

En esta práctica deberéis implementar una GAN condicional con el dataset FashionMNIST.

Podéis basaros en este ejemplo: https://keras.io/examples/generative/conditional_gan/.

Lo único que debéis cambiar es la entrada, tanto del G como del D, para incluir la clase que queréis asociar con la imagen generada.

```
In [1]: # montamos la unidad drive donde tenemos los datos en la carpeta drive/My Drive
         from google.colab import drive
         drive.mount('/content/drive')
         Mounted at /content/drive
In [31]: RESULTS_PATH = "/content/results/"
         BASE PATH = "/content/drive/MyDrive/ASIGNATURAS/VIU/06MIAR Aprendizaje no Supervisa
         %mkdir $RESULTS PATH
         %ls $BASE PATH
         cgan_generator_model_001.h5 cgan_generator_model_080.h5 generated_plot_e050.png
         cgan generator model 010.h5 cgan generator model 090.h5 generated plot e060.png
         cgan_generator_model_020.h5 cgan_generator_model_100.h5 generated_plot_e070.png
         cgan_generator_model_030.h5 generated_plot_e001.png
                                                                   generated_plot_e080.png
         cgan_generator_model_040.h5 generated_plot_e010.png
                                                                   generated_plot_e090.png
         cgan_generator_model_050.h5 generated_plot_e020.png
                                                                   generated_plot_e100.png
         cgan_generator_model_060.h5 generated_plot_e030.png
                                                                   generated_plot_e101.png
         cgan generator model 070.h5 generated plot e040.png
         # importamos las librerías necesarias
In [30]:
         import numpy as np
         import os
         from tensorflow.keras.datasets.fashion mnist import load data
         from tensorflow.keras.optimizers import Adam
         from tensorflow.keras.models import Model
         from tensorflow.keras.layers import Input, Embedding, Concatenate, Dense, Reshape,
         import matplotlib.pyplot as plt
In [28]:
         # definimos el discriminador: en este caso va a ser convolucional
         def define_discriminator(in_shape=(28, 28, 1), n_classes=10):
             # En esta ocasión vamos a usar la API funcional de KERAS
             # creamos la entrada de la información condicional
             in label = Input(shape=(1,))
             # embedding para entradas categóricas
             emb = Embedding(n_classes, 50)(in_label)
             # debemos añadir una capa densa que nos transforme el escalar que representa
             # nuestra clase a una imagen de (28, 28) para luego poder concatenar esa
             # información con la imagen
             n_nodes = in_shape[0] * in_shape[1]
             # mapping_cond_inf = Dense(n_nodes)(in_label)
             mapping cond inf = Dense(n nodes)(emb)
             # canal adicional para las etiquetas
             mapping_cond_inf = Reshape((in_shape[0], in_shape[1], 1))(mapping_cond_inf)
             # entrada de la imagen
             in_image = Input(shape=in_shape)
             # concatenamos la info condicional con la imagen
             merge = Concatenate()([in_image, mapping_cond_inf])
             # downsample
```

```
fe = Conv2D(128, (3, 3), padding='same')(merge)
fe = MaxPooling2D((2, 2))(fe)
fe = LeakyReLU(alpha=0.2)(fe)
# downsample
fe = Conv2D(128, (3, 3), padding='same')(fe)
fe = MaxPooling2D((2, 2))(fe)
fe = LeakyReLU(alpha=0.2)(fe)
fe = Flatten()(fe)
fe = Dropout(0.4)(fe)
out_layer = Dense(1, activation='sigmoid')(fe)
# definimos y compilamos el modelo (debemos indicarle las dos entradas que
# va a tener: in_label e in_image)
model = Model([in_image, in_label], out_layer, name="DISCRIMINATOR")
opt = Adam(learning_rate=0.0002, beta_1=0.5)
model.compile(loss='binary crossentropy', optimizer=opt, metrics=['accuracy'])
model.summary()
return model
```

```
In [27]: # definimos el generador
         def define_generator(latent_dim, n_classes=10):
             # Aquí también vamos a utilizar la API funcional de Keras
             # creamos la entrada de la información condicional
             in_label = Input(shape=(1,))
             emb = Embedding(n_classes, 50)(in_label)
             n_nodes = 7 * 7
             mapping_cond_inf = Dense(n_nodes)(emb)
             mapping_cond_inf = Reshape((7, 7, 1))(mapping_cond_inf)
             # creamos la entrada de la información condicional
             in label = Input(shape=(1,))
             # embedding para entradas categóricas
             emb = Embedding(n_classes, 50)(in_label)
             # debemos añadir una capa densa que nos transforme el escalar que representa
             # nuestra clase a una matriz de (N, N) para luego poder concatenar esa
             # información con la imagen
             n_nodes = 7 * 7 # Pista: N*N, donde N debe coincidir con Las
             # dimensiones de "gen" más abajo para poder ser concatenado ##
             # mapping cond inf = Dense(## Aquí tu código. Pista: número de neuronas ##)(in
             mapping cond inf = Dense(n nodes)(emb)
             mapping_cond_inf = Reshape((7, 7, 1))(mapping_cond_inf)
             # entrada del código latene
             in_lat = Input(shape=(latent_dim,))
             # vamos a mapear nuestro código latente a un espacio bidimensional de mayor
             # número de dimensiones para poder tratar con él con nuestra CNN
             n nodes = 128 * 7 * 7
             gen = Dense(n nodes)(in lat)
             gen = LeakyReLU(alpha=0.2)(gen)
             gen = Reshape((7, 7, 128))(gen)
             # concatenamos el código latente y la información
             merge = Concatenate()([gen, mapping_cond_inf])
             # aumentamos a 14x14
             gen = Conv2DTranspose(128, (4,4), padding='same')(merge)
             gen = UpSampling2D((2, 2))(gen)
             gen = LeakyReLU(alpha=0.2)(gen)
             # aumentamos a 28x28
             gen = Conv2DTranspose(128, (4,4), padding='same')(gen)
             gen = UpSampling2D((2, 2))(gen)
             gen = LeakyReLU(alpha=0.2)(gen)
             # salida del modelo (una imagen en escala de grises de 28x28)
             out_layer = Conv2D(1, (7,7), activation='tanh', padding='same')(gen)
             # definimos el modelo
             model = Model([in_lat, in_label], out_layer, name="GENERATOR")
```

```
model.summary()
             return model
In [26]: # definimos el modelo GAN combinando generador y discriminador, para entrenar el ge
         def define_gan(g_model, d_model):
             # pesos del discriminador congelados
             d model.trainable = False
             # obtener las entradas de ruido y etiquetas del modelo generador
             gen_noise, gen_label = g_model.input
             # obtener la imagen de salida del modelo generador
             gen output = g model.output
             # conectar la salida de imagen y la entrada de etiqueta del generador como entr
             gan_output = d_model([gen_output, gen_label])
             # definir el modelo gan como la toma de ruido y etiqueta y la salida de una cla
             model = Model([gen_noise, gen_label], gan_output)
             # compilamos modelo
             opt = Adam(learning_rate=0.0002, beta_1=0.5)
             model.compile(loss='binary_crossentropy', optimizer=opt)
             return model
In [14]: # definimos las funciones para cargar el MNIST
         def load_real_samples():
             # cargamos el dataset - ESTA VEZ QUEREMOS LAS IMÁGENES Y LAS CLASES
             (trainX, trainY), (_, _) = load_data()
             # expandimos la dimensión del batch
             X = np.expand dims(trainX, axis=-1)
             # convertimos a float32
             X = X.astype('float32')
             # escalamos entre -1 y 1
             X = (X - 127.5) / 127.5
             # devolvemos tanto las imágenes como las clases
             return [X, trainY]
         # nos creamos una función que nos devuelva n samples del dataset (imagen, clase)
         # y generamos las etiquetas de entrenamiento GAN: 1
         def generate_real_samples(dataset, n_samples):
             # separamos las imágenes de las etiquetas
             images, labels = dataset
             # seleccionamos n_samples muestras aleatoriamente
             ix = np.random.randint(0, images.shape[0], n_samples)
             # las cogemos junto a su correspondiente clase
             X, labels = images[ix], labels[ix]
             # generamos las etiquetas para entrenar la GAN (1)
             y = np.ones((n_samples, 1))
             # debemos devolver, por un lado, X y labels (para condicionar la GAN),
             # y por el otro, la etiqueta que le asignamos: en este caso, al estar
             # entrenando el discriminador, etiqueta = 1
             return [X, labels], y
In [16]: # generamos los vectores latentes que introduciremos al generador
         def generate_latent_points(latent_dim, batch_size, n_classes=10):
             # generamos un vector de batch_size * latent_dim números aleatorios
             # latent_dim es la dimensión del vector latente
             # batch_size es el número de elementos por batch
             x input = np.random.randn(latent dim * batch size)
             # redimensionamos el vector para que tenga un tamaño (batch size, latent dim)
             z_input = x_input.reshape(batch_size, latent_dim)
             # generamos clases aleatoriamente: La imagen producida por este código
             # latente y clase deberá ser una imagen realista que pertenezca a dicha
             # clase!
             labels = np.random.randint(0, n_classes, batch_size)
```

debemos devolver tanto el vector de ruido como la "clase": z_input y labels

return [z_input, labels]

```
# creamos datos fake con el generador (dinero falsificado)
         def generate fake samples(g model, latent dim, n samples):
             # usamos la función anterior para generar los vectores latentes que
             # necesitamos para generar muestras fake acompañados de las clases
             # a las que queremos que pertenezcan las imágenes generadas
             z_input, labels_input = generate_latent_points(latent_dim, n_samples)
             # le introducimos los vectores latentes y las clases al generador para obtener
             # muestras similares a las reales
             images = g_model.predict([z_input, labels_input])
             # le asignamos la etiqueta 0 (porque utilizaremos esta función para
             # entrenar el D)
             y = np.zeros((n_samples,1))
             # debemos devolver, por un lado, images y labels_inputs (para condicionar la GA
             # y por el otro, la etiqueta que le asignamos: en este caso, al estar
             # entrenando el generador, etiqueta = 0
             return [images, labels_input], y
In [32]: # función para guardar las imágenes generadas
         def save_plot(examples, epoch, n=10, figsize=(20, 20)):
             examples = (examples * 127.5) + 127.5
             plt.figure(figsize=figsize)
             for i in range(n * n):
                 plt.subplot(n, n, 1 + i)
                 plt.axis('off')
                 plt.imshow(examples[i, :, :, 0], cmap='gray_r')
             # quardamos las imágenes
             filename = os.path.join(RESULTS PATH, 'generated plot e%03d.png' % (epoch+1))
             plt.savefig(filename)
             plt.close()
In [33]: # función para entrenar la GAN: el discriminador y el generador
         def train(g_model, d_model, gan_model, dataset, latent_dim, n_epochs=100, n_batch=2
             bat per epo = int(dataset[0].shape[0] / n batch)
             half batch = int(n batch / 2)
             # bucle para las epochs
             for epoch in range(n_epochs):
                 # bucle para los batch
                 for batch in range(bat_per_epo):
                     # en esta ocasión vamos a separar las pérdidas del discriminador
                     # cuando le metemos imágenes reales y cuando le metemos imágenes
                     # fake para ver cómo lo hace con cada tipo
                     # recordad que lo ideal es que llegue a un 50% de acc en cada uno
                     # preparamos los datos reales
                     [X_real, labels_real], y_real = generate_real_samples(dataset, half_bat
                     # actualizamos el discriminador
                     d_loss1, _ = d_model.train_on_batch([X_real, labels_real], y_real)
                     # generamos datos falsos
                     [X fake, labels fake], y fake = generate fake samples(g model, latent d
                     # actualizamos el discriminador
                     d_loss2, _ = d_model.train_on_batch([X_fake, labels_fake], y_fake)
```

