Music Mood Classification from Spotify Playlists

Deep Learning Class 1/2022

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```
# installing spotipy
!pip install spotipy -q # Start writing code here...
```

```
WARNING: You are using pip version 22.0.4; however, version 22.3.1 is available.
You should consider upgrading via the '/root/venv/bin/python -m pip install --upgrade pip' command.
```

```
# importing the necessary packages
import spotipy
sp = spotipy.Spotify()
from spotipy.oauth2 import SpotifyClientCredentials
import spotipy.util as util
import sys
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

```
import keras
```

```
2022-12-20 16:25:11.578600: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2022-12-20 16:25:11.882544: I tensorflow/core/util/util.cc:169] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point
2022-12-20 16:25:11.889717: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'libcudart.so.11.0'; dlerror: libcudart.so.1
2022-12-20 16:25:11.889749: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU set up on your machine.
2022-12-20 16:25:11.978360: E tensorflow/stream_executor/cuda/cuda_blas.cc:2981] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS whe
2022-12-20 16:25:14.196838: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'libnvinfer.so.7'; dlerror: libnvinfer.so.7:
2022-12-20 16:25:14.196920: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'libnvinfer_plugin.so.7'; dlerror: libnvinfe
2022-12-20 16:25:14.196939: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Cannot dlopen some TensorRT libraries. If you would like to use Nvic
```

```
import seaborn as sns
```

