## Actividad Autoencodes

November 22, 2023

## 0.1 Actividad: Autoencodes

Implementen un autoencoder para la base de datos de "Emojis". Para ello, sigan los siguientes pasos:

1. Dividan aleatoriamente su conjunto de datos de tal manera que el 80% de los datos sean para entrenamiento y un 20% para prueba. Procuren que en la división las clases mantengan la misma proporción tanto en los datos de entrenamiento como en los de prueba respecto a las proporciones.

```
[]: import numpy as np
from sklearn.model_selection import train_test_split
from collections import Counter

data = np.loadtxt("emojis.txt")
x = data[:,1:]
y = data[:,0]

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.
42,stratify=y)
```

2. Sigan los pasos del tutorial "Building autoencoders with Keras" para ajustar un autoencoder de una capa oculta para los datos de Emojis utilizando los datos de entrenamiento.

```
[]: import keras
from keras import layers
import matplotlib.pyplot as plt

encoding_dim = 32

input_img = keras.Input(shape=(x_train.shape[1]))
encoded = layers.Dense(encoding_dim, activation='relu')(input_img)
decoded = layers.Dense(x_train.shape[1], activation='sigmoid')(encoded)

autoencoder = keras.Model(input_img, decoded)
encoder = keras.Model(input_img, encoded)

encoded_input = keras.Input(shape=(encoding_dim,))
```

```
decoder_layer = autoencoder.layers[-1]
decoder = keras.Model(encoded_input, decoder_layer(encoded_input))
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(x_train, x_train,
                epochs=50,
                batch_size=256,
                 shuffle=True,
                 validation_data=(x_test, x_test))
# 3. Utilicen algunas imágenes del conjunto de prueba para ver la salida de la
 ⇔capa intermedia
# y de la capa de decodificación.
encoded_imgs = encoder.predict(x_test)
decoded_imgs = decoder.predict(encoded_imgs)
n = 5
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(32, 32))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
    # Display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(32, 32))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
#4. Evalúen el error cuadrático medio entre las imágenes de prueba
# y su correspondiente salida.
from sklearn.metrics import mean_squared_error
mse_test = mean_squared_error(x_test, decoded_imgs)
print(f'MSE | Datos de prueba: {mse_test}')
Epoch 1/50
```

```
Epoch 2/50
8/8 [============= ] - Os 26ms/step - loss: 0.5918 - val_loss:
0.5232
Epoch 3/50
0.4589
Epoch 4/50
0.4285
Epoch 5/50
0.4150
Epoch 6/50
0.4030
Epoch 7/50
0.3913
Epoch 8/50
0.3810
Epoch 9/50
0.3724
Epoch 10/50
0.3649
Epoch 11/50
0.3587
Epoch 12/50
0.3526
Epoch 13/50
0.3469
Epoch 14/50
0.3419
Epoch 15/50
0.3373
Epoch 16/50
0.3331
Epoch 17/50
0.3292
```

```
Epoch 18/50
0.3257
Epoch 19/50
0.3224
Epoch 20/50
0.3192
Epoch 21/50
8/8 [============= ] - Os 15ms/step - loss: 0.3172 - val_loss:
0.3162
Epoch 22/50
0.3133
Epoch 23/50
0.3105
Epoch 24/50
0.3078
Epoch 25/50
0.3053
Epoch 26/50
0.3029
Epoch 27/50
0.3005
Epoch 28/50
0.2983
Epoch 29/50
0.2961
Epoch 30/50
0.2941
Epoch 31/50
0.2921
Epoch 32/50
0.2901
Epoch 33/50
0.2882
```

```
Epoch 34/50
8/8 [============= ] - Os 17ms/step - loss: 0.2840 - val_loss:
0.2864
Epoch 35/50
0.2845
Epoch 36/50
0.2827
Epoch 37/50
8/8 [============= ] - Os 16ms/step - loss: 0.2780 - val_loss:
0.2811
Epoch 38/50
0.2793
Epoch 39/50
0.2776
Epoch 40/50
0.2760
Epoch 41/50
0.2744
Epoch 42/50
0.2729
Epoch 43/50
0.2713
Epoch 44/50
0.2698
Epoch 45/50
0.2683
Epoch 46/50
0.2669
Epoch 47/50
0.2656
Epoch 48/50
0.2642
Epoch 49/50
0.2629
```