preparamos los puntos en el espacio latente: serán la entrada al

[z_input, labels_input] = generate_latent_points(latent_dim, n_batch)

creamos etiquetas invertidas para el generador: utilizamos el D(x) # para que piense que las muestras que le introducimos son reales, y # en caso de que diga que no son reales, aprovechamos la información # de sus gradientes para actualizar el G(z) para que la próxima vez

modelo GAN con el que entrenaremos el generador

```
\# los datos generados por G(z) sean más plausibles (parecidos a los
                     # reales)
                     y_gan = np.ones((n_batch, 1))
                     # como acabamos de ver, entrenamos el generador de forma que actualice
                     # sus pesos usando los gradientes del discriminador
                     # tened en cuenta que en este modelo (gan_model) el discriminador está
                     # congelado, por lo que no se actualizan sus pesos: no queremos "untar'
                     # a nuestro policía, lo que queremos es fabricar dinero más realista.
                     g_loss = gan_model.train_on_batch([z_input, labels_input], y_gan)
                     # mostramos el progreso
                     print('>%d, %d/%d, d1=%.3f, d2=%.3f g=%.3f' %
                           (epoch+1, batch+1, bat_per_epo, d_loss1, d_loss2, g_loss))
                 # evaluamos el desempeño del modelo cada 10 épocas
                 if (epoch+1) % 10 == 0 or epoch == 0:
                     # preparamos los datos reales
                     [X_real, labels_real], y_real = generate_real_samples(dataset, half_bat
                     # evaluamos el discriminador con datos reales
                     _, acc_real = d_model.evaluate([X_real, labels_real], y_real, verbose=@
                     # preparamos ejemplos fake
                     [X_fake, labels_fake], y_fake = generate_fake_samples(g_model, latent_c
                     # evaluamos el discriminador con datos fake
                     _, acc_fake = d_model.evaluate([X_fake, labels_fake], y_fake, verbose=@
                     # mostramos cómo de bueno es nuestro policía
                     print('>Accuracy real: %.0f%%, fake: %.0f%%' % (acc_real*100, acc_fake*
                     # quardamos las imágenes generadas
                     save_plot(X_fake, epoch)
                     # guardamos el generador para tenerlo disponible más tarde
                     filename = os.path.join(RESULTS_PATH,'cgan_generator_model_%03d.h5' % (
                     g model.save(filename)
In [34]: # size of the latent space
         latent_dim = 100
         # create the discriminator
         d_model = define_discriminator()
         # create the generator
         g_model = define_generator(latent_dim)
```

create the gan

Load image data

dataset = load_real_samples()

gan_model = define_gan(g_model, d_model)

Layer (type)	Output Shape	Param #	Connected to
input_16 (InputLayer)	[(None, 1)]	0	[]
embedding_9 (Embedding) [0]']	(None, 1, 50)	500	['input_16[0]
dense_15 (Dense) [0][0]']	(None, 1, 784)	39984	['embedding_9
input_17 (InputLayer)	[(None, 28, 28, 1)]	0	[]
reshape_12 (Reshape) [0]']	(None, 28, 28, 1)	0	['dense_15[0]
<pre>concatenate_6 (Concatenate [0]',)</pre>	(None, 28, 28, 2)	0	['input_17[0] 'reshape_12
[0][0]']			resnape_12
conv2d_9 (Conv2D) 5[0][0]']	(None, 28, 28, 128)	2432	['concatenate_
<pre>max_pooling2d_6 (MaxPoolin [0]'] g2D)</pre>	(None, 14, 14, 128)	0	['conv2d_9[0]
leaky_re_lu_15 (LeakyReLU) i_6[0][0]']	(None, 14, 14, 128)	0	['max_pooling2
conv2d_10 (Conv2D) L5[0][0]']	(None, 14, 14, 128)	147584	['leaky_re_lu_
<pre>max_pooling2d_7 (MaxPoolin [0]'] g2D)</pre>	(None, 7, 7, 128)	0	['conv2d_10[0]
leaky_re_lu_16 (LeakyReLU) i_7[0][0]']	(None, 7, 7, 128)	0	['max_pooling2
flatten_3 (Flatten) L6[0][0]']	(None, 6272)	0	['leaky_re_lu_
dropout_3 (Dropout) [0]']	(None, 6272)	0	['flatten_3[0]
dense_16 (Dense)	(None, 1)	6273	['dropout_3[0]

Non-trainable params: 0 (0.00 Byte)

Model: "GENERATOR"