Load Data

```
cid = '1226a18bba7e474fa487766459065c89'
secret = '8d6d22a323b7484188b56913e0a96b3a'

client_credentials_manager = SpotifyClientCredentials(client_id=cid, client_secret=secret)

sp = spotipy.Spotify(client_credentials_manager = client_credentials_manager)
```

```
import pandas as pd
def call_playlist(creator, playlist_id):

    #step1

    playlist_features_list = ["artist","album","track_name", "track_id","danceability",
    "energy","key","loudness","mode", "speechiness","instrumentalness","liveness",
    "valence","tempo", "duration_ms","time_signature"]

    playlist_df = pd.DataFrame(columns = playlist_features_list)

    #step2

    playlist = sp.user_playlist_tracks(creator, playlist_id)["items"]
    for track in playlist:
        # Create empty dict
        playlist_features = {}
        # Get metadata
        playlist_features["artist"] = track["track"]["album"]["artists"][0]["name"]
        playlist_features["album"] = track["track"]["album"]["name"]
        playlist_features["track_name"] = track["track"]["name"]
        playlist_features["track_id"] = track["track"]["id"]

        # Get audio features
        audio_features = sp.audio_features(playlist_features["track_id"])[0]
        for feature in playlist_features_list[4:]:
            playlist_features[feature] = audio_features[feature]

        # Concat the dfs
        track_df = pd.DataFrame(playlist_features, index = [0])
        playlist_df = pd.concat([playlist_df, track_df], ignore_index = True)

    #Step 3

    return playlist_df
```

```
# Happy, Sad, Relaxing, and Energetic.
playlists = {
    'Energetic':   ["https://open.spotify.com/playlist/37i9dQZF1DWSnRSDTCsoPk?si=24909a5a1ab34fd6",
                    "https://open.spotify.com/playlist/37i9dQZF1DX0vHZ8elq0UK?si=ea161adbd78b4dcb"],
    'Relaxing':["https://open.spotify.com/playlist/37i9dQZF1DX0bGxKepv6YZ?si=931137c667f74148",
                "https://open.spotify.com/playlist/37i9dQZF1DX6ziVCJnEm59?si=0d1a15dc45dd4f0e",],
    'Sad':["https://open.spotify.com/playlist/37i9dQZF1DX3YSRoSdA634?si=e5598132ae074898",
           "https://open.spotify.com/playlist/37i9dQZF1DWW2hj3ZtMbuO?si=33d14d014ae640dd",],
    'Happy':   ["https://open.spotify.com/playlist/37i9dQZF1DXdPec7aLTmlC?si=bcf07083bc6748b5",
                "https://open.spotify.com/playlist/37i9dQZF1DWXahxq4Q8el6?si=a522054163fd427d",]
}

tracks = pd.DataFrame()
moods = []

for mood, links in playlists.items():
    print (mood)
    for link in links:
        id = link[34:56]
        try:
            tracks_dum = call_playlist("spotify", id)
            # ids = [foo['track']['id'] for foo in pl_tracks]
        except:
            print (link)
            continue
        tracks_dum['mood'] = mood
        tracks = tracks.append(tracks_dum)
```

```
print(tracks)
```

```
Energetic
             artist                           album  \
0     LE SSERAFIM                        FEARLESS
1               BTS                           Proof
2            NAYEON                       IM NAYEON
3               PSY                         PSY 9th
4           (G)I-DLE                     I NEVER DIE
..              ...                             ...
95    Shawn Mendes            Shawn Mendes (Deluxe)
96      Little Mix     Get Weird (Expanded Edition)
97           Madism                  Pumped Up Kicks
98       Katy Perry                   Teenage Dream
99   One Direction  Take Me Home (Expanded Edition)

                              track_name               track_id  \
0                               FEARLESS  296nXCOv97WJNRWzIBQnoj
1                                 Butter  6jjYDGxVJsWS0a5wlVF5vS
2                                   POP!  31OMJTQTd6J34faYwASc33
3   That That (prod. & feat. SUGA of BTS)  7GNRUsU3M4XNDDB9xle5Dz
4                                 TOMBOY  0IGUXY4JbK18bu9oD4mPIm
..                                   ...                     ...
95                    If I Can't Have You  2bT1PH7Cw3J9p3t7nlXCdh
96                            Black Magic  6rmXhRIemCTPyMYZRDN7Qg
97                        Pumped Up Kicks  3Dzso9Q2WwupEclqgxBZht
98                 The One That Got Away  6hkOqJ5mE093AQf2lbZnsG
99                               Kiss You  4My8w8AA1JpG6E5SiAPvJL

    danceability  energy key  loudness mode  speechiness  instrumentalness  \
0          0.863   0.620   7    -7.167    1       0.1350          0.003240
1          0.759   0.459   8    -5.187    1       0.0948          0.000000
2          0.795   0.859   2    -2.994    1       0.0542          0.000000
3          0.905   0.962   4    -3.197    1       0.0856          0.000000
4          0.755   0.870   1    -2.414    0       0.0936          0.000000
..           ...     ...  ..       ...  ...          ...               ...
95         0.691   0.823   2    -4.197    1       0.0623          0.000000
96         0.776   0.875   4    -5.535    1       0.0575          0.000000
97         0.669   0.687   0    -4.753    1       0.0430          0.000016
98         0.691   0.795   1    -4.021    0       0.0355          0.000001
99         0.637   0.930   4    -2.632    1       0.0511          0.000000

    liveness  valence    tempo duration_ms time_signature       mood
0     0.1290    0.432  103.971      168437              4  Energetic
1     0.0788    0.695  109.997      164952              4  Energetic
2     0.0321    0.356   96.986      168107              4  Energetic
3     0.0272    0.906  129.969      174647              4  Energetic
4     0.0917    0.645  124.032      174387              4  Energetic
..       ...      ...      ...         ...            ...        ...
95    0.1340    0.870  123.935      191467              4  Energetic
96    0.3140    0.849  111.988      211786              4  Energetic
97    0.3080    0.386  123.903      145161              4  Energetic
98    0.1560    0.876  133.971      227333              4  Energetic
99    0.4520    0.886   90.014      182867              4  Energetic

[200 rows x 17 columns]
Relaxing
https://open.spotify.com/playlist/37i9dQZF1DX0bGxKepv6YZ?si=931137c667f74148
             artist                 album  \
0       LE SSERAFIM              FEARLESS
```

```
tracks['mood'].unique()
len(tracks['track_name'].unique())
```

```
606
```

```
tracks.reset_index(drop=True, inplace=True)
```

```
tracks.to_csv('tracks_data.csv')
```

