CLASIFICACIÓN MULTIPLE - POPULARIDAD

Integrantes de equipo:

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DESCRIPCION DEL PROBLEMA

La industria de la musica es bastante popular en la actualidad, como lo que escucha las personajes cambia con el tiempo, ya sea por tendencias o moda, mucho de lo que determina su popularidad suele ser subjetivo o circunstancial. Sim embargo tomando en cuenta datos tecnicos o variables presentes en la musica, se tendra como objetivo el determinar si es popular o no.

Este proyecto se enfocara en un problema de clasificacion multiple, el cual hara uso de una dataset de Spotify de pistas en un rango de 125 géneros diferentes. Cada pista tiene algunas funciones de audio asociadas. Los datos están en formato CSV, que es tabular y se puede cargar rápidamente.

Link del Dataset: https://www.kaggle.com/datasets/maharshipandya/-spotify-tracks-dataset?resource=download

ANALISIS EXPLORATORIO

Primero, nosotros necesitamos tener la dataset descargada y almacenada en una carpeta en drive para su proximo uso, ademas de importar las librerias necesarias.

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers,regularizers
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from keras.models import Sequential
from keras.layers import Dense
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
```

Nosotros cargamos la dataset usando pandas read_csv, junto con el link de donde esta nuestra data en drive

```
# Obtenemos el dataset de las Canciones de Spotify y lo almacenamos en un DataFrame
df = pd.read_csv("https://drive.google.com/uc?id=1gAkvuBkYAEKCdf9CYqePni8TacqkwWt3")
df
```

	Unnamed: 0	track_id	artists	album_name	track_name	popularity	duration_ms
0	0	5SuOikwiRyPMVoIQDJUgSV	Gen Hoshino	Comedy	Comedy	73	230666
1	1	4qPNDBW1i3p13qLCt0Ki3A	Ben Woodward	Ghost (Acoustic)	Ghost - Acoustic	55	149610
2	2	1iJBSr7s7jYXzM8EGcbK5b	Ingrid Michaelson;ZAYN	To Begin Again	To Begin Again	57	210826
3	3	6lfxq3CG4xtTiEg7opyCyx	Kina Grannis	Crazy Rich Asians (Original Motion Picture Sou...	Can't Help Falling In Love	71	201933
4	4	5vjLSffimiIP26QG5WcN2K	Chord Overstreet	Hold On	Hold On	82	198853
...	...	...	...	...	...	...	...
				#mindfulness - Soft Rain	Sleep My		

PRE-PROCESAMIENTO DE LOS DATOS

```
# Convertimos la columna 'popularity' en 'popularity_class'(0:baja, 1:media, 2:alta)
df['popularity_class'] = 0
df.loc[df['popularity'] > 30, 'popularity_class'] = 1
df.loc[df['popularity'] > 70, 'popularity_class'] = 2
```

```
# Extraemos una muestra de 100 000 registros aleatorios
df_sample = df.sample(100000)

# Filtramos las entradas y la salida que usaremos para el modelo
columns = ['danceability','energy','loudness','speechiness','acousticness','instrumentalness','valence','tempo','popularity_class']
df_columns = df_sample[columns]
df_columns.nunique() # visualizamos la cantidad de valores únicos de las columnas
```

```
danceability         1151
energy               2041
loudness            18807
speechiness          1478
acousticness         4995
instrumentalness     5326
valence              1777
tempo               42471
popularity_class        3
dtype: int64
```