	=======================================		
input_20 (InputLayer)	[(None, 100)]	0	[]
<pre>input_19 (InputLayer)</pre>	[(None, 1)]	0	[]
dense_19 (Dense) [0]']	(None, 6272)	633472	['input_20[0]
<pre>embedding_11 (Embedding) [0]']</pre>	(None, 1, 50)	500	['input_19[0]
<pre>leaky_re_lu_17 (LeakyReLU) [0]']</pre>	(None, 6272)	0	['dense_19[0]
dense_18 (Dense) [0][0]']	(None, 1, 49)	2499	['embedding_11
reshape_15 (Reshape) 17[0][0]']	(None, 7, 7, 128)	0	['leaky_re_lu_
reshape_14 (Reshape) [0]']	(None, 7, 7, 1)	0	['dense_18[0]
<pre>concatenate_7 (Concatenate [0][0]',</pre>	(None, 7, 7, 129)	0	['reshape_15
) [0][0]']			'reshape_14
<pre>conv2d_transpose_6 (Conv2D 7[0][0]'] Transpose)</pre>	(None, 7, 7, 128)	264320	['concatenate_
<pre>up_sampling2d_6 (UpSamplin pose_6[0][0]'] g2D)</pre>	(None, 14, 14, 128)	0	['conv2d_trans
<pre>leaky_re_lu_18 (LeakyReLU) d_6[0][0]']</pre>	(None, 14, 14, 128)	0	['up_sampling2
<pre>conv2d_transpose_7 (Conv2D 18[0][0]'] Transpose)</pre>	(None, 14, 14, 128)	262272	['leaky_re_lu_
<pre>up_sampling2d_7 (UpSamplin pose_7[0][0]'] g2D)</pre>	(None, 28, 28, 128)	0	['conv2d_trans
<pre>leaky_re_lu_19 (LeakyReLU) d_7[0][0]']</pre>	(None, 28, 28, 128)	0	['up_sampling2
conv2d_11 (Conv2D) 19[0][0]']	(None, 28, 28, 1)	6273	['leaky_re_lu_
			=========
Total params: 1169336 (4.46 Trainable params: 1169336 (4 Non-trainable params: 0 (0.0	.46 MB)		

```
>1, 1/234, d1=0.686, d2=0.703 g=0.682
4/4 [======= ] - 0s 6ms/step
>1, 2/234, d1=0.565, d2=0.738 g=0.653
4/4 [=======] - 0s 3ms/step
>1, 3/234, d1=0.489, d2=0.787 g=0.626
4/4 [======= ] - 0s 3ms/step
>1, 4/234, d1=0.438, d2=0.811 g=0.621
>1, 5/234, d1=0.397, d2=0.804 g=0.658
>1, 6/234, d1=0.385, d2=0.753 g=0.713
4/4 [========] - 0s 5ms/step
>1, 7/234, d1=0.378, d2=0.681 g=0.778
4/4 [======== ] - 0s 6ms/step
>1, 8/234, d1=0.382, d2=0.615 g=0.864
>1, 9/234, d1=0.341, d2=0.549 g=0.951
>1, 10/234, d1=0.331, d2=0.494 g=1.042
4/4 [======= ] - 0s 3ms/step
>1, 11/234, d1=0.305, d2=0.436 g=1.153
4/4 [=======] - 0s 3ms/step
>1, 12/234, d1=0.337, d2=0.394 g=1.240
>1, 13/234, d1=0.285, d2=0.341 g=1.338
4/4 [======== ] - 0s 3ms/step
>1, 14/234, d1=0.275, d2=0.308 g=1.443
4/4 [======== ] - 0s 3ms/step
>1, 15/234, d1=0.284, d2=0.279 g=1.522
4/4 [======= ] - 0s 3ms/step
>1, 16/234, d1=0.258, d2=0.254 g=1.601
4/4 [=======] - 0s 3ms/step
>1, 17/234, d1=0.202, d2=0.229 g=1.709
4/4 [======== ] - 0s 3ms/step
>1, 18/234, d1=0.187, d2=0.204 g=1.816
4/4 [======== ] - 0s 3ms/step
>1, 19/234, d1=0.181, d2=0.184 g=1.911
4/4 [======= ] - 0s 4ms/step
>1, 20/234, d1=0.174, d2=0.173 g=1.993
4/4 [======== ] - 0s 3ms/step
>1, 21/234, d1=0.139, d2=0.150 g=2.086
4/4 [======== ] - 0s 3ms/step
>1, 22/234, d1=0.196, d2=0.139 g=2.140
>1, 23/234, d1=0.107, d2=0.134 g=2.225
4/4 [=======] - 0s 6ms/step
>1, 24/234, d1=0.155, d2=0.125 g=2.271
>1, 25/234, d1=0.111, d2=0.115 g=2.368
4/4 [=======] - 0s 6ms/step
>1, 26/234, d1=0.138, d2=0.103 g=2.417
>1, 27/234, d1=0.121, d2=0.103 g=2.465
>1, 28/234, d1=0.090, d2=0.095 g=2.550
4/4 [=======] - 0s 4ms/step
>1, 29/234, d1=0.132, d2=0.089 g=2.557
4/4 [======== ] - 0s 3ms/step
>1, 30/234, d1=0.117, d2=0.093 g=2.579
4/4 [======== ] - 0s 5ms/step
>1, 31/234, d1=0.099, d2=0.088 g=2.620
4/4 [======== ] - 0s 3ms/step
>1, 32/234, d1=0.087, d2=0.084 g=2.711
```

```
>1, 33/234, d1=0.078, d2=0.078 g=2.757
4/4 [======= ] - 0s 7ms/step
>1, 34/234, d1=0.051, d2=0.069 g=2.859
4/4 [=======] - 0s 5ms/step
>1, 35/234, d1=0.081, d2=0.064 g=2.898
4/4 [======= ] - 0s 12ms/step
>1, 36/234, d1=0.119, d2=0.073 g=2.892
>1, 37/234, d1=0.048, d2=0.062 g=2.947
>1, 38/234, d1=0.067, d2=0.056 g=2.992
4/4 [=======] - 0s 6ms/step
>1, 39/234, d1=0.054, d2=0.057 g=3.092
4/4 [======== ] - 0s 6ms/step
>1, 40/234, d1=0.044, d2=0.049 g=3.203
>1, 41/234, d1=0.082, d2=0.051 g=3.147
>1, 42/234, d1=0.051, d2=0.049 g=3.184
4/4 [======= ] - 0s 5ms/step
>1, 43/234, d1=0.022, d2=0.042 g=3.323
4/4 [=======] - 0s 5ms/step
>1, 44/234, d1=0.055, d2=0.044 g=3.330
4/4 [=======] - 0s 6ms/step
>1, 45/234, d1=0.030, d2=0.040 g=3.419
>1, 46/234, d1=0.041, d2=0.037 g=3.470
>1, 47/234, d1=0.061, d2=0.039 g=3.441
4/4 [======= ] - 0s 7ms/step
>1, 48/234, d1=0.033, d2=0.036 g=3.465
4/4 [======== ] - 0s 4ms/step
>1, 49/234, d1=0.039, d2=0.036 g=3.507
>1, 50/234, d1=0.036, d2=0.035 g=3.564
4/4 [======== ] - 0s 5ms/step
>1, 51/234, d1=0.042, d2=0.033 g=3.584
4/4 [======= ] - 0s 5ms/step
>1, 52/234, d1=0.035, d2=0.033 g=3.615
>1, 53/234, d1=0.020, d2=0.030 g=3.716
>1, 54/234, d1=0.024, d2=0.026 g=3.777
>1, 55/234, d1=0.038, d2=0.027 g=3.774
4/4 [======= ] - 0s 4ms/step
>1, 56/234, d1=0.044, d2=0.029 g=3.742
>1, 57/234, d1=0.010, d2=0.025 g=3.920
4/4 [=======] - 0s 4ms/step
>1, 58/234, d1=0.012, d2=0.021 g=3.997
>1, 59/234, d1=0.031, d2=0.021 g=3.986
>1, 60/234, d1=0.011, d2=0.020 g=4.072
4/4 [=======] - 0s 7ms/step
>1, 61/234, d1=0.031, d2=0.022 g=4.063
4/4 [======== ] - 0s 4ms/step
>1, 62/234, d1=0.022, d2=0.020 g=4.078
4/4 [======= ] - 0s 3ms/step
>1, 63/234, d1=0.023, d2=0.020 g=4.084
4/4 [=======] - 0s 7ms/step
>1, 64/234, d1=0.021, d2=0.019 g=4.140
```

```
>1, 65/234, d1=0.025, d2=0.019 g=4.112
4/4 [======= ] - 0s 4ms/step
>1, 66/234, d1=0.049, d2=0.023 g=4.015
4/4 [=======] - 0s 3ms/step
>1, 67/234, d1=0.025, d2=0.022 g=4.037
4/4 [======= ] - 0s 4ms/step
>1, 68/234, d1=0.018, d2=0.020 g=4.126
>1, 69/234, d1=0.008, d2=0.017 g=4.204
>1, 70/234, d1=0.009, d2=0.015 g=4.368
4/4 [=======] - 0s 9ms/step
>1, 71/234, d1=0.010, d2=0.014 g=4.410
4/4 [======== ] - 0s 5ms/step
>1, 72/234, d1=0.022, d2=0.015 g=4.330
>1, 73/234, d1=0.008, d2=0.015 g=4.404
>1, 74/234, d1=0.010, d2=0.013 g=4.479
4/4 [======= ] - 0s 5ms/step
>1, 75/234, d1=0.017, d2=0.014 g=4.462
4/4 [=======] - 0s 7ms/step
>1, 76/234, d1=0.012, d2=0.014 g=4.526
>1, 77/234, d1=0.016, d2=0.014 g=4.482
>1, 78/234, d1=0.024, d2=0.015 g=4.470
>1, 79/234, d1=0.008, d2=0.015 g=4.382
4/4 [======= ] - 0s 5ms/step
>1, 80/234, d1=0.014, d2=0.721 g=3.381
4/4 [======== ] - 0s 5ms/step
>1, 81/234, d1=0.161, d2=21.684 g=0.000
4/4 [======== ] - 0s 5ms/step
>1, 82/234, d1=0.424, d2=16.108 g=0.000
4/4 [======== ] - 0s 6ms/step
>1, 83/234, d1=0.228, d2=9.256 g=0.003
4/4 [======= ] - 0s 10ms/step
>1, 84/234, d1=0.142, d2=4.881 g=0.068
>1, 85/234, d1=0.115, d2=2.064 g=0.513
>1, 86/234, d1=0.145, d2=0.846 g=1.100
>1, 87/234, d1=0.127, d2=0.329 g=1.708
4/4 [======= ] - 0s 4ms/step
>1, 88/234, d1=0.084, d2=0.161 g=2.206
>1, 89/234, d1=0.085, d2=0.107 g=2.558
4/4 [=======] - 0s 5ms/step
>1, 90/234, d1=0.082, d2=0.084 g=2.697
>1, 91/234, d1=0.047, d2=0.065 g=2.879
>1, 92/234, d1=0.044, d2=0.061 g=2.982
4/4 [=======] - 0s 4ms/step
>1, 93/234, d1=0.038, d2=0.055 g=3.089
4/4 [=======] - 0s 4ms/step
>1, 94/234, d1=0.036, d2=0.047 g=3.217
4/4 [======== ] - 0s 4ms/step
>1, 95/234, d1=0.059, d2=0.044 g=3.270
4/4 [======== ] - 0s 3ms/step
>1, 96/234, d1=0.031, d2=0.046 g=3.193
```

```
>1, 97/234, d1=0.027, d2=0.057 g=3.086
4/4 [======= ] - 0s 4ms/step
>1, 98/234, d1=0.022, d2=0.203 g=1.863
4/4 [=======] - 0s 3ms/step
>1, 99/234, d1=0.026, d2=6.153 g=0.063
4/4 [======= ] - 0s 3ms/step
>1, 100/234, d1=0.107, d2=1.686 g=1.489
>1, 101/234, d1=0.576, d2=0.162 g=2.577
>1, 102/234, d1=0.756, d2=0.166 g=2.037
4/4 [=======] - 0s 3ms/step
>1, 103/234, d1=0.524, d2=0.356 g=1.431
>1, 104/234, d1=0.352, d2=0.597 g=0.949
>1, 105/234, d1=0.254, d2=1.036 g=0.675
>1, 106/234, d1=0.241, d2=0.663 g=1.029
4/4 [======= ] - 0s 4ms/step
>1, 107/234, d1=0.248, d2=0.648 g=0.906
4/4 [=======] - 0s 4ms/step
>1, 108/234, d1=0.205, d2=0.588 g=0.922
>1, 109/234, d1=0.224, d2=0.649 g=0.869
4/4 [======= ] - 0s 4ms/step
>1, 110/234, d1=0.246, d2=0.706 g=0.777
>1, 111/234, d1=0.240, d2=0.887 g=0.586
4/4 [======= ] - 0s 5ms/step
>1, 112/234, d1=0.245, d2=0.884 g=0.581
4/4 [======== ] - 0s 5ms/step
>1, 113/234, d1=0.203, d2=0.961 g=0.518
>1, 114/234, d1=0.258, d2=0.908 g=0.568
4/4 [======== ] - 0s 4ms/step
>1, 115/234, d1=0.222, d2=0.940 g=0.555
4/4 [======= ] - 0s 4ms/step
>1, 116/234, d1=0.224, d2=0.977 g=0.530
4/4 [=======] - 0s 5ms/step
>1, 117/234, d1=0.235, d2=0.957 g=0.543
>1, 118/234, d1=0.259, d2=0.962 g=0.533
>1, 119/234, d1=0.284, d2=0.962 g=0.545
4/4 [======= ] - 0s 8ms/step
>1, 120/234, d1=0.318, d2=0.942 g=0.545
>1, 121/234, d1=0.291, d2=0.956 g=0.561
4/4 [=======] - 0s 6ms/step
>1, 122/234, d1=0.295, d2=0.934 g=0.569
>1, 123/234, d1=0.397, d2=0.943 g=0.569
>1, 124/234, d1=0.403, d2=0.936 g=0.567
4/4 [======= ] - 0s 6ms/step
>1, 125/234, d1=0.298, d2=0.933 g=0.583
4/4 [=======] - 0s 4ms/step
>1, 126/234, d1=0.386, d2=0.901 g=0.618
4/4 [======== ] - 0s 5ms/step
>1, 127/234, d1=0.387, d2=0.843 g=0.714
4/4 [======== ] - 0s 15ms/step
>1, 128/234, d1=0.410, d2=0.770 g=0.716
```

```
>1, 129/234, d1=0.399, d2=1.050 g=0.518
4/4 [======= ] - 0s 5ms/step
>1, 130/234, d1=0.410, d2=0.984 g=0.583
4/4 [=======] - 0s 6ms/step
>1, 131/234, d1=0.440, d2=0.979 g=0.560
4/4 [======= ] - 0s 5ms/step
>1, 132/234, d1=0.464, d2=1.052 g=0.526
>1, 133/234, d1=0.525, d2=1.053 g=0.547
>1, 134/234, d1=0.477, d2=1.034 g=0.551
4/4 [=======] - 0s 8ms/step
>1, 135/234, d1=0.558, d2=1.039 g=0.558
4/4 [======== ] - 0s 6ms/step
>1, 136/234, d1=0.513, d2=1.008 g=0.570
>1, 137/234, d1=0.553, d2=0.992 g=0.585
4/4 [======= ] - 0s 5ms/step
>1, 138/234, d1=0.603, d2=0.956 g=0.600
4/4 [======= ] - 0s 5ms/step
>1, 139/234, d1=0.610, d2=0.994 g=0.618
4/4 [=======] - 0s 5ms/step
>1, 140/234, d1=0.635, d2=0.946 g=0.632
4/4 [======== ] - 0s 5ms/step
>1, 141/234, d1=0.686, d2=0.926 g=0.644
>1, 142/234, d1=0.714, d2=0.940 g=0.641
>1, 143/234, d1=0.697, d2=0.915 g=0.649
4/4 [======= ] - 0s 4ms/step
>1, 144/234, d1=0.694, d2=0.914 g=0.680
>1, 145/234, d1=0.716, d2=0.939 g=0.698
>1, 146/234, d1=0.769, d2=0.880 g=0.713
4/4 [======== ] - 0s 8ms/step
>1, 147/234, d1=0.726, d2=0.863 g=0.739
4/4 [======= ] - 0s 6ms/step
>1, 148/234, d1=0.687, d2=0.829 g=0.771
4/4 [=======] - 0s 4ms/step
>1, 149/234, d1=0.758, d2=0.801 g=0.770
>1, 150/234, d1=0.736, d2=0.830 g=0.737
>1, 151/234, d1=0.703, d2=0.789 g=0.777
4/4 [======= ] - 0s 7ms/step
>1, 152/234, d1=0.710, d2=0.759 g=0.832
>1, 153/234, d1=0.704, d2=0.715 g=0.860
4/4 [======] - 0s 8ms/step
>1, 154/234, d1=0.705, d2=0.711 g=0.879
>1, 155/234, d1=0.723, d2=0.697 g=0.881
>1, 156/234, d1=0.667, d2=0.713 g=0.834
4/4 [=======] - 0s 5ms/step
>1, 157/234, d1=0.653, d2=0.698 g=0.920
4/4 [=======] - 0s 7ms/step
>1, 158/234, d1=0.626, d2=0.619 g=1.000
4/4 [======== ] - 0s 5ms/step
>1, 159/234, d1=0.613, d2=0.764 g=0.772
4/4 [======== ] - 0s 4ms/step
>1, 160/234, d1=0.573, d2=0.871 g=0.791
```

```
>1, 161/234, d1=0.609, d2=0.611 g=1.062
4/4 [======= ] - 0s 4ms/step
>1, 162/234, d1=0.607, d2=0.461 g=1.275
4/4 [=======] - 0s 8ms/step
>1, 163/234, d1=0.536, d2=0.359 g=1.430
4/4 [======= ] - 0s 7ms/step
>1, 164/234, d1=0.481, d2=0.306 g=1.532
>1, 165/234, d1=0.413, d2=0.282 g=1.639
>1, 166/234, d1=0.434, d2=0.262 g=1.681
4/4 [=======] - 0s 5ms/step
>1, 167/234, d1=0.307, d2=0.230 g=1.785
4/4 [======== ] - 0s 7ms/step
>1, 168/234, d1=0.330, d2=0.229 g=1.823
>1, 169/234, d1=0.304, d2=0.203 g=1.913
>1, 170/234, d1=0.331, d2=0.187 g=1.919
4/4 [======= ] - 0s 4ms/step
>1, 171/234, d1=0.298, d2=0.185 g=1.888
4/4 [=======] - 0s 4ms/step
>1, 172/234, d1=0.224, d2=0.178 g=1.986
4/4 [======== ] - 0s 5ms/step
>1, 173/234, d1=0.239, d2=0.174 g=2.050
>1, 174/234, d1=0.278, d2=0.167 g=2.051
>1, 175/234, d1=0.254, d2=0.171 g=2.064
4/4 [======= ] - 0s 3ms/step
>1, 176/234, d1=0.218, d2=0.163 g=2.082
>1, 177/234, d1=0.177, d2=0.154 g=2.109
4/4 [======== ] - 0s 3ms/step
>1, 178/234, d1=0.209, d2=0.195 g=1.927
4/4 [======== ] - 0s 3ms/step
>1, 179/234, d1=0.247, d2=0.316 g=1.565
4/4 [======= ] - 0s 4ms/step
>1, 180/234, d1=0.217, d2=2.766 g=0.166
4/4 [======== ] - 0s 3ms/step
>1, 181/234, d1=0.284, d2=1.875 g=0.418
>1, 182/234, d1=0.304, d2=1.125 g=0.759
>1, 183/234, d1=0.402, d2=0.969 g=0.808
4/4 [======= ] - 0s 4ms/step
>1, 184/234, d1=0.425, d2=0.967 g=0.781
>1, 185/234, d1=0.601, d2=0.869 g=0.817
4/4 [=======] - 0s 4ms/step
>1, 186/234, d1=0.597, d2=0.872 g=0.815
>1, 187/234, d1=0.720, d2=0.708 g=0.907
>1, 188/234, d1=0.822, d2=0.781 g=0.890
4/4 [======= ] - 0s 4ms/step
>1, 189/234, d1=0.805, d2=0.728 g=0.932
4/4 [======== ] - 0s 5ms/step
>1, 190/234, d1=0.813, d2=0.696 g=0.904
4/4 [======== ] - 0s 7ms/step
>1, 191/234, d1=0.815, d2=0.681 g=0.951
4/4 [======== ] - 0s 8ms/step
>1, 192/234, d1=0.811, d2=0.681 g=0.966
```

```
>1, 193/234, d1=0.791, d2=0.668 g=0.999
4/4 [======= ] - 0s 4ms/step
>1, 194/234, d1=0.801, d2=0.624 g=1.038
4/4 [=======] - 0s 5ms/step
>1, 195/234, d1=0.791, d2=0.592 g=1.002
4/4 [======= ] - 0s 4ms/step
>1, 196/234, d1=0.776, d2=0.625 g=1.002
>1, 197/234, d1=0.750, d2=0.630 g=0.990
>1, 198/234, d1=0.716, d2=0.589 g=1.006
4/4 [=======] - 0s 5ms/step
>1, 199/234, d1=0.701, d2=0.607 g=0.998
4/4 [======== ] - 0s 5ms/step
>1, 200/234, d1=0.723, d2=0.733 g=0.886
>1, 201/234, d1=0.716, d2=0.629 g=0.992
>1, 202/234, d1=0.723, d2=0.608 g=0.993
4/4 [======= ] - 0s 6ms/step
>1, 203/234, d1=0.652, d2=0.689 g=0.907
4/4 [=======] - 0s 4ms/step
>1, 204/234, d1=0.722, d2=0.754 g=0.850
>1, 205/234, d1=0.709, d2=0.631 g=0.975
4/4 [======= ] - 0s 4ms/step
>1, 206/234, d1=0.679, d2=0.536 g=1.104
>1, 207/234, d1=0.572, d2=0.541 g=1.131
4/4 [======= ] - 0s 4ms/step
>1, 208/234, d1=0.584, d2=0.854 g=0.754
4/4 [======== ] - 0s 4ms/step
>1, 209/234, d1=0.652, d2=1.007 g=0.683
4/4 [======== ] - 0s 5ms/step
>1, 210/234, d1=0.671, d2=0.664 g=1.018
4/4 [======== ] - 0s 4ms/step
>1, 211/234, d1=0.683, d2=0.501 g=1.217
4/4 [======= ] - 0s 3ms/step
>1, 212/234, d1=0.628, d2=0.440 g=1.279
4/4 [=======] - 0s 4ms/step
>1, 213/234, d1=0.586, d2=0.591 g=1.014
>1, 214/234, d1=0.614, d2=0.970 g=0.644
>1, 215/234, d1=0.622, d2=0.922 g=0.740
4/4 [======= ] - 0s 5ms/step
>1, 216/234, d1=0.719, d2=0.670 g=0.969
>1, 217/234, d1=0.685, d2=0.516 g=1.161
4/4 [=======] - 0s 5ms/step
>1, 218/234, d1=0.621, d2=0.481 g=1.202
>1, 219/234, d1=0.571, d2=0.610 g=0.986
>1, 220/234, d1=0.622, d2=1.001 g=0.662
4/4 [=======] - 0s 5ms/step
>1, 221/234, d1=0.643, d2=0.908 g=0.765
4/4 [=======] - 0s 4ms/step
>1, 222/234, d1=0.710, d2=0.602 g=1.039
4/4 [======== ] - 0s 5ms/step
>1, 223/234, d1=0.700, d2=0.525 g=1.139
4/4 [======== ] - 0s 6ms/step
>1, 224/234, d1=0.695, d2=0.567 g=1.064
```

```
>1, 225/234, d1=0.706, d2=0.708 g=0.872
4/4 [======= ] - 0s 4ms/step
>1, 226/234, d1=0.681, d2=0.761 g=0.827
4/4 [=======] - 0s 4ms/step
>1, 227/234, d1=0.711, d2=0.701 g=0.928
4/4 [======= ] - 0s 13ms/step
>1, 228/234, d1=0.805, d2=0.579 g=1.032
>1, 229/234, d1=0.680, d2=0.532 g=1.072
4/4 [======== ] - 0s 5ms/step
>1, 230/234, d1=0.677, d2=0.535 g=1.080
4/4 [=======] - 0s 3ms/step
>1, 231/234, d1=0.660, d2=0.589 g=0.972
4/4 [======= ] - 0s 4ms/step
>1, 232/234, d1=0.674, d2=0.788 g=0.789
>1, 233/234, d1=0.686, d2=0.806 g=0.777
4/4 [======= ] - 0s 4ms/step
>1, 234/234, d1=0.724, d2=0.639 g=0.987
8/8 [======= ] - 0s 3ms/step
>Accuracy real: 49%, fake: 100%
```