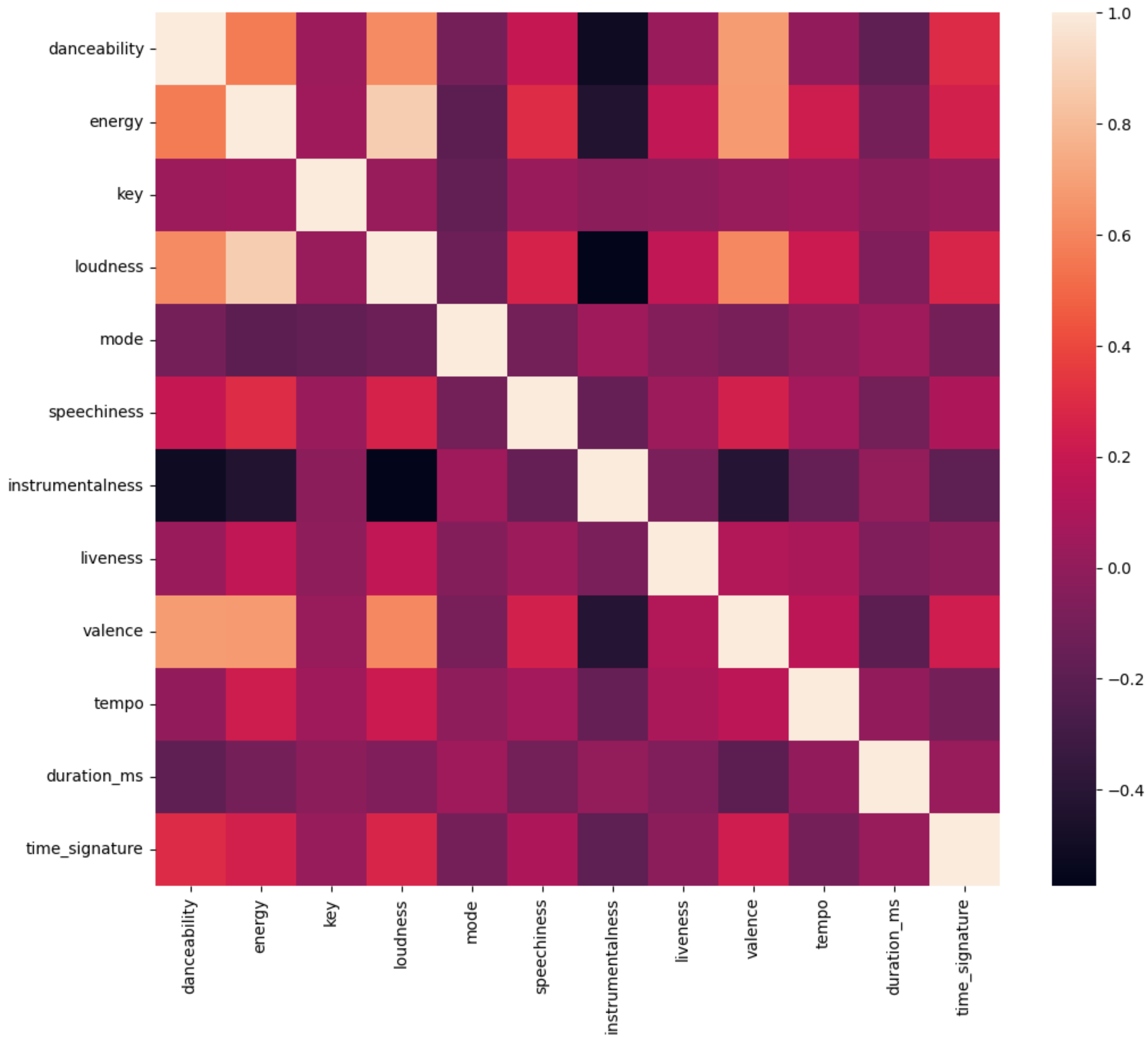
```
raw_track = pd.read_csv('tracks_data.csv')
raw_track.drop('Unnamed: 0', axis=1, inplace=True)
raw_track
```