```
# Visualizamos algunos registros filtrados por el valor de 'popularity_class'
df_columns.query('popularity_class == 1')
```

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	valence	tempo	popularity_class
23775	0.731	0.988	-5.174	0.1220	0.00251	0.799000	0.155	125.993	1
9365	0.661	0.529	-5.330	0.0312	0.64800	0.000000	0.328	121.892	1
104241	0.304	0.328	-10.311	0.0351	0.56000	0.000000	0.243	119.675	1
72140	0.582	0.928	-4.659	0.0635	0.00876	0.000005	0.565	113.043	1
77744	0.504	0.743	-6.529	0.1050	0.55500	0.000000	0.707	90.425	1
...	...	...	...	...	...	...	...	...	...
47429	0.521	0.721	-7.699	0.0254	0.00348	0.011300	0.611	97.578	1
105246	0.736	0.289	-11.398	0.0494	0.93000	0.839000	0.150	68.987	1
89948	0.664	0.893	-3.627	0.1500	0.07480	0.000000	0.773	104.007	1
19813	0.666	0.252	-17.614	0.0264	0.54800	0.022100	0.547	94.111	1
12978	0.439	0.446	-8.113	0.0319	0.68100	0.000000	0.300	142.837	1

50287 rows × 9 columns

```
# Visualizamos algunas estadísticas de nuestros datos
df_columns.describe()
```

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	valenc
count	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.00000
mean	0.566666	0.641036	-8.260964	0.084568	0.315636	0.156273	0.47408
std	0.173611	0.251811	5.034996	0.105598	0.332711	0.309847	0.25935
min	0.000000	0.000000	-49.531000	0.000000	0.000000	0.000000	0.00000
25%	0.456000	0.471000	-10.013000	0.035900	0.017000	0.000000	0.26000
50%	0.580000	0.684000	-7.004000	0.048900	0.170000	0.000042	0.46400
75%	0.694000	0.854000	-5.004000	0.084400	0.599000	0.049000	0.68300
max	0.985000	1.000000	4.532000	0.965000	0.996000	1.000000	0.99400

```
# Pasamos los datos del DF a un arreglo
data = df_columns.values

# Separamos las características de las etiquetas
x_data = data[:, :-1]
y_data = data[:, -1]

print("X:")
print(x_data)
print("y:")
print(y_data)
```

```
X:
[[ 5.23000e-01  9.12000e-01 -2.24300e+00 ...  0.00000e+00  8.24000e-01
   1.61906e+02]
 [ 5.17000e-01  6.09000e-01 -5.70200e+00 ...  0.00000e+00  2.39000e-01
   9.20930e+01]
 [ 7.31000e-01  9.88000e-01 -5.17400e+00 ...  7.99000e-01  1.55000e-01
   1.25993e+02]
 ...
 [ 6.66000e-01  2.52000e-01 -1.76140e+01 ...  2.21000e-02  5.47000e-01
   9.41110e+01]
 [ 4.39000e-01  4.46000e-01 -8.11300e+00 ...  0.00000e+00  3.00000e-01
   1.42837e+02]
 [ 4.20000e-01  6.46000e-01 -7.61500e+00 ...  1.53000e-02  8.77000e-01
   1.42209e+02]]
y:
[0. 0. 1. ... 1. 1. 0.]
```

```
# Verificamos las dimensiones de los arreglos
print("X:")
print(x_data.shape)
print("y:")
print(y_data.shape)
```

```
X:
(100000, 8)
y:
(100000,)
```

```
# Obtenemos la media y la desviación estándar de cada característica
x_mean = x_data.mean(axis = 0)
x_std = x_data.std(axis = 0)

# Normalizamos las características del modelo y convertimos a float32
x_data = (x_data - x_mean) / x_std
x_data= x_data.astype(np.float32)

# Verificamos los datos normalizados
x_data
```

```
array([[-0.25151557,  1.0760666 ,  1.1952331 , ..., -0.5043599 ,
         1.3491517 ,  1.3268516 ],
       [-0.2860758 , -0.1272223 ,  0.5082381 , ..., -0.5043599 ,
        -0.9064179 , -1.000805  ],
       [ 0.946572  ,  1.3778816 ,  0.6131046 , ...,  2.0743487 ,
        -1.2302946 ,  0.12946522],
       ...,
       [ 0.5721696 , -1.5449587 , -1.8576149 , ..., -0.43303394,
```