/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWar ning: You are saving your model as an HDF5 file via `model.save()`. This file form at is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.

saving_api.save_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.

```
>2, 1/234, d1=0.733, d2=0.517 g=1.107
4/4 [======= ] - 0s 4ms/step
>2, 2/234, d1=0.725, d2=0.580 g=1.046
4/4 [=======] - 0s 4ms/step
>2, 3/234, d1=0.629, d2=0.652 g=0.888
4/4 [=======] - 0s 5ms/step
>2, 4/234, d1=0.666, d2=0.691 g=0.856
>2, 5/234, d1=0.686, d2=0.659 g=0.867
>2, 6/234, d1=0.663, d2=0.636 g=0.956
4/4 [=======] - 0s 5ms/step
>2, 7/234, d1=0.625, d2=0.561 g=1.035
>2, 8/234, d1=0.624, d2=0.510 g=1.121
>2, 9/234, d1=0.605, d2=0.477 g=1.142
>2, 10/234, d1=0.569, d2=0.499 g=1.098
4/4 [======= ] - 0s 5ms/step
>2, 11/234, d1=0.545, d2=0.650 g=0.878
4/4 [=======] - 0s 4ms/step
>2, 12/234, d1=0.567, d2=0.902 g=0.685
>2, 13/234, d1=0.627, d2=0.813 g=0.812
>2, 14/234, d1=0.611, d2=0.605 g=1.001
>2, 15/234, d1=0.648, d2=0.498 g=1.133
4/4 [======= ] - 0s 3ms/step
>2, 16/234, d1=0.627, d2=0.475 g=1.114
4/4 [=======] - 0s 4ms/step
>2, 17/234, d1=0.632, d2=0.601 g=0.932
>2, 18/234, d1=0.630, d2=0.756 g=0.768
4/4 [======== ] - 0s 4ms/step
>2, 19/234, d1=0.561, d2=0.732 g=0.796
4/4 [======= ] - 0s 5ms/step
>2, 20/234, d1=0.627, d2=0.699 g=0.878
4/4 [=======] - 0s 4ms/step
>2, 21/234, d1=0.642, d2=0.600 g=0.940
>2, 22/234, d1=0.617, d2=0.557 g=1.027
>2, 23/234, d1=0.574, d2=0.529 g=1.009
4/4 [======= ] - 0s 4ms/step
>2, 24/234, d1=0.577, d2=0.584 g=0.945
>2, 25/234, d1=0.544, d2=0.695 g=0.823
4/4 [=======] - 0s 6ms/step
>2, 26/234, d1=0.602, d2=0.756 g=0.762
>2, 27/234, d1=0.605, d2=0.694 g=0.881
>2, 28/234, d1=0.633, d2=0.592 g=0.975
4/4 [========] - 0s 5ms/step
>2, 29/234, d1=0.616, d2=0.575 g=0.956
4/4 [======== ] - 0s 6ms/step
>2, 30/234, d1=0.623, d2=0.628 g=0.905
4/4 [======== ] - 0s 6ms/step
>2, 31/234, d1=0.577, d2=0.650 g=0.847
4/4 [=======] - 0s 4ms/step
>2, 32/234, d1=0.590, d2=0.656 g=0.878
```

```
>2, 33/234, d1=0.591, d2=0.667 g=0.899
4/4 [======= ] - 0s 4ms/step
>2, 34/234, d1=0.631, d2=0.612 g=0.908
4/4 [=======] - 0s 4ms/step
>2, 35/234, d1=0.605, d2=0.625 g=0.928
4/4 [======= ] - 0s 3ms/step
>2, 36/234, d1=0.568, d2=0.575 g=0.901
>2, 37/234, d1=0.611, d2=0.641 g=0.830
>2, 38/234, d1=0.563, d2=0.663 g=0.831
4/4 [=======] - 0s 4ms/step
>2, 39/234, d1=0.577, d2=0.630 g=0.866
>2, 40/234, d1=0.593, d2=0.645 g=0.879
4/4 [======== ] - 0s 4ms/step
>2, 41/234, d1=0.587, d2=0.627 g=0.876
>2, 42/234, d1=0.565, d2=0.627 g=0.869
4/4 [======= ] - 0s 4ms/step
>2, 43/234, d1=0.595, d2=0.637 g=0.873
4/4 [=======] - 0s 4ms/step
>2, 44/234, d1=0.576, d2=0.647 g=0.880
>2, 45/234, d1=0.609, d2=0.646 g=0.864
>2, 46/234, d1=0.614, d2=0.629 g=0.863
>2, 47/234, d1=0.577, d2=0.639 g=0.876
4/4 [======= ] - 0s 5ms/step
>2, 48/234, d1=0.635, d2=0.615 g=0.855
>2, 49/234, d1=0.551, d2=0.658 g=0.849
>2, 50/234, d1=0.634, d2=0.627 g=0.849
4/4 [======== ] - 0s 3ms/step
>2, 51/234, d1=0.589, d2=0.635 g=0.870
4/4 [======= ] - 0s 3ms/step
>2, 52/234, d1=0.625, d2=0.639 g=0.869
4/4 [=======] - 0s 4ms/step
>2, 53/234, d1=0.594, d2=0.634 g=0.888
>2, 54/234, d1=0.593, d2=0.643 g=0.898
>2, 55/234, d1=0.628, d2=0.611 g=0.885
4/4 [======= ] - 0s 4ms/step
>2, 56/234, d1=0.608, d2=0.627 g=0.890
>2, 57/234, d1=0.618, d2=0.626 g=0.931
4/4 [=======] - 0s 4ms/step
>2, 58/234, d1=0.650, d2=0.597 g=0.971
>2, 59/234, d1=0.616, d2=0.574 g=0.973
>2, 60/234, d1=0.616, d2=0.553 g=0.996
4/4 [=======] - 0s 4ms/step
>2, 61/234, d1=0.588, d2=0.573 g=0.942
>2, 62/234, d1=0.613, d2=0.674 g=0.827
4/4 [======== ] - 0s 7ms/step
>2, 63/234, d1=0.626, d2=0.718 g=0.822
4/4 [======== ] - 0s 4ms/step
>2, 64/234, d1=0.607, d2=0.656 g=0.937
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>2, 65/234, d1=0.609, d2=0.537 g=1.081
4/4 [======= ] - 0s 4ms/step
>2, 66/234, d1=0.574, d2=0.492 g=1.145
4/4 [=======] - 0s 4ms/step
>2, 67/234, d1=0.590, d2=0.497 g=1.089
4/4 [======= ] - 0s 4ms/step
>2, 68/234, d1=0.548, d2=0.650 g=0.905
>2, 69/234, d1=0.595, d2=0.843 g=0.744
>2, 70/234, d1=0.648, d2=0.828 g=0.786
4/4 [=======] - 0s 3ms/step
>2, 71/234, d1=0.636, d2=0.708 g=0.941
4/4 [======== ] - 0s 5ms/step
>2, 72/234, d1=0.607, d2=0.533 g=1.143
4/4 [======== ] - 0s 4ms/step
>2, 73/234, d1=0.591, d2=0.455 g=1.243
>2, 74/234, d1=0.606, d2=0.420 g=1.274
4/4 [======= ] - 0s 3ms/step
>2, 75/234, d1=0.588, d2=0.458 g=1.160
4/4 [=======] - 0s 4ms/step
>2, 76/234, d1=0.529, d2=0.531 g=1.021
>2, 77/234, d1=0.581, d2=0.698 g=0.796
>2, 78/234, d1=0.582, d2=1.009 g=0.640
>2, 79/234, d1=0.583, d2=0.764 g=0.873
4/4 [======= ] - 0s 4ms/step
>2, 80/234, d1=0.630, d2=0.522 g=1.117
4/4 [=======] - 0s 5ms/step
>2, 81/234, d1=0.608, d2=0.416 g=1.253
>2, 82/234, d1=0.566, d2=0.392 g=1.299
4/4 [======== ] - 0s 7ms/step
>2, 83/234, d1=0.487, d2=0.508 g=1.121
4/4 [======= ] - 0s 8ms/step
>2, 84/234, d1=0.502, d2=0.677 g=0.886
4/4 [======== ] - 0s 3ms/step
>2, 85/234, d1=0.541, d2=0.763 g=0.777
>2, 86/234, d1=0.562, d2=0.746 g=0.815
>2, 87/234, d1=0.635, d2=0.701 g=0.877
4/4 [=======] - 0s 6ms/step
>2, 88/234, d1=0.697, d2=0.620 g=0.975
>2, 89/234, d1=0.685, d2=0.515 g=1.059
4/4 [=======] - 0s 9ms/step
>2, 90/234, d1=0.684, d2=0.463 g=1.139
>2, 91/234, d1=0.667, d2=0.480 g=1.205
>2, 92/234, d1=0.635, d2=0.481 g=1.185
4/4 [======= ] - 0s 4ms/step
>2, 93/234, d1=0.602, d2=0.522 g=1.162
>2, 94/234, d1=0.606, d2=0.646 g=0.996
4/4 [======== ] - 0s 3ms/step
>2, 95/234, d1=0.707, d2=0.915 g=0.758
4/4 [=======] - 0s 4ms/step
>2, 96/234, d1=0.770, d2=0.787 g=0.917
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>2, 97/234, d1=0.770, d2=0.533 g=1.126
4/4 [======= ] - 0s 4ms/step
>2, 98/234, d1=0.756, d2=0.469 g=1.222
4/4 [=======] - 0s 5ms/step
>2, 99/234, d1=0.673, d2=0.475 g=1.192
4/4 [======= ] - 0s 4ms/step
>2, 100/234, d1=0.704, d2=0.487 g=1.145
>2, 101/234, d1=0.678, d2=0.531 g=1.143
>2, 102/234, d1=0.733, d2=0.567 g=1.128
4/4 [=======] - 0s 4ms/step
>2, 103/234, d1=0.694, d2=0.523 g=1.135
>2, 104/234, d1=0.789, d2=0.521 g=1.133
4/4 [======== ] - 0s 4ms/step
>2, 105/234, d1=0.794, d2=0.512 g=1.125
>2, 106/234, d1=0.751, d2=0.528 g=1.168
4/4 [======= ] - 0s 3ms/step
>2, 107/234, d1=0.756, d2=0.503 g=1.224
>2, 108/234, d1=0.704, d2=0.446 g=1.277
>2, 109/234, d1=0.689, d2=0.399 g=1.351
>2, 110/234, d1=0.617, d2=0.387 g=1.384
>2, 111/234, d1=0.595, d2=0.356 g=1.493
4/4 [======= ] - 0s 3ms/step
>2, 112/234, d1=0.584, d2=0.311 g=1.556
>2, 113/234, d1=0.544, d2=0.317 g=1.560
>2, 114/234, d1=0.507, d2=0.300 g=1.592
4/4 [======== ] - 0s 4ms/step
>2, 115/234, d1=0.530, d2=0.339 g=1.514
4/4 [======= ] - 0s 4ms/step
>2, 116/234, d1=0.460, d2=0.363 g=1.459
>2, 117/234, d1=0.526, d2=0.422 g=1.366
>2, 118/234, d1=0.540, d2=0.596 g=1.067
>2, 119/234, d1=0.559, d2=1.072 g=0.705
4/4 [======= ] - 0s 4ms/step
>2, 120/234, d1=0.678, d2=1.324 g=0.574
>2, 121/234, d1=0.715, d2=0.915 g=0.735
4/4 [=======] - 0s 4ms/step
>2, 122/234, d1=0.737, d2=0.639 g=0.966
>2, 123/234, d1=0.732, d2=0.499 g=1.123
>2, 124/234, d1=0.597, d2=0.401 g=1.266
4/4 [=======] - 0s 4ms/step
>2, 125/234, d1=0.529, d2=0.341 g=1.405
4/4 [=======] - 0s 4ms/step
>2, 126/234, d1=0.469, d2=0.310 g=1.464
4/4 [======== ] - 0s 3ms/step
>2, 127/234, d1=0.446, d2=0.274 g=1.535
4/4 [======== ] - 0s 3ms/step
>2, 128/234, d1=0.397, d2=0.267 g=1.552
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>2, 129/234, d1=0.359, d2=0.249 g=1.645
4/4 [======= ] - 0s 3ms/step
>2, 130/234, d1=0.323, d2=0.239 g=1.686
4/4 [=======] - 0s 3ms/step
>2, 131/234, d1=0.326, d2=0.217 g=1.735
4/4 [======= ] - 0s 6ms/step
>2, 132/234, d1=0.289, d2=0.207 g=1.793
>2, 133/234, d1=0.290, d2=0.199 g=1.831
>2, 134/234, d1=0.268, d2=0.199 g=1.848
4/4 [=======] - 0s 4ms/step
>2, 135/234, d1=0.218, d2=0.210 g=1.916
4/4 [======== ] - 0s 4ms/step
>2, 136/234, d1=0.250, d2=0.224 g=1.825
>2, 137/234, d1=0.214, d2=0.406 g=1.594
>2, 138/234, d1=0.253, d2=0.885 g=1.054
4/4 [======= ] - 0s 4ms/step
>2, 139/234, d1=0.349, d2=1.487 g=0.661
4/4 [=======] - 0s 4ms/step
>2, 140/234, d1=0.491, d2=1.329 g=0.689
>2, 141/234, d1=0.765, d2=0.987 g=0.891
4/4 [======= ] - 0s 4ms/step
>2, 142/234, d1=0.916, d2=0.700 g=1.189
>2, 143/234, d1=1.021, d2=0.466 g=1.301
4/4 [======= ] - 0s 4ms/step
>2, 144/234, d1=0.936, d2=0.419 g=1.476
4/4 [======== ] - 0s 7ms/step
>2, 145/234, d1=0.816, d2=0.364 g=1.512
>2, 146/234, d1=0.720, d2=0.314 g=1.599
4/4 [======== ] - 0s 5ms/step
>2, 147/234, d1=0.631, d2=0.292 g=1.676
4/4 [======= ] - 0s 4ms/step
>2, 148/234, d1=0.629, d2=0.282 g=1.636
>2, 149/234, d1=0.567, d2=0.277 g=1.593
>2, 150/234, d1=0.455, d2=0.283 g=1.601
>2, 151/234, d1=0.498, d2=0.338 g=1.570
4/4 [=======] - 0s 8ms/step
>2, 152/234, d1=0.476, d2=0.354 g=1.533
>2, 153/234, d1=0.455, d2=0.410 g=1.416
4/4 [=======] - 0s 9ms/step
>2, 154/234, d1=0.603, d2=0.530 g=1.306
>2, 155/234, d1=0.637, d2=0.657 g=1.031
>2, 156/234, d1=0.647, d2=0.857 g=0.949