5. Agreguen un factor de regularización a la capa intermedia y repitan los pasos 3 y 4 con este nuevo modelo.

```
[]: import keras
     from keras import layers
     import matplotlib.pyplot as plt
     from keras import regularizers
     encoding_dim = 32
     input_img = keras.Input(shape=(x_train.shape[1]))
     # Agregamos un factor de regularización a nuestra capa intermedia
     encoded = layers.Dense(encoding_dim, activation='relu',
                     activity_regularizer=regularizers.l1(10e-5))(input_img)
     decoded = layers.Dense(x_train.shape[1], activation='sigmoid')(encoded)
     autoencoder = keras.Model(input_img, decoded)
     encoder = keras.Model(input_img, encoded)
     encoded_input = keras.Input(shape=(encoding_dim,))
     decoder_layer = autoencoder.layers[-1]
     decoder = keras.Model(encoded_input, decoder_layer(encoded_input))
     autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
     autoencoder.fit(x_train, x_train,
                     epochs=100,
                     batch_size=256,
```

```
shuffle=True,
            validation_data=(x_test, x_test))
# 3. Utilicen algunas imágenes del conjunto de prueba para ver la salida de la
 ⇔capa intermedia
# y de la capa de decodificación.
encoded_imgs = encoder.predict(x_test)
decoded_imgs = decoder.predict(encoded_imgs)
plt.figure(figsize=(20, 4))
for i in range(n):
   # Display original
   ax = plt.subplot(2, n, i + 1)
   plt.imshow(x_test[i].reshape(32, 32))
   plt.gray()
   ax.get_xaxis().set_visible(False)
   ax.get_yaxis().set_visible(False)
   # Display reconstruction
   ax = plt.subplot(2, n, i + 1 + n)
   plt.imshow(decoded_imgs[i].reshape(32, 32))
   plt.gray()
   ax.get_xaxis().set_visible(False)
   ax.get_yaxis().set_visible(False)
#4. Evalúen el error cuadrático medio entre las imágenes de prueba
# y su correspondiente salida.
from sklearn.metrics import mean_squared_error
mse_test = mean_squared_error(x_test, decoded_imgs)
print(f'MSE | Datos de prueba: {mse_test}')
Epoch 1/100
0.6510