	artist	album	track_name	track_id	danceability	energy	key	loudness	mode	speechiness	instrumentalness	liveness	valence
0	LE SSERAFIM	FEARLESS	FEARLESS	296nXCOv97WJNRWzIBQnoj	0.863	0.620	7	-7.167	1	0.1350	0.00324	0.1290	0.432
1	BTS	Proof	Butter	6jjYDGxVJsWS0a5wlVF5vS	0.759	0.459	8	-5.187	1	0.0948	0.00000	0.0788	0.695
2	NAYEON	IM NAYEON	POP!	3lOMJTQTd6J34faYwASc33	0.795	0.859	2	-2.994	1	0.0542	0.00000	0.0321	0.356
3	PSY	PSY 9th	That That (prod. & feat. SUGA of BTS)	7GNRUsU3M4XNDDB9xle5Dz	0.905	0.962	4	-3.197	1	0.0856	0.00000	0.0272	0.906
4	(G)I-DLE	I NEVER DIE	TOMBOY	0IGUXY4JbK18bu9oD4mPIm	0.755	0.870	1	-2.414	0	0.0936	0.00000	0.0917	0.645
...	...	...	...	...	...	...	...	...	...	...	...	...	...
626	Rachel Portman	The Duchess (Original Motion Picture Soundtrack)	End Titles	1CxT3WZkSuEAxPOKAPzDDl	0.175	0.171	4	-19.589	0	0.0411	0.90000	0.2080	0.074
627	Christopher Willis	The Personal History of David Copperfield (Ori...	Adventures of a London Gentleman	16iqQIS5kz8tj2EeoDvq7i	0.267	0.272	4	-12.788	1	0.0375	0.82400	0.1990	0.150
628	Ilan Eshkeri	Stardust - Music From The Motion Picture	Flying Vessel	1kmkBb6u7bA37GxDaNPils	0.221	0.383	7	-12.740	1	0.0474	0.90900	0.1440	0.074
629	Ennio Morricone	Nuovo Cinema Paradiso (Original Motion Picture...	Nuovo Cinema Paradiso	4xx3UI7cLCk1awQPAPLeHj	0.274	0.148	10	-16.815	1	0.0367	0.88900	0.1210	0.188
630	Various Artists	The Lion King	Under the Stars - From "The Lion King"/Score	37lotBTQcBbYI7vEoGsOfg	0.292	0.161	7	-20.812	1	0.0407	0.56000	0.1230	0.108

631 rows × 17 columns

Visualized Data Correlation

```
tracks_corr = raw_track.corr()
fig, ax = plt.subplots(figsize=(12,10))         # Sample figsize in inches
sns.heatmap(tracks_corr, ax=ax)
plt.show()
```




```
import tensorflow as tf
from keras import Sequential, callbacks
from keras import optimizers, models
from keras.layers import Dense, Flatten, Dropout, Input, Resizing
from keras.utils import to_categorical
from keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
import time
```

```
print(f"Number of duplicated tracks is {sum(raw_track['track_name'].duplicated())}")
```

```
Number of duplicated tracks is 25
```

```
raw_track.columns
```

```
Index(['artist', 'album', 'track_name', 'track_id', 'danceability', 'energy',
       'key', 'loudness', 'mode', 'speechiness', 'instrumentalness',
       'liveness', 'valence', 'tempo', 'duration_ms', 'time_signature',
       'mood'],
      dtype='object')
```