```
         0.28112987, -0.93352234],
       [-0.7353586 , -0.77453613,  0.02938719, ..., -0.5043599 ,
        -0.6712218 ,  0.6910662 ],
       [-0.84479934,  0.01971398,  0.12829542, ..., -0.45498037,
         1.5535026 ,  0.67012787]], dtype=float32)
```

```python
# Separamos aleatoriamente los datos de entrenamiento(80%) y de prueba(20%)
X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.2, random_state=20)
```

```python
# Definimos el modelo
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(8,)))
model.add(layers.Dropout(0.125))
model.add(Dense(512, activation='relu'))
# model.add(layers.Dropout(0.125))
model.add(Dense(512, activation='relu'))
# model.add(layers.Dropout(0.125))
model.add(Dense(512*1, activation='relu'))
model.add(Dense(3, activation='softmax'))

# Compilamos el modelo
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics='accuracy')

# Entrenamos el modelo
history = model.fit(X_train, y_train, validation_split=0.2, epochs=100, batch_size=1024)
```

```
Epoch 1/100
63/63 [==============================] - 2s 9ms/step - loss: 0.8104 - accuracy: 0.5655 - val_loss: 0.7958 - val_accuracy: 0.5860
Epoch 2/100
63/63 [==============================] - 0s 6ms/step - loss: 0.7830 - accuracy: 0.5914 - val_loss: 0.7855 - val_accuracy: 0.5954
Epoch 3/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7759 - accuracy: 0.6007 - val_loss: 0.7784 - val_accuracy: 0.5989
Epoch 4/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7705 - accuracy: 0.6031 - val_loss: 0.7803 - val_accuracy: 0.5960
Epoch 5/100
63/63 [==============================] - 0s 6ms/step - loss: 0.7685 - accuracy: 0.6081 - val_loss: 0.7751 - val_accuracy: 0.6044
Epoch 6/100
63/63 [==============================] - 0s 6ms/step - loss: 0.7625 - accuracy: 0.6135 - val_loss: 0.7716 - val_accuracy: 0.6060
Epoch 7/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7587 - accuracy: 0.6162 - val_loss: 0.7689 - val_accuracy: 0.6089
Epoch 8/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7568 - accuracy: 0.6169 - val_loss: 0.7668 - val_accuracy: 0.6133
Epoch 9/100
63/63 [==============================] - 1s 9ms/step - loss: 0.7531 - accuracy: 0.6203 - val_loss: 0.7661 - val_accuracy: 0.6090
Epoch 10/100
63/63 [==============================] - 1s 8ms/step - loss: 0.7504 - accuracy: 0.6219 - val_loss: 0.7618 - val_accuracy: 0.6150
Epoch 11/100
63/63 [==============================] - 0s 8ms/step - loss: 0.7460 - accuracy: 0.6283 - val_loss: 0.7630 - val_accuracy: 0.6190
Epoch 12/100