Epoch 2/100
0.5381
Epoch 3/100
0.4704
Epoch 4/100
```

```
0.4396
Epoch 5/100
0.4262
Epoch 6/100
0.4158
Epoch 7/100
0.4045
Epoch 8/100
0.3944
Epoch 9/100
0.3863
Epoch 10/100
0.3792
Epoch 11/100
0.3731
Epoch 12/100
0.3672
Epoch 13/100
0.3617
Epoch 14/100
0.3565
Epoch 15/100
0.3520
Epoch 16/100
0.3479
Epoch 17/100
0.3440
Epoch 18/100
0.3402
Epoch 19/100
0.3364
Epoch 20/100
```

```
0.3327
Epoch 21/100
0.3293
Epoch 22/100
0.3259
Epoch 23/100
0.3229
Epoch 24/100
0.3197
Epoch 25/100
0.3168
Epoch 26/100
0.3140
Epoch 27/100
0.3114
Epoch 28/100
0.3088
Epoch 29/100
0.3066
Epoch 30/100
0.3044
Epoch 31/100
0.3023
Epoch 32/100
0.3004
Epoch 33/100
0.2986
Epoch 34/100
0.2968
Epoch 35/100
0.2951
Epoch 36/100
```

```
0.2936
Epoch 37/100
0.2920
Epoch 38/100
0.2905
Epoch 39/100
0.2892
Epoch 40/100
0.2878
Epoch 41/100
0.2864
Epoch 42/100
0.2851
Epoch 43/100
0.2838
Epoch 44/100
0.2826
Epoch 45/100
0.2815
Epoch 46/100
0.2803
Epoch 47/100
0.2791
Epoch 48/100
0.2780
Epoch 49/100
0.2769
Epoch 50/100
0.2759
Epoch 51/100
0.2748
Epoch 52/100
```

```
0.2738
Epoch 53/100
0.2728
Epoch 54/100
0.2718
Epoch 55/100
0.2708
Epoch 56/100
0.2699
Epoch 57/100
0.2690
Epoch 58/100
0.2682
Epoch 59/100
0.2673
Epoch 60/100
0.2665
Epoch 61/100
0.2657
Epoch 62/100
0.2649
Epoch 63/100
0.2641
Epoch 64/100
0.2634
Epoch 65/100
0.2627
Epoch 66/100
0.2619
Epoch 67/100
0.2612
Epoch 68/100
```

```
0.2606
Epoch 69/100
0.2599
Epoch 70/100
0.2592
Epoch 71/100
0.2586
Epoch 72/100
0.2580
Epoch 73/100
0.2574
Epoch 74/100
0.2568
Epoch 75/100
0.2562
Epoch 76/100
0.2557
Epoch 77/100
0.2551
Epoch 78/100
0.2546
Epoch 79/100
0.2541
Epoch 80/100
0.2536
Epoch 81/100
0.2531
Epoch 82/100
0.2526
Epoch 83/100
0.2522
Epoch 84/100
```

```
0.2518
Epoch 85/100
0.2513
Epoch 86/100
0.2510
Epoch 87/100
0.2505
Epoch 88/100
0.2502
Epoch 89/100
0.2498
Epoch 90/100
0.2495
Epoch 91/100
0.2491
Epoch 92/100
0.2487
Epoch 93/100
0.2484
Epoch 94/100
0.2481
Epoch 95/100
0.2479
Epoch 96/100
0.2476
Epoch 97/100
0.2473
Epoch 98/100
0.2471
Epoch 99/100
0.2468
Epoch 100/100
```