4/4 [=======] - 0s 6ms/step
>2, 157/234, d1=0.658, d2=0.721 g=1.024
4/4 [=======] - 0s 4ms/step
>2, 158/234, d1=0.803, d2=0.548 g=1.234
4/4 [======== ] - 0s 3ms/step
>2, 159/234, d1=0.741, d2=0.389 g=1.406
>2, 160/234, d1=0.670, d2=0.311 g=1.493
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>2, 161/234, d1=0.609, d2=0.291 g=1.559
4/4 [======= ] - 0s 4ms/step
>2, 162/234, d1=0.561, d2=0.285 g=1.526
4/4 [=======] - 0s 3ms/step
>2, 163/234, d1=0.410, d2=0.328 g=1.617
4/4 [======= ] - 0s 4ms/step
>2, 164/234, d1=0.402, d2=0.351 g=1.583
4/4 [======== ] - 0s 3ms/step
>2, 165/234, d1=0.424, d2=0.364 g=1.469
>2, 166/234, d1=0.421, d2=0.439 g=1.409
4/4 [=======] - 0s 4ms/step
>2, 167/234, d1=0.538, d2=0.491 g=1.373
>2, 168/234, d1=0.538, d2=0.506 g=1.235
>2, 169/234, d1=0.601, d2=0.582 g=1.257
>2, 170/234, d1=0.683, d2=0.543 g=1.290
4/4 [======= ] - 0s 3ms/step
>2, 171/234, d1=0.674, d2=0.479 g=1.342
4/4 [======= ] - 0s 3ms/step
>2, 172/234, d1=0.666, d2=0.437 g=1.375
>2, 173/234, d1=0.740, d2=0.392 g=1.422
>2, 174/234, d1=0.628, d2=0.362 g=1.546
>2, 175/234, d1=0.573, d2=0.303 g=1.574
4/4 [======= ] - 0s 3ms/step
>2, 176/234, d1=0.599, d2=0.305 g=1.608
4/4 [======== ] - 0s 3ms/step
>2, 177/234, d1=0.546, d2=0.291 g=1.606
4/4 [======== ] - 0s 5ms/step
>2, 178/234, d1=0.462, d2=0.277 g=1.662
4/4 [======== ] - 0s 4ms/step
>2, 179/234, d1=0.467, d2=0.298 g=1.671
4/4 [======= ] - 0s 4ms/step
>2, 180/234, d1=0.444, d2=0.285 g=1.719
4/4 [======== ] - 0s 3ms/step
>2, 181/234, d1=0.516, d2=0.296 g=1.632
>2, 182/234, d1=0.426, d2=0.326 g=1.626
>2, 183/234, d1=0.458, d2=0.342 g=1.603
4/4 [======= ] - 0s 4ms/step
>2, 184/234, d1=0.424, d2=0.377 g=1.469
>2, 185/234, d1=0.484, d2=0.481 g=1.335
4/4 [=======] - 0s 5ms/step
>2, 186/234, d1=0.495, d2=0.559 g=1.273
>2, 187/234, d1=0.566, d2=0.628 g=1.185
>2, 188/234, d1=0.585, d2=0.596 g=1.120
4/4 [=======] - 0s 4ms/step
>2, 189/234, d1=0.626, d2=0.560 g=1.156
>2, 190/234, d1=0.560, d2=0.431 g=1.277
4/4 [======== ] - 0s 3ms/step
>2, 191/234, d1=0.545, d2=0.360 g=1.469
4/4 [======== ] - 0s 3ms/step
>2, 192/234, d1=0.517, d2=0.318 g=1.526
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>2, 193/234, d1=0.439, d2=0.277 g=1.706
4/4 [======= ] - 0s 4ms/step
>2, 194/234, d1=0.425, d2=0.249 g=1.751
4/4 [=======] - 0s 4ms/step
>2, 195/234, d1=0.352, d2=0.225 g=1.795
4/4 [======= ] - 0s 4ms/step
>2, 196/234, d1=0.320, d2=0.239 g=1.871
>2, 197/234, d1=0.324, d2=0.236 g=1.796
>2, 198/234, d1=0.316, d2=0.243 g=1.750
4/4 [=======] - 0s 4ms/step
>2, 199/234, d1=0.297, d2=0.379 g=1.575
>2, 200/234, d1=0.285, d2=0.441 g=1.433
>2, 201/234, d1=0.414, d2=0.589 g=1.165
>2, 202/234, d1=0.504, d2=0.721 g=1.118
4/4 [======= ] - 0s 4ms/step
>2, 203/234, d1=0.554, d2=0.703 g=1.143
4/4 [======== ] - 0s 5ms/step
>2, 204/234, d1=0.700, d2=0.610 g=1.281
>2, 205/234, d1=0.682, d2=0.498 g=1.410
4/4 [======= ] - 0s 4ms/step
>2, 206/234, d1=0.716, d2=0.408 g=1.550
>2, 207/234, d1=0.665, d2=0.288 g=1.704
4/4 [======= ] - 0s 5ms/step
>2, 208/234, d1=0.600, d2=0.258 g=1.796
4/4 [======== ] - 0s 5ms/step
>2, 209/234, d1=0.518, d2=0.271 g=1.856
>2, 210/234, d1=0.493, d2=0.249 g=1.925
4/4 [======== ] - 0s 5ms/step
>2, 211/234, d1=0.440, d2=0.259 g=1.928
4/4 [======= ] - 0s 4ms/step
>2, 212/234, d1=0.447, d2=0.253 g=1.920
>2, 213/234, d1=0.397, d2=0.243 g=1.791
>2, 214/234, d1=0.387, d2=0.310 g=1.813
>2, 215/234, d1=0.474, d2=0.356 g=1.663
4/4 [======= ] - 0s 5ms/step
>2, 216/234, d1=0.418, d2=0.439 g=1.572
>2, 217/234, d1=0.470, d2=0.560 g=1.443
4/4 [=======] - 0s 8ms/step
>2, 218/234, d1=0.587, d2=0.703 g=1.202
>2, 219/234, d1=0.673, d2=0.670 g=1.182
>2, 220/234, d1=0.688, d2=0.450 g=1.487
4/4 [=======] - 0s 5ms/step
>2, 221/234, d1=0.614, d2=0.302 g=1.667
4/4 [=======] - 0s 6ms/step
>2, 222/234, d1=0.615, d2=0.251 g=1.750
4/4 [======== ] - 0s 4ms/step
>2, 223/234, d1=0.425, d2=0.249 g=1.836
4/4 [======== ] - 0s 5ms/step
>2, 224/234, d1=0.375, d2=0.227 g=1.871
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>2, 225/234, d1=0.340, d2=0.231 g=1.874
4/4 [======= ] - 0s 6ms/step
>2, 226/234, d1=0.354, d2=0.292 g=1.748
4/4 [=======] - 0s 4ms/step
>2, 227/234, d1=0.318, d2=0.365 g=1.638
4/4 [======= ] - 0s 4ms/step
>2, 228/234, d1=0.361, d2=0.447 g=1.633
>2, 229/234, d1=0.537, d2=0.481 g=1.499
>2, 230/234, d1=0.539, d2=0.498 g=1.462
4/4 [=======] - 0s 4ms/step
>2, 231/234, d1=0.536, d2=0.478 g=1.567
>2, 232/234, d1=0.677, d2=0.437 g=1.620
4/4 [======== ] - 0s 8ms/step
>2, 233/234, d1=0.603, d2=0.370 g=1.628
>2, 234/234, d1=0.687, d2=0.344 g=1.757
4/4 [======= ] - 0s 6ms/step
>3, 1/234, d1=0.664, d2=0.283 g=1.857
>3, 2/234, d1=0.497, d2=0.272 g=1.859
>3, 3/234, d1=0.486, d2=0.240 g=1.902
>3, 4/234, d1=0.397, d2=0.224 g=1.981
4/4 [======== ] - 0s 8ms/step
>3, 5/234, d1=0.345, d2=0.210 g=2.050
4/4 [======= ] - 0s 4ms/step
>3, 6/234, d1=0.342, d2=0.230 g=2.038
>3, 7/234, d1=0.361, d2=0.209 g=2.017
>3, 8/234, d1=0.388, d2=0.294 g=1.784
4/4 [======== ] - 0s 4ms/step
>3, 9/234, d1=0.403, d2=0.348 g=1.679
4/4 [======= ] - 0s 4ms/step
>3, 10/234, d1=0.380, d2=0.404 g=1.549
>3, 11/234, d1=0.459, d2=0.471 g=1.471
>3, 12/234, d1=0.548, d2=0.507 g=1.346
>3, 13/234, d1=0.431, d2=0.479 g=1.453
4/4 [======= ] - 0s 4ms/step
>3, 14/234, d1=0.537, d2=0.375 g=1.541
>3, 15/234, d1=0.520, d2=0.316 g=1.675
4/4 [=======] - 0s 4ms/step
>3, 16/234, d1=0.466, d2=0.253 g=1.774
>3, 17/234, d1=0.471, d2=0.233 g=1.867
>3, 18/234, d1=0.431, d2=0.236 g=1.879
4/4 [=======] - 0s 3ms/step
>3, 19/234, d1=0.333, d2=0.248 g=1.978
4/4 [======== ] - 0s 3ms/step
>3, 20/234, d1=0.331, d2=0.231 g=2.055
4/4 [======== ] - 0s 4ms/step
>3, 21/234, d1=0.324, d2=0.195 g=2.004
4/4 [======== ] - 0s 4ms/step
>3, 22/234, d1=0.339, d2=0.268 g=1.792
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>3, 23/234, d1=0.283, d2=0.323 g=1.839
4/4 [======= ] - 0s 5ms/step
>3, 24/234, d1=0.365, d2=0.401 g=1.688
4/4 [=======] - 0s 4ms/step
>3, 25/234, d1=0.333, d2=0.441 g=1.620
4/4 [======= ] - 0s 5ms/step
>3, 26/234, d1=0.448, d2=0.501 g=1.511
>3, 27/234, d1=0.554, d2=0.437 g=1.595
>3, 28/234, d1=0.572, d2=0.431 g=1.583
4/4 [=======] - 0s 4ms/step
>3, 29/234, d1=0.575, d2=0.443 g=1.702
>3, 30/234, d1=0.545, d2=0.302 g=1.922
>3, 31/234, d1=0.517, d2=0.260 g=2.054
>3, 32/234, d1=0.432, d2=0.219 g=2.264
4/4 [======= ] - 0s 4ms/step
>3, 33/234, d1=0.493, d2=0.182 g=2.224
4/4 [=======] - 0s 6ms/step
>3, 34/234, d1=0.407, d2=0.200 g=2.208
4/4 [========] - 0s 4ms/step
>3, 35/234, d1=0.359, d2=0.207 g=2.109
>3, 36/234, d1=0.283, d2=0.205 g=2.248
>3, 37/234, d1=0.343, d2=0.195 g=2.254
4/4 [======= ] - 0s 4ms/step
>3, 38/234, d1=0.224, d2=0.205 g=2.217
4/4 [======== ] - 0s 5ms/step
>3, 39/234, d1=0.274, d2=0.223 g=2.075
>3, 40/234, d1=0.331, d2=0.271 g=1.865
4/4 [======== ] - 0s 4ms/step
>3, 41/234, d1=0.308, d2=0.454 g=1.767
4/4 [======= ] - 0s 5ms/step
>3, 42/234, d1=0.332, d2=0.529 g=1.550
>3, 43/234, d1=0.519, d2=0.630 g=1.377
>3, 44/234, d1=0.547, d2=0.464 g=1.513
>3, 45/234, d1=0.532, d2=0.351 g=1.741
4/4 [======= ] - 0s 4ms/step
>3, 46/234, d1=0.548, d2=0.237 g=2.012
>3, 47/234, d1=0.465, d2=0.233 g=2.143
4/4 [=======] - 0s 4ms/step
>3, 48/234, d1=0.412, d2=0.198 g=2.111
>3, 49/234, d1=0.284, d2=0.209 g=2.223
>3, 50/234, d1=0.350, d2=0.202 g=2.185
4/4 [======= ] - 0s 4ms/step
>3, 51/234, d1=0.297, d2=0.255 g=2.082
4/4 [=======] - 0s 7ms/step
>3, 52/234, d1=0.266, d2=0.274 g=2.102
4/4 [======== ] - 0s 6ms/step
>3, 53/234, d1=0.285, d2=0.347 g=1.862
4/4 [======== ] - 0s 6ms/step
>3, 54/234, d1=0.349, d2=0.393 g=1.773
```

```
>3, 55/234, d1=0.340, d2=0.442 g=1.639
4/4 [======= ] - 0s 3ms/step
>3, 56/234, d1=0.455, d2=0.421 g=1.617
4/4 [=======] - 0s 3ms/step
>3, 57/234, d1=0.484, d2=0.441 g=1.667
4/4 [======= ] - 0s 4ms/step
>3, 58/234, d1=0.536, d2=0.363 g=1.740
>3, 59/234, d1=0.505, d2=0.380 g=1.918
>3, 60/234, d1=0.492, d2=0.231 g=2.147
4/4 [=======] - 0s 7ms/step
>3, 61/234, d1=0.480, d2=0.199 g=2.322
4/4 [======== ] - 0s 5ms/step
>3, 62/234, d1=0.441, d2=0.180 g=2.356
>3, 63/234, d1=0.405, d2=0.199 g=2.488
>3, 64/234, d1=0.369, d2=0.170 g=2.443
4/4 [======= ] - 0s 3ms/step
>3, 65/234, d1=0.304, d2=0.178 g=2.435
4/4 [=======] - 0s 6ms/step
>3, 66/234, d1=0.289, d2=0.203 g=2.476
4/4 [=======] - 0s 4ms/step
>3, 67/234, d1=0.301, d2=0.205 g=2.194
>3, 68/234, d1=0.280, d2=0.297 g=1.913
>3, 69/234, d1=0.387, d2=0.614 g=1.714
4/4 [======= ] - 0s 6ms/step
>3, 70/234, d1=0.410, d2=0.852 g=1.410
4/4 [=======] - 0s 7ms/step
>3, 71/234, d1=0.591, d2=0.590 g=1.535
>3, 72/234, d1=0.650, d2=0.279 g=1.990
4/4 [======== ] - 0s 4ms/step
>3, 73/234, d1=0.685, d2=0.208 g=2.110
4/4 [======= ] - 0s 6ms/step
>3, 74/234, d1=0.469, d2=0.224 g=2.059
>3, 75/234, d1=0.327, d2=0.213 g=2.212
>3, 76/234, d1=0.367, d2=0.181 g=2.263
>3, 77/234, d1=0.289, d2=0.170 g=2.298
4/4 [======= ] - 0s 3ms/step
>3, 78/234, d1=0.288, d2=0.173 g=2.372
>3, 79/234, d1=0.238, d2=0.182 g=2.488
4/4 [=======] - 0s 3ms/step