63/63 [==============================] - 0s 8ms/step - loss: 0.7415 - accuracy: 0.6300 - val_loss: 0.7605 - val_accuracy: 0.6235
Epoch 13/100
63/63 [==============================] - 1s 8ms/step - loss: 0.7377 - accuracy: 0.6345 - val_loss: 0.7582 - val_accuracy: 0.6286
Epoch 14/100
63/63 [==============================] - 1s 8ms/step - loss: 0.7325 - accuracy: 0.6370 - val_loss: 0.7550 - val_accuracy: 0.6227
Epoch 15/100
63/63 [==============================] - 1s 10ms/step - loss: 0.7278 - accuracy: 0.6415 - val_loss: 0.7532 - val_accuracy: 0.6258
Epoch 16/100
63/63 [==============================] - 0s 7ms/step - loss: 0.7240 - accuracy: 0.6441 - val_loss: 0.7588 - val_accuracy: 0.6236
Epoch 17/100
63/63 [==============================] - 0s 6ms/step - loss: 0.7201 - accuracy: 0.6455 - val_loss: 0.7512 - val_accuracy: 0.6276
Epoch 18/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7114 - accuracy: 0.6528 - val_loss: 0.7503 - val_accuracy: 0.6311
Epoch 19/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7070 - accuracy: 0.6553 - val_loss: 0.7525 - val_accuracy: 0.6256
Epoch 20/100
63/63 [==============================] - 0s 5ms/step - loss: 0.7013 - accuracy: 0.6581 - val_loss: 0.7531 - val_accuracy: 0.6244
Epoch 21/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6941 - accuracy: 0.6630 - val_loss: 0.7531 - val_accuracy: 0.6316
Epoch 22/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6871 - accuracy: 0.6706 - val_loss: 0.7441 - val_accuracy: 0.6349
Epoch 23/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6790 - accuracy: 0.6718 - val_loss: 0.7533 - val_accuracy: 0.6296
Epoch 24/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6727 - accuracy: 0.6744 - val_loss: 0.7554 - val_accuracy: 0.6343
Epoch 25/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6652 - accuracy: 0.6792 - val_loss: 0.7468 - val_accuracy: 0.6409
Epoch 26/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6577 - accuracy: 0.6846 - val_loss: 0.7552 - val_accuracy: 0.6340
Epoch 27/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6474 - accuracy: 0.6911 - val_loss: 0.7569 - val_accuracy: 0.6390
Epoch 28/100
```

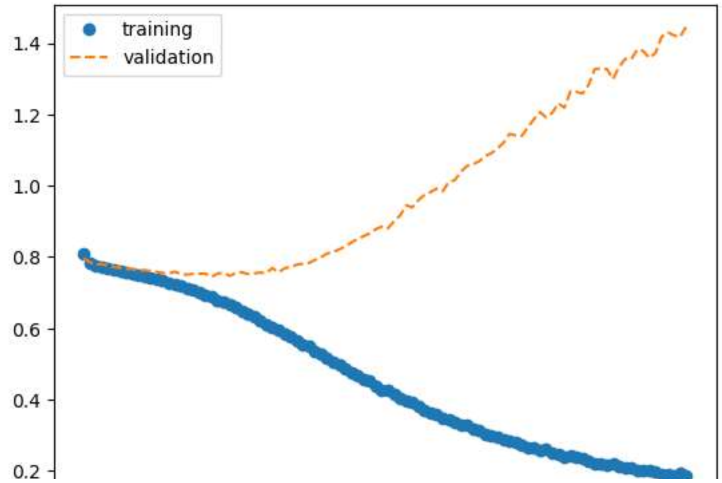
```
63/63 [==============================] - 0s 5ms/step - loss: 0.6394 - accuracy: 0.6936 - val_loss: 0.7518 - val_accuracy: 0.6418
Epoch 29/100
63/63 [==============================] - 0s 5ms/step - loss: 0.6319 - accuracy: 0.6986 - val_loss: 0.7540 - val_accuracy: 0.6424
```

```
# Guardamos los datos del entrenamiento
history_dict = history.history
history_dict
```