6. Implemente un autoencoder profundo agregando más capas internas, y evalúen este nuevo modelo tal como se hizo en los dos modelos anteriores.

```
[]: encoding_dim = 32
     input_img = keras.Input(shape=(x_train.shape[1],))
     encoded = layers.Dense(128, activation='relu')(input_img)
     encoded = layers.Dense(64, activation='relu')(encoded)
     encoded = layers.Dense(encoding_dim, activation='relu')(encoded)
     decoded = layers.Dense(64, activation='relu')(encoded)
     decoded = layers.Dense(128, activation='relu')(decoded)
     decoded = layers.Dense(x_train.shape[1], activation='sigmoid')(decoded)
     autoencoder = keras.Model(input_img, decoded)
     autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
     autoencoder.fit(x_train, x_train,
                     epochs=100,
                     batch_size=256,
                     shuffle=True,
                     validation_data=(x_test, x_test))
     # 3. Utilicen algunas imágenes del conjunto de prueba para ver la salida de la
     ⇔capa intermedia
     # y de la capa de decodificación.
     decoded_imgs = autoencoder.predict(x_test)
     plt.figure(figsize=(20, 4))
     for i in range(n):
```

```
# Display original
  ax = plt.subplot(2, n, i + 1)
  plt.imshow(x_test[i].reshape(32, 32))
  plt.gray()
  ax.get_xaxis().set_visible(False)
  ax.get_yaxis().set_visible(False)
  # Display reconstruction
  ax = plt.subplot(2, n, i + 1 + n)
  plt.imshow(decoded_imgs[i].reshape(32, 32))
  plt.gray()
  ax.get_xaxis().set_visible(False)
  ax.get_yaxis().set_visible(False)
#4. Evalúen el error cuadrático medio entre las imágenes de prueba
# y su correspondiente salida.
from sklearn.metrics import mean_squared_error
mse_test = mean_squared_error(x_test, decoded_imgs)
print(f'MSE | Datos de prueba: {mse_test}')
Epoch 1/100
0.6087
Epoch 2/100
0.4682
Epoch 3/100
0.4297
Epoch 4/100
0.4141
Epoch 5/100
0.4041
Epoch 6/100
0.3923
Epoch 7/100
0.3809
Epoch 8/100
8/8 [============= ] - Os 19ms/step - loss: 0.3803 - val_loss:
0.3742
Epoch 9/100
```

```
0.3690
Epoch 10/100
0.3654
Epoch 11/100
0.3607
Epoch 12/100
0.3539
Epoch 13/100
0.3461
Epoch 14/100
0.3399
Epoch 15/100
0.3350
Epoch 16/100
0.3307
Epoch 17/100
0.3267
Epoch 18/100
0.3237
Epoch 19/100
0.3210
Epoch 20/100
0.3182
Epoch 21/100
0.3152
Epoch 22/100
0.3117
Epoch 23/100
0.3075
Epoch 24/100
0.3034
Epoch 25/100
```

```
0.3001
Epoch 26/100
0.2969
Epoch 27/100
0.2946
Epoch 28/100
0.2926
Epoch 29/100
0.2907
Epoch 30/100
0.2887
Epoch 31/100
0.2870
Epoch 32/100
0.2857
Epoch 33/100
0.2840
Epoch 34/100
0.2822
Epoch 35/100
0.2807
Epoch 36/100
0.2793
Epoch 37/100
0.2782
Epoch 38/100
0.2767
Epoch 39/100
0.2753
Epoch 40/100
0.2740
Epoch 41/100
```

```
0.2734
Epoch 42/100
0.2720
Epoch 43/100
0.2709
Epoch 44/100
0.2704
Epoch 45/100
0.2693
Epoch 46/100
0.2685
Epoch 47/100
0.2673
Epoch 48/100
0.2667
Epoch 49/100
0.2661
Epoch 50/100
0.2650
Epoch 51/100
0.2643
Epoch 52/100
0.2636
Epoch 53/100
0.2632
Epoch 54/100
0.2622
Epoch 55/100
0.2616
Epoch 56/100
0.2608
Epoch 57/100
```

```
0.2602
Epoch 58/100
0.2600
Epoch 59/100
0.2594
Epoch 60/100
0.2590
Epoch 61/100
0.2584
Epoch 62/100
0.2578
Epoch 63/100
0.2580
Epoch 64/100
0.2573
Epoch 65/100
0.2568
Epoch 66/100
0.2570
Epoch 67/100
0.2563
Epoch 68/100
0.2562
Epoch 69/100
0.2557
Epoch 70/100
0.2560
Epoch 71/100
0.2555
Epoch 72/100
0.2549
Epoch 73/100
```

```
0.2549
Epoch 74/100
0.2545
Epoch 75/100
0.2544
Epoch 76/100
0.2541
Epoch 77/100
0.2537
Epoch 78/100
0.2535
Epoch 79/100
0.2533
Epoch 80/100
0.2526
Epoch 81/100
0.2525
Epoch 82/100
0.2527
Epoch 83/100
0.2521
Epoch 84/100
0.2516
Epoch 85/100
0.2516
Epoch 86/100
0.2510
Epoch 87/100
0.2509
Epoch 88/100
0.2507
Epoch 89/100
```

```
0.2510
Epoch 90/100
0.2500
Epoch 91/100
0.2503
Epoch 92/100
0.2503
Epoch 93/100
0.2504
Epoch 94/100
0.2500
Epoch 95/100
0.2499
Epoch 96/100
0.2496
Epoch 97/100
0.2494
Epoch 98/100
0.2492
Epoch 99/100
0.2486
Epoch 100/100
0.2488
16/16 [========= ] - Os 2ms/step
MSE | Datos de prueba: 0.07815937762367585
```