Cleaned and Visualized Data

```
tracks_deduplica = raw_track[~raw_track['track_name'].duplicated()].copy()
tracks_deduplica.drop(['artist', 'album', 'track_id', 'duration_ms', 'time_signature', 'key', 'mode'], axis=1, inplace=True)
tracks_deduplica.set_index('track_name', inplace=True)
```

```
tracks_deduplica
```

track_name	danceability	energy	loudness	speechiness	instrumentalness	liveness	valence	tempo	mood
FEARLESS	0.863	0.620	-7.167	0.1350	0.00324	0.1290	0.4320	103.971	Energetic
Butter	0.759	0.459	-5.187	0.0948	0.00000	0.0788	0.6950	109.997	Energetic
POP!	0.795	0.859	-2.994	0.0542	0.00000	0.0321	0.3560	96.986	Energetic
That That (prod. & feat. SUGA of BTS)	0.905	0.962	-3.197	0.0856	0.00000	0.0272	0.9060	129.969	Energetic
TOMBOY	0.755	0.870	-2.414	0.0936	0.00000	0.0917	0.6450	124.032	Energetic
...	...	...	...	...	...	...	...	...	...
End Titles	0.175	0.171	-19.589	0.0411	0.90000	0.2080	0.0746	122.278	Happy
Adventures of a London Gentleman	0.267	0.272	-12.788	0.0375	0.82400	0.1990	0.1500	125.267	Happy
Flying Vessel	0.221	0.383	-12.740	0.0474	0.90900	0.1440	0.0749	96.289	Happy
Nuovo Cinema Paradiso	0.274	0.148	-16.815	0.0367	0.88900	0.1210	0.1880	127.323	Happy
Under the Stars - From "The Lion King"/Score	0.292	0.161	-20.812	0.0407	0.56000	0.1230	0.1080	107.308	Happy

606 rows × 9 columns

```
DeepnoteChart(tracks_deduplica, """{"mark":{"clip":true,"type":"bar","color":"#4c78a8","tooltip":true},"config":{"legend":{}},"$schema":"https://vega.github.io/schema/vega-l
```

```
<__main__.DeepnoteChart at 0x7fd34427c100>
```

Preprocessing Data

```
train, test = train_test_split(tracks_deduplica, test_size = 0.25, stratify = tracks_deduplica['mood'], random_state = 43)
```

```
print(f"Number of rows in training set: {len(train)}")
print(f"Number of rows in test set: {len(test)}")
```

```
Number of rows in training set: 454
Number of rows in test set: 152
```

```
train.iloc[:, 0:-1]
```

track_name	danceability	energy	loudness	speechiness	instrumentalness	liveness	valence	tempo
Recording 15	0.5520	0.126	-18.014	0.0306	0.015300	0.1090	0.4390	92.441
Sorry	0.5130	0.250	-9.376	0.0367	0.000000	0.1170	0.3510	74.103
Another Love	0.4450	0.537	-8.532	0.0400	0.000017	0.0944	0.1310	122.769
Sinking Ship	0.3700	0.174	-19.316	0.0377	0.002900	0.1100	0.1810	92.750
All I Want	0.1880	0.411	-9.733	0.0484	0.153000	0.0843	0.1590	187.376
...	...	...	...	...	...	...	...	...
two queens in a king sized bed	0.3610	0.218	-14.989	0.0338	0.000577	0.0748	0.1670	114.476
This Feeling	0.5750	0.571	-7.906	0.0439	0.000000	0.0912	0.4490	105.049
Main Titles from the HBO Miniseries Band of Brothers - Instrumental	0.0842	0.176	-17.619	0.0376	0.970000	0.1020	0.0392	84.325
ASAP	0.7640	0.802	-4.217	0.0351	0.000000	0.1890	0.3230	132.020
Myth	0.4450	0.708	-6.268	0.0293	0.090800	0.1710	0.4140	141.965

454 rows × 8 columns

```
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
scaler = MinMaxScaler()
encoder = LabelEncoder()
train.iloc[:, 0:-1] = scaler.fit_transform(train.iloc[:, 0:-1])
test.iloc[:, 0:-1] = scaler.fit_transform(test.iloc[:, 0:-1])
train.iloc[:, 0:-1]
```