```
{'loss': [0.81043541431427,
  0.783037543296814,
  0.7758663892745972,
  0.7705049514770508,
  0.7685242891311646,
  0.7624958157539368,
  0.758703351020813,
  0.7567902207374573,
  0.7531402707099915,
  0.7504097819328308,
  0.746046781539917,
  0.7415114045143127,
  0.7376968264579773,
  0.7325431108474731,
  0.7278305292129517,
  0.724018394947052,
  0.7201322317123413,
  0.7114274501800537,
  0.7070450782775879,
  0.7013481855392456,
  0.6941251158714294,
  0.6871050000190735,
  0.679010272026062,
  0.6727263331413269,
  0.6652444005012512,
  0.6577200889587402,
  0.6474365592002869,
  0.6393818855285645,
  0.6318901181221008,
  0.6209021210670471,
  0.6115968823432922,
  0.6022710800170898,
  0.595801591873169,
  0.58481764793396,
  0.5761724710464478,
  0.5635596513748169,
  0.5544502139091492,
  0.5483798980712891,
  0.5335936546325684,
  0.5265988707542419,
  0.5144517421722412,
  0.5052611827850342,
  0.4970416724681854,
  0.4858230650424957,
  0.47665101289749146,
  0.4662398397922516,
  0.45778217911720276,
  0.4506412744522095,
  0.4391242563724518,
  0.4277111291885376,
  0.42490658164024353,
  0.41359302401542664,
  0.40362775325775146,
  0.3968048691749573,
  0.3917872905731201,
  0.38151267170906067,
  0.37148287892341614,
  0.3641209900379181,
```

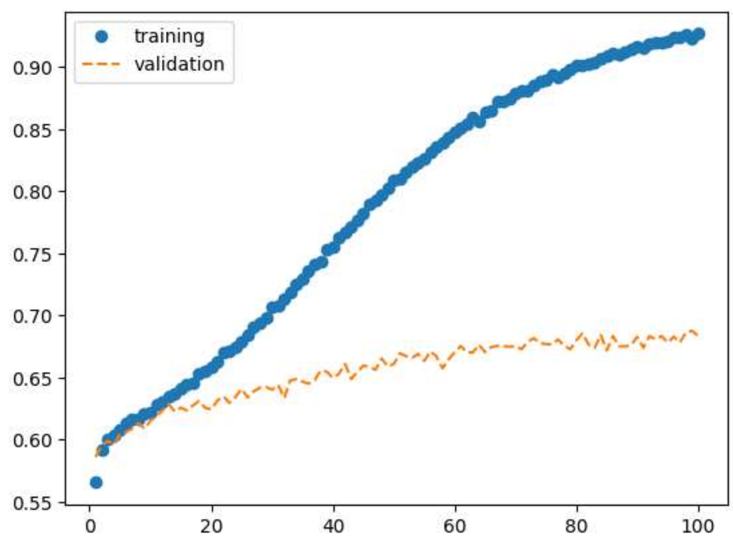
```
# Guardamos los valores de perdida en dos arreglos para entrenamiento y validacion
i=0
loss_values = history_dict["loss"][i:]
val_loss_values = history_dict["val_loss"][i:]

# Graficamos los valores de perdida
epoch = range(1, len(loss_values) + 1)
plt.plot(epoch, loss_values, 'o', label = 'training')
plt.plot(epoch, val_loss_values, '--', label = 'validation')
plt.legend()
plt.show()
```




```
# Guardamos los valores de precisión en dos arreglos para entrenamiento y validacion
i=0
loss_values = history_dict["accuracy"][i:]
val_loss_values = history_dict["val_accuracy"][i:]

# Graficamos los valores de precisión
epoch = range(1, len(loss_values) + 1)
plt.plot(epoch, loss_values, 'o', label = 'training')
plt.plot(epoch, val_loss_values, '--', label = 'validation')
plt.legend()
plt.show()
```




```
# evaluamos el modelo
model.evaluate(X_test, y_test)
```

```
625/625 [==============================] - 2s 2ms/step - loss: 1.4669 - accuracy: 0.6852
[1.4668784141540527, 0.6851500272750854]
```

```
# Predecimos en base a los datos de prueba
y_predict_prob = model.predict(X_test)

# Convertimos las probabilidades en clases
y_predict = np.argmax(y_predict_prob, axis=1)
```

```
625/625 [==============================] - 1s 2ms/step
```

```
# Verificamos algunos casos individuales
pos = 31
print("y: " , y_test[pos])
print("y predict:", y_predict[pos])
```

```
y:  1.0
y predict: 1
```

```
# Matriz de Confusion
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_predict) * 100))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_predict))
```

```
Accuracy: 68.52%
Confusion Matrix:
[[6300 2657  134]
 [2887 7026  168]
 [ 205  246  377]]
```