generate Images

[ ]:
```
imgs = generator.predict(tf.random.normal((16, 128, 1)))
```

[ ]:
```
fig, ax = plt.subplots(ncols=4, nrows=4, figsize=(15, 15))
for r in range(4):
  for c in range(4):
    ax[r][c].imshow(imgs[(r + 1) * (c + 1) - 1])
```



4.0.1 *To Produce actual images we shall have to train the model upto atleast 2000 epochs. But due to limited resources we are ending here.*

5.2 Save the model

[ ]:
```python
generator.save('generator.h5')
discriminator.save('discriminator.h5')
```

```
WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
```