track_name	danceability	energy	loudness	speechiness	instrumentalness	liveness	valence	tempo
Recording 15	0.550786	0.120590	0.496789	0.012735	0.015773	0.126440	0.431391	0.221722
Sorry	0.505043	0.249032	0.743342	0.025066	0.000000	0.138107	0.336981	0.091529
Another Love	0.425287	0.546311	0.767433	0.031736	0.000017	0.105148	0.100955	0.437040
Sinking Ship	0.337321	0.170309	0.459626	0.027087	0.002990	0.127898	0.154597	0.223916
All I Want	0.123856	0.415798	0.733153	0.048716	0.157732	0.090419	0.130995	0.895727
...	...	...	...	...	...	...	...	...
two queens in a king sized bed	0.326765	0.215885	0.583131	0.019204	0.000595	0.076564	0.139577	0.378163
This Feeling	0.577762	0.581529	0.785300	0.039620	0.000000	0.100481	0.442120	0.311234
Main Titles from the HBO Miniseries Band of Brothers - Instrumental	0.002111	0.172381	0.508063	0.026885	1.000000	0.116232	0.002468	0.164101
ASAP	0.799437	0.820803	0.890595	0.021831	0.000000	0.243109	0.306941	0.502719
Myth	0.425287	0.723436	0.832054	0.010107	0.093608	0.216859	0.404570	0.573325

454 rows × 8 columns

```
train.iloc[:, -1] = encoder.fit_transform(train.iloc[:, -1])
test.iloc[:, -1] = encoder.fit_transform(test.iloc[:, -1])
```

```
x_train = train.iloc[:, 0:-1].astype('float32')
x_test = test.iloc[:, 0:-1].astype('float32')
y_train = to_categorical(train['mood'], num_classes=4)
y_test = to_categorical(test['mood'], num_classes=4)
```

Build Model

```
import keras
keras.__version__
```

```
'2.10.0'
```

```
sgd = optimizers.SGD(learning_rate=0.0015, momentum=0.8, nesterov=True)
model = Sequential()
model.add(Input(shape=(8,)))
model.add(Dense(32, activation='relu'))
model.add(Dense(16, activation='relu'))
model.add(Dense(4, activation='softmax'))
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_6 (Dense)             (None, 32)                288

 dense_7 (Dense)             (None, 16)                528

 dense_8 (Dense)             (None, 4)                 68

=================================================================
Total params: 884
Trainable params: 884
Non-trainable params: 0
_________________________________________________________________
```