>3, 80/234, d1=0.213, d2=0.161 g=2.465
>3, 81/234, d1=0.203, d2=0.131 g=2.653
>3, 82/234, d1=0.225, d2=0.114 g=2.478
4/4 [======= ] - 0s 4ms/step
>3, 83/234, d1=0.205, d2=0.364 g=2.330
4/4 [======== ] - 0s 5ms/step
>3, 84/234, d1=0.237, d2=0.536 g=1.939
4/4 [======== ] - 0s 4ms/step
>3, 85/234, d1=0.309, d2=0.522 g=1.812
4/4 [======== ] - 0s 5ms/step
>3, 86/234, d1=0.593, d2=0.509 g=1.744
```

```
>3, 87/234, d1=0.604, d2=0.474 g=1.930
4/4 [======= ] - 0s 5ms/step
>3, 88/234, d1=0.786, d2=0.388 g=2.101
>3, 89/234, d1=0.600, d2=0.251 g=2.440
4/4 [======= ] - 0s 6ms/step
>3, 90/234, d1=0.561, d2=0.236 g=2.490
>3, 91/234, d1=0.516, d2=0.226 g=2.529
>3, 92/234, d1=0.377, d2=0.185 g=2.595
4/4 [========] - 0s 5ms/step
>3, 93/234, d1=0.341, d2=0.182 g=2.591
>3, 94/234, d1=0.343, d2=0.142 g=2.670
>3, 95/234, d1=0.337, d2=0.178 g=2.594
>3, 96/234, d1=0.248, d2=0.176 g=2.474
4/4 [======= ] - 0s 5ms/step
>3, 97/234, d1=0.242, d2=0.155 g=2.476
4/4 [=======] - 0s 6ms/step
>3, 98/234, d1=0.282, d2=0.195 g=2.259
4/4 [========] - 0s 5ms/step
>3, 99/234, d1=0.311, d2=0.249 g=2.070
>3, 100/234, d1=0.334, d2=0.306 g=2.007
>3, 101/234, d1=0.323, d2=0.383 g=1.921
4/4 [======= ] - 0s 4ms/step
>3, 102/234, d1=0.334, d2=0.473 g=1.652
4/4 [======== ] - 0s 5ms/step
>3, 103/234, d1=0.352, d2=0.425 g=1.551
>3, 104/234, d1=0.386, d2=0.476 g=1.771
4/4 [======== ] - 0s 5ms/step
>3, 105/234, d1=0.434, d2=0.304 g=2.017
4/4 [======= ] - 0s 5ms/step
>3, 106/234, d1=0.491, d2=0.226 g=2.140
4/4 [=======] - 0s 4ms/step
>3, 107/234, d1=0.365, d2=0.187 g=2.146
>3, 108/234, d1=0.382, d2=0.229 g=2.270
>3, 109/234, d1=0.283, d2=0.211 g=2.355
4/4 [======= ] - 0s 3ms/step
>3, 110/234, d1=0.258, d2=0.191 g=2.404
>3, 111/234, d1=0.269, d2=0.210 g=2.185
4/4 [=======] - 0s 3ms/step
>3, 112/234, d1=0.182, d2=0.298 g=2.107
>3, 113/234, d1=0.321, d2=0.317 g=1.923
>3, 114/234, d1=0.318, d2=0.407 g=1.854
4/4 [======= ] - 0s 4ms/step
>3, 115/234, d1=0.403, d2=0.402 g=1.884
4/4 [=======] - 0s 3ms/step
>3, 116/234, d1=0.418, d2=0.332 g=1.994
4/4 [======== ] - 0s 4ms/step
>3, 117/234, d1=0.415, d2=0.273 g=2.189
4/4 [======== ] - 0s 4ms/step
>3, 118/234, d1=0.436, d2=0.221 g=2.349
```

```
>3, 119/234, d1=0.431, d2=0.206 g=2.339
4/4 [======= ] - 0s 3ms/step
>3, 120/234, d1=0.482, d2=0.205 g=2.171
4/4 [=======] - 0s 4ms/step
>3, 121/234, d1=0.349, d2=0.291 g=2.290
4/4 [======= ] - 0s 5ms/step
>3, 122/234, d1=0.359, d2=0.216 g=2.346
4/4 [======== ] - 0s 3ms/step
>3, 123/234, d1=0.301, d2=0.271 g=2.328
>3, 124/234, d1=0.409, d2=0.380 g=1.773
4/4 [=======] - 0s 3ms/step
>3, 125/234, d1=0.415, d2=0.512 g=1.516
>3, 126/234, d1=0.448, d2=0.536 g=1.766
4/4 [======== ] - 0s 4ms/step
>3, 127/234, d1=0.463, d2=0.305 g=2.125
>3, 128/234, d1=0.476, d2=0.293 g=2.009
4/4 [======= ] - 0s 4ms/step
>3, 129/234, d1=0.388, d2=0.524 g=1.438
4/4 [======== ] - 0s 3ms/step
>3, 130/234, d1=0.465, d2=0.523 g=1.728
>3, 131/234, d1=0.510, d2=0.532 g=1.768
>3, 132/234, d1=0.689, d2=0.747 g=1.307
>3, 133/234, d1=0.691, d2=0.512 g=1.424
4/4 [======= ] - 0s 3ms/step
>3, 134/234, d1=0.603, d2=0.781 g=1.038
>3, 135/234, d1=0.603, d2=0.874 g=0.953
>3, 136/234, d1=0.735, d2=0.755 g=0.915
4/4 [======== ] - 0s 4ms/step
>3, 137/234, d1=0.757, d2=0.940 g=0.974
4/4 [======= ] - 0s 4ms/step
>3, 138/234, d1=0.683, d2=0.922 g=0.809
4/4 [======== ] - 0s 5ms/step
>3, 139/234, d1=0.825, d2=0.980 g=0.732
>3, 140/234, d1=0.781, d2=1.130 g=0.598
>3, 141/234, d1=0.764, d2=1.071 g=0.657
4/4 [======= ] - 0s 5ms/step
>3, 142/234, d1=0.818, d2=1.046 g=0.630
>3, 143/234, d1=0.797, d2=1.021 g=0.684
4/4 [=======] - 0s 4ms/step
>3, 144/234, d1=0.802, d2=0.908 g=0.700
>3, 145/234, d1=0.918, d2=0.963 g=0.713
>3, 146/234, d1=0.712, d2=0.935 g=0.754
4/4 [=======] - 0s 4ms/step
>3, 147/234, d1=0.703, d2=0.941 g=0.695
>3, 148/234, d1=0.764, d2=0.974 g=0.627
4/4 [======== ] - 0s 4ms/step
>3, 149/234, d1=0.798, d2=0.991 g=0.617
4/4 [======== ] - 0s 5ms/step
>3, 150/234, d1=0.704, d2=0.866 g=0.679
```

```
>3, 151/234, d1=0.743, d2=0.892 g=0.702
4/4 [======= ] - 0s 5ms/step
>3, 152/234, d1=0.747, d2=0.843 g=0.687
4/4 [=======] - 0s 5ms/step
>3, 153/234, d1=0.884, d2=0.872 g=0.725
4/4 [=======] - 0s 5ms/step
>3, 154/234, d1=0.756, d2=0.796 g=0.724
>3, 155/234, d1=0.663, d2=0.818 g=0.756
>3, 156/234, d1=0.648, d2=0.766 g=0.757
4/4 [=======] - 0s 4ms/step
>3, 157/234, d1=0.760, d2=0.751 g=0.787
>3, 158/234, d1=0.657, d2=0.731 g=0.819
>3, 159/234, d1=0.708, d2=0.713 g=0.802
>3, 160/234, d1=0.619, d2=0.675 g=0.860
4/4 [======= ] - 0s 6ms/step
>3, 161/234, d1=0.533, d2=0.648 g=0.899
4/4 [=======] - 0s 6ms/step
>3, 162/234, d1=0.543, d2=0.618 g=0.956
4/4 [======== ] - 0s 5ms/step
>3, 163/234, d1=0.587, d2=0.624 g=0.911
4/4 [======= ] - 0s 4ms/step
>3, 164/234, d1=0.554, d2=0.619 g=0.903
>3, 165/234, d1=0.670, d2=0.671 g=0.825
4/4 [======= ] - 0s 3ms/step
>3, 166/234, d1=0.550, d2=0.752 g=0.834
>3, 167/234, d1=0.599, d2=0.691 g=0.834
>3, 168/234, d1=0.579, d2=0.679 g=0.831
4/4 [======== ] - 0s 4ms/step
>3, 169/234, d1=0.571, d2=0.767 g=0.859
4/4 [======= ] - 0s 4ms/step
>3, 170/234, d1=0.561, d2=0.685 g=0.882
4/4 [=======] - 0s 4ms/step
>3, 171/234, d1=0.652, d2=0.647 g=0.907
>3, 172/234, d1=0.678, d2=0.694 g=0.838
>3, 173/234, d1=0.602, d2=0.714 g=0.790
4/4 [======= ] - 0s 4ms/step
>3, 174/234, d1=0.682, d2=0.736 g=0.784
>3, 175/234, d1=0.604, d2=0.721 g=0.843
4/4 [======] - 0s 4ms/step
>3, 176/234, d1=0.563, d2=0.711 g=0.860
>3, 177/234, d1=0.625, d2=0.655 g=0.825
>3, 178/234, d1=0.538, d2=0.695 g=0.815
4/4 [======= ] - 0s 5ms/step
>3, 179/234, d1=0.606, d2=0.644 g=0.836
4/4 [======== ] - 0s 3ms/step
>3, 180/234, d1=0.614, d2=0.666 g=0.860
4/4 [======== ] - 0s 5ms/step
>3, 181/234, d1=0.618, d2=0.639 g=0.834
4/4 [======== ] - 0s 4ms/step
>3, 182/234, d1=0.638, d2=0.645 g=0.864
```

```
>3, 183/234, d1=0.583, d2=0.672 g=0.832
4/4 [======= ] - 0s 4ms/step
>3, 184/234, d1=0.565, d2=0.638 g=0.852
4/4 [=======] - 0s 5ms/step
>3, 185/234, d1=0.604, d2=0.678 g=0.850
4/4 [=======] - 0s 3ms/step
>3, 186/234, d1=0.564, d2=0.682 g=0.852
>3, 187/234, d1=0.611, d2=0.676 g=0.837
>3, 188/234, d1=0.585, d2=0.739 g=0.841
4/4 [=======] - 0s 5ms/step
>3, 189/234, d1=0.562, d2=0.682 g=0.843
4/4 [======== ] - 0s 4ms/step
>3, 190/234, d1=0.667, d2=0.715 g=0.830
4/4 [======== ] - 0s 5ms/step
>3, 191/234, d1=0.618, d2=0.779 g=0.814
>3, 192/234, d1=0.623, d2=0.775 g=0.781
4/4 [======= ] - 0s 4ms/step
>3, 193/234, d1=0.627, d2=0.833 g=0.788
4/4 [=======] - 0s 5ms/step
>3, 194/234, d1=0.644, d2=0.824 g=0.784
>3, 195/234, d1=0.706, d2=0.773 g=0.870
4/4 [======= ] - 0s 5ms/step
>3, 196/234, d1=0.712, d2=0.673 g=0.933
>3, 197/234, d1=0.692, d2=0.615 g=0.971
4/4 [======= ] - 0s 5ms/step
>3, 198/234, d1=0.696, d2=0.583 g=1.049
4/4 [======== ] - 0s 5ms/step
>3, 199/234, d1=0.662, d2=0.533 g=1.094
>3, 200/234, d1=0.645, d2=0.498 g=1.131
4/4 [======== ] - 0s 4ms/step
>3, 201/234, d1=0.593, d2=0.478 g=1.127
4/4 [======= ] - 0s 4ms/step
>3, 202/234, d1=0.613, d2=0.512 g=1.077
4/4 [=======] - 0s 4ms/step
>3, 203/234, d1=0.627, d2=0.561 g=0.974
>3, 204/234, d1=0.491, d2=0.700 g=0.831
>3, 205/234, d1=0.486, d2=0.786 g=0.759
4/4 [======= ] - 0s 4ms/step
>3, 206/234, d1=0.671, d2=0.819 g=0.747
>3, 207/234, d1=0.625, d2=0.795 g=0.744
4/4 [=======] - 0s 4ms/step
>3, 208/234, d1=0.662, d2=0.746 g=0.776
>3, 209/234, d1=0.737, d2=0.677 g=0.835
>3, 210/234, d1=0.672, d2=0.687 g=0.828
4/4 [======= ] - 0s 5ms/step
>3, 211/234, d1=0.711, d2=0.716 g=0.894
4/4 [=======] - 0s 4ms/step
>3, 212/234, d1=0.685, d2=0.656 g=0.893
4/4 [======== ] - 0s 4ms/step
>3, 213/234, d1=0.644, d2=0.631 g=0.904
4/4 [======== ] - 0s 5ms/step
>3, 214/234, d1=0.617, d2=0.591 g=0.950
```

```
>3, 215/234, d1=0.677, d2=0.605 g=0.929
4/4 [======= ] - 0s 5ms/step
>3, 216/234, d1=0.678, d2=0.601 g=0.950
4/4 [=======] - 0s 7ms/step
>3, 217/234, d1=0.653, d2=0.619 g=0.900
4/4 [======= ] - 0s 5ms/step
>3, 218/234, d1=0.654, d2=0.633 g=0.884
>3, 219/234, d1=0.649, d2=0.643 g=0.897
4/4 [======== ] - 0s 3ms/step
>3, 220/234, d1=0.678, d2=0.681 g=0.892
4/4 [=======] - 0s 6ms/step
>3, 221/234, d1=0.653, d2=0.639 g=0.896
4/4 [======= ] - 0s 5ms/step
>3, 222/234, d1=0.643, d2=0.658 g=0.900
4/4 [======== ] - 0s 5ms/step
>3, 223/234, d1=0.707, d2=0.588 g=0.923
4/4 [=======] - 0s 5ms/step
>3, 224/234, d1=0.759, d2=0.673 g=0.896
4/4 [======= ] - 0s 5ms/step
>3, 225/234, d1=0.688, d2=0.667 g=0.914
4/4 [======= ] - 0s 5ms/step
>3, 226/234, d1=0.676, d2=0.615 g=0.913
4/4 [=======] - 0s 6ms/step
>3, 227/234, d1=0.677, d2=0.603 g=0.915
>3, 228/234, d1=0.764, d2=0.601 g=0.931
>3, 229/234, d1=0.683, d2=0.600 g=0.913
4/4 [======= ] - 0s 7ms/step
>3, 230/234, d1=0.695, d2=0.626 g=0.943
4/4 [======== ] - 0s 6ms/step
>3, 231/234, d1=0.759, d2=0.570 g=0.924
>3, 232/234, d1=0.686, d2=0.595 g=0.945
4/4 [======== ] - 0s 6ms/step
>3, 233/234, d1=0.684, d2=0.578 g=0.945
4/4 [======= ] - 0s 3ms/step
>3, 234/234, d1=0.711, d2=0.623 g=0.927
```