7. Agreguen ruido binario a algunas imágenes de prueba (es decir, prendan o apaguen algunos pixeles de manera aleatoria), y verifiquen la salida del autoencoder profundo. ¿El modelo es capaz de eliminar ruido en las imágenes de entrada?

```
[]: x_train = np.reshape(x_train, (len(x_train), 32, 32, 1))
     x_{test} = np.reshape(x_{test}, (len(x_{test}), 32, 32, 1))
     noise_factor = 0.5
     x_train_noisy = x_train + noise_factor * np.random.normal(loc=0.0, scale=1.0, ___
      ⇔size=x_train.shape)
     x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, 
      ⇔size=x_test.shape)
     x_train_noisy = np.clip(x_train_noisy, 0., 1.)
     x_test_noisy = np.clip(x_test_noisy, 0., 1.)
     plt.figure(figsize=(20, 2))
     for i in range(1, n + 1):
         ax = plt.subplot(1, n, i)
         plt.imshow(x_test_noisy[i].reshape(32, 32))
         plt.gray()
         ax.get_xaxis().set_visible(False)
         ax.get_yaxis().set_visible(False)
     plt.show()
```











```
input_img = keras.Input(shape=(32, 32, 1))

x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
encoded = layers.MaxPooling2D((2, 2), padding='same')(x)

x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(encoded)
x = layers.UpSampling2D((2, 2))(x)
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(x)
x = layers.UpSampling2D((2, 2))(x)
```

```
decoded = layers.Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)
autoencoder = keras.Model(input_img, decoded)
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(x_train_noisy, x_train,
        epochs=100,
        batch_size=128,
        shuffle=True,
        validation_data=(x_test_noisy, x_test),
        callbacks=[TensorBoard(log_dir='/tmp/tb', histogram_freq=0,__
→write_graph=False)])
Epoch 1/100
val_loss: 0.5131
Epoch 2/100
val_loss: 0.4967
Epoch 3/100
val_loss: 0.4848
Epoch 4/100
val loss: 0.4649
Epoch 5/100
val_loss: 0.4291
Epoch 6/100
val_loss: 0.3865
Epoch 7/100
val_loss: 0.3520
Epoch 8/100
val_loss: 0.3273
Epoch 9/100
val_loss: 0.3106
Epoch 10/100
val_loss: 0.2966
Epoch 11/100
val_loss: 0.2843
Epoch 12/100
```

```
val_loss: 0.2775
Epoch 13/100
val_loss: 0.2655
Epoch 14/100
val loss: 0.2582
Epoch 15/100
val_loss: 0.2516
Epoch 16/100
val_loss: 0.2466
Epoch 17/100
val_loss: 0.2432
Epoch 18/100
val_loss: 0.2395
Epoch 19/100
val loss: 0.2366
Epoch 20/100
val_loss: 0.2327
Epoch 21/100
val_loss: 0.2326
Epoch 22/100
val_loss: 0.2275
Epoch 23/100
val_loss: 0.2241
Epoch 24/100
val loss: 0.2216
Epoch 25/100
val_loss: 0.2205
Epoch 26/100
val_loss: 0.2171
Epoch 27/100
val_loss: 0.2138
Epoch 28/100
```

```
val_loss: 0.2120
Epoch 29/100
val_loss: 0.2103
Epoch 30/100
val loss: 0.2076
Epoch 31/100
val_loss: 0.2058
Epoch 32/100
val_loss: 0.2055
Epoch 33/100
val_loss: 0.2030
Epoch 34/100
val_loss: 0.2054
Epoch 35/100
val loss: 0.2001
Epoch 36/100
val_loss: 0.2001
Epoch 37/100
val_loss: 0.1987
Epoch 38/100
val_loss: 0.1976
Epoch 39/100
val_loss: 0.1965
Epoch 40/100
val loss: 0.1948
Epoch 41/100
val_loss: 0.1939
Epoch 42/100
val_loss: 0.1944
Epoch 43/100
val_loss: 0.1956
Epoch 44/100
```

```
val_loss: 0.1929
Epoch 45/100
val_loss: 0.1916
Epoch 46/100
val loss: 0.1918
Epoch 47/100
val_loss: 0.1890
Epoch 48/100
val_loss: 0.1883
Epoch 49/100
val_loss: 0.1876
Epoch 50/100
val_loss: 0.1869
Epoch 51/100
val loss: 0.1860
Epoch 52/100
val_loss: 0.1856
Epoch 53/100
val_loss: 0.1849
Epoch 54/100
val_loss: 0.1850
Epoch 55/100
val_loss: 0.1844
Epoch 56/100
val loss: 0.1838
Epoch 57/100
val_loss: 0.1830
Epoch 58/100
val_loss: 0.1823
Epoch 59/100
val_loss: 0.1819
Epoch 60/100
```