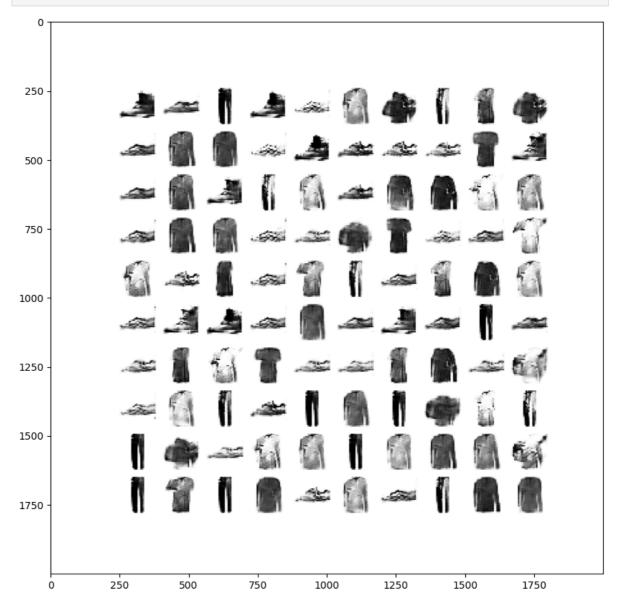
No se me guardó el notebook y perdí el notebook ejecutado, pero estuve entrenándolo 100 épocas y tengo los pesos en google Drive. No voy a repetir las horas de ejecución que estuve porque fueron muchas y ya me quedan pocas unidades de ejecución de Google Colab, y también por cuestión de tiempo. Voy a mostrar las imágenes generadas y cargar los pesos.

```
%1s $RESULTS PATH # pesos generados por el entrenamiento de 3 épocas anterior
In [36]:
         cgan_generator_model_001.h5 generated_plot_e001.png
In [37]: %ls $BASE_PATH # pesos generados por
         cgan generator model 001.h5
                                      cgan generator model 080.h5
                                                                   generated plot e050.png
                                      cgan_generator_model_090.h5
         cgan_generator_model_010.h5
                                                                   generated_plot_e060.png
         cgan generator model 020.h5
                                      cgan generator model 100.h5 generated plot e070.png
         cgan_generator_model_030.h5
                                      generated_plot_e001.png
                                                                   generated plot e080.png
         cgan_generator_model_040.h5
                                      generated_plot_e010.png
                                                                   generated_plot_e090.png
         cgan_generator_model_050.h5
                                      generated_plot_e020.png
                                                                   generated_plot_e100.png
         cgan_generator_model_060.h5
                                                                   generated_plot_e101.png
                                      generated_plot_e030.png
```

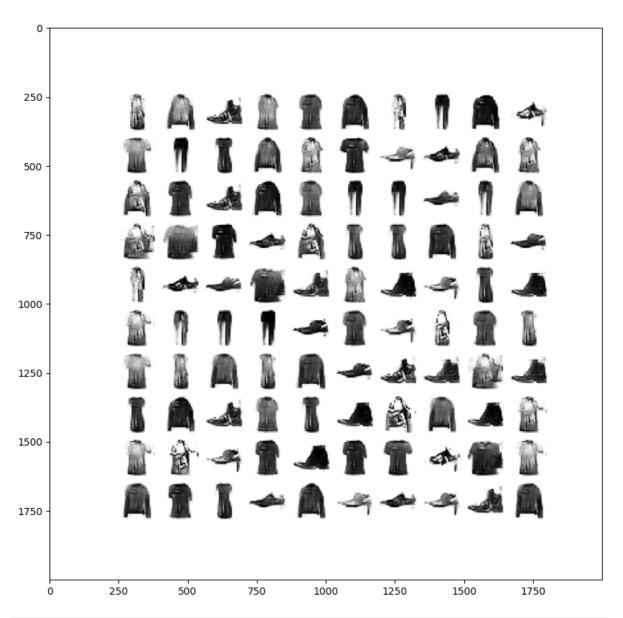
generated_plot_e040.png

cgan_generator_model_070.h5

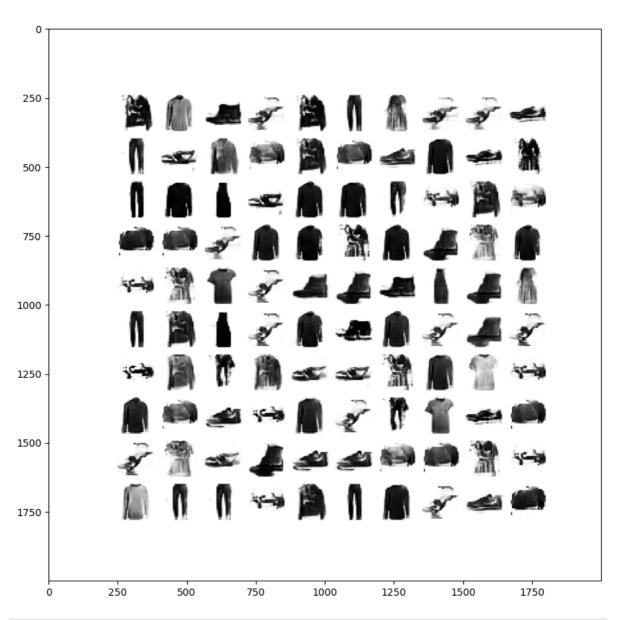
```
In [38]: plt.figure(figsize=(10, 10))
  plt.imshow(plt.imread(os.path.join(BASE_PATH,'generated_plot_e001.png')))
  plt.show()
```



```
In [39]: plt.figure(figsize=(10, 10))
   plt.imshow(plt.imread(os.path.join(BASE_PATH,'generated_plot_e010.png')))
   plt.show()
```



In [40]: plt.figure(figsize=(10, 10))
 plt.imshow(plt.imread(os.path.join(BASE_PATH,'generated_plot_e100.png')))
 plt.show()



```
In [51]: # vamos a generar imágenes de una determinada clase
from tensorflow.keras.models import load_model

# cargamos el modelo
model = load_model(os.path.join(BASE_PATH,'cgan_generator_model_100.h5'))
# generate images
latent_points, labels = generate_latent_points(100, 100)
# specify labels
labels = np.asarray([x for _ in range(10) for x in range(10)])
# generate images
X = model.predict([latent_points, labels])
# scale from [-1,1] to [0,1]
X = (X + 1) / 2.0
# plot the result
save_plot(X, 100)
```

WARNING:tensorflow:No training configuration found in the save file, so the model was *not* compiled. Compile it manually.

WARNING:tensorflow:5 out of the last 13 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7a8b51b52200> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) crea ting @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

```
In [53]: plt.figure(figsize=(10, 10))
  plt.imshow(plt.imread(os.path.join(RESULTS_PATH,'generated_plot_e101.png')))
  plt.show()
```