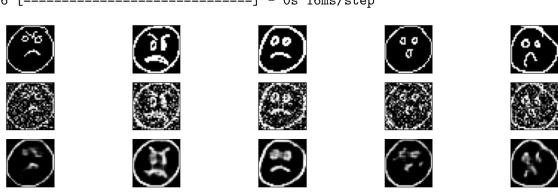
```
val_loss: 0.1825
Epoch 61/100
val_loss: 0.1832
Epoch 62/100
val loss: 0.1817
Epoch 63/100
val_loss: 0.1799
Epoch 64/100
val_loss: 0.1832
Epoch 65/100
val_loss: 0.1811
Epoch 66/100
val_loss: 0.1785
Epoch 67/100
val loss: 0.1779
Epoch 68/100
val_loss: 0.1779
Epoch 69/100
val_loss: 0.1777
Epoch 70/100
val_loss: 0.1826
Epoch 71/100
val_loss: 0.1770
Epoch 72/100
val loss: 0.1775
Epoch 73/100
val_loss: 0.1761
Epoch 74/100
val_loss: 0.1766
Epoch 75/100
val_loss: 0.1753
Epoch 76/100
```

```
val_loss: 0.1751
Epoch 77/100
val_loss: 0.1766
Epoch 78/100
val loss: 0.1742
Epoch 79/100
val_loss: 0.1741
Epoch 80/100
val_loss: 0.1734
Epoch 81/100
val_loss: 0.1735
Epoch 82/100
val_loss: 0.1730
Epoch 83/100
val loss: 0.1730
Epoch 84/100
val_loss: 0.1740
Epoch 85/100
val_loss: 0.1723
Epoch 86/100
val_loss: 0.1742
Epoch 87/100
val_loss: 0.1725
Epoch 88/100
val loss: 0.1729
Epoch 89/100
val_loss: 0.1711
Epoch 90/100
16/16 [============ ] - 4s 224ms/step - loss: 0.1666 -
val_loss: 0.1714
Epoch 91/100
val_loss: 0.1709
Epoch 92/100
```

```
val_loss: 0.1726
  Epoch 93/100
  16/16 [============ ] - 4s 225ms/step - loss: 0.1661 -
  val_loss: 0.1703
  Epoch 94/100
  val loss: 0.1705
  Epoch 95/100
  val_loss: 0.1702
  Epoch 96/100
  val_loss: 0.1700
  Epoch 97/100
  val_loss: 0.1715
  Epoch 98/100
  val_loss: 0.1693
  Epoch 99/100
  val loss: 0.1688
  Epoch 100/100
  val_loss: 0.1720
[]: <keras.src.callbacks.History at 0x26625c0aaf0>
[]: decoded_imgs = autoencoder.predict(x_test_noisy)
   n = 5 # número de imágenes a mostrar
   plt.figure(figsize=(15, 4))
   for i in range(n):
     # Muestra la imagen original
     ax = plt.subplot(3, n, i + 1)
     plt.imshow(x_test[i].reshape(32, 32))
     plt.gray()
     ax.get_xaxis().set_visible(False)
     ax.get_yaxis().set_visible(False)
     # Muestra la imagen ruidosa
     ax = plt.subplot(3, n, i + 1 + n)
     plt.imshow(x_test_noisy[i].reshape(32, 32))
     plt.gray()
     ax.get_xaxis().set_visible(False)
     ax.get_yaxis().set_visible(False)
```

```
# Muestra la imagen reconstruida
ax = plt.subplot(3, n, i + 1 + 2*n)
plt.imshow(decoded_imgs[i].reshape(32, 32))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
```

16/16 [=======] - Os 16ms/step



¿El modelo es capaz de eliminar ruido en las imágenes de entrada?

Si, el modelo es capaz de eliminar el ruido de las imágenes, esto se debe a que gracias a nuestro modelo es capaz de aprender a extraer las características esenciales de las imágenes originales y a reconstruirlas a una imagen más limpia en base a ello.

Cabe mencionar que nuestro modelo usa capas convolucionales, que son capaces de extraer características visuales de alto nivel de las imágenes, y que son más eficientes y robustas que las capas densas. Las capas convolucionales también preservan la estructura espacial de las imágenes, lo que facilita la reconstrucción.