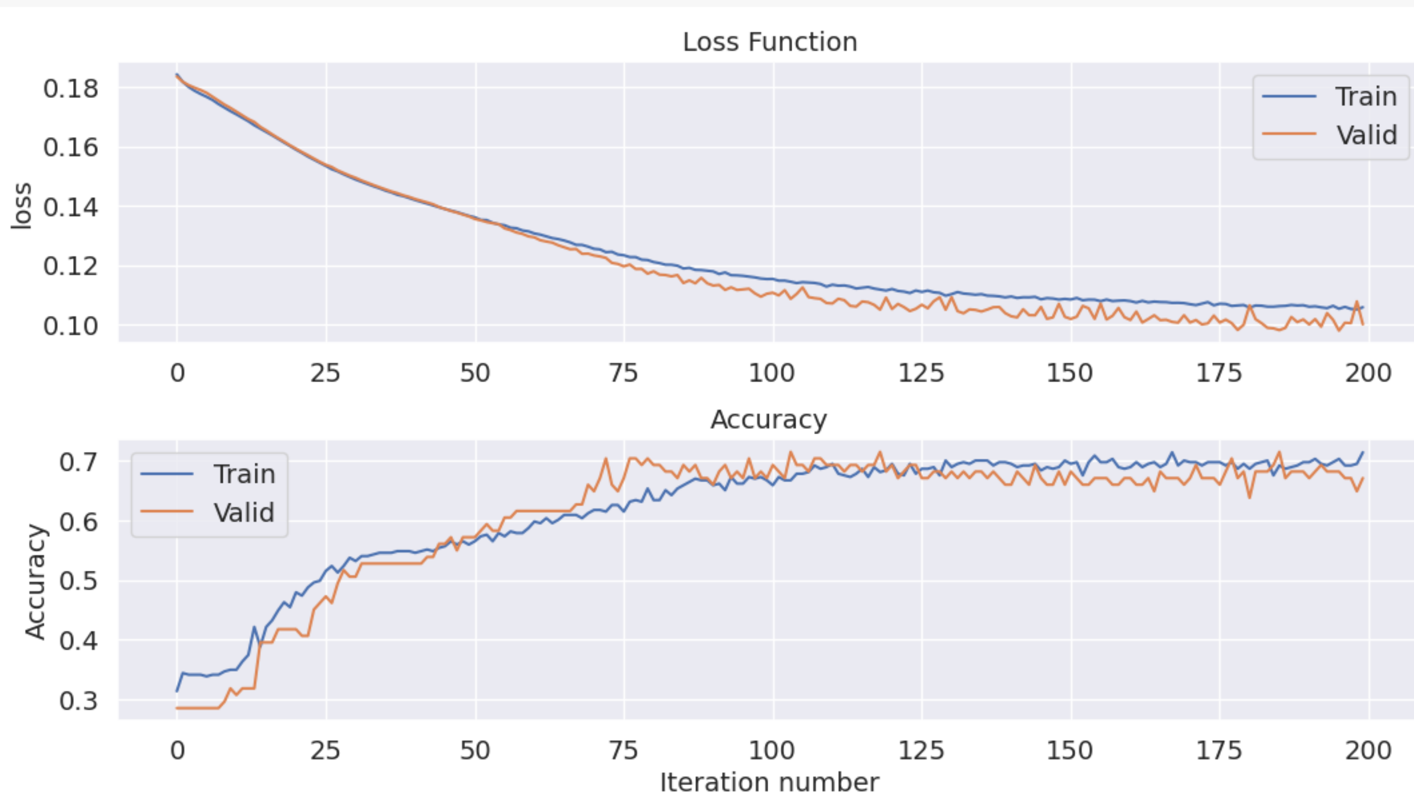
```
model.compile(optimizer=sgd, loss='mse', metrics=['accuracy'])
history = model.fit(x_train, y_train, batch_size=1, validation_split=0.2, epochs=200)
```

```
Epoch 1/200
363/363 [==============================] - 1s 2ms/step - loss: 0.1843 - accuracy: 0.3140 - val_loss: 0.1836 - val_accuracy: 0.2857
Epoch 2/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1818 - accuracy: 0.3444 - val_loss: 0.1818 - val_accuracy: 0.2857
Epoch 3/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1800 - accuracy: 0.3416 - val_loss: 0.1806 - val_accuracy: 0.2857
Epoch 4/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1787 - accuracy: 0.3416 - val_loss: 0.1798 - val_accuracy: 0.2857
Epoch 5/200
```

```
363/363 [==============================] - 0s 1ms/step - loss: 0.1777 - accuracy: 0.3416 - val_loss: 0.1790 - val_accuracy: 0.2857
Epoch 6/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1767 - accuracy: 0.3388 - val_loss: 0.1780 - val_accuracy: 0.2857
Epoch 7/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1756 - accuracy: 0.3416 - val_loss: 0.1767 - val_accuracy: 0.2857
Epoch 8/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1743 - accuracy: 0.3416 - val_loss: 0.1754 - val_accuracy: 0.2857
Epoch 9/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1731 - accuracy: 0.3471 - val_loss: 0.1741 - val_accuracy: 0.2967
Epoch 10/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1719 - accuracy: 0.3499 - val_loss: 0.1730 - val_accuracy: 0.3187
Epoch 11/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1708 - accuracy: 0.3499 - val_loss: 0.1717 - val_accuracy: 0.3077
Epoch 12/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1696 - accuracy: 0.3636 - val_loss: 0.1704 - val_accuracy: 0.3187
Epoch 13/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1685 - accuracy: 0.3747 - val_loss: 0.1692 - val_accuracy: 0.3187
Epoch 14/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1671 - accuracy: 0.4215 - val_loss: 0.1682 - val_accuracy: 0.3187
Epoch 15/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1660 - accuracy: 0.3884 - val_loss: 0.1666 - val_accuracy: 0.3956
Epoch 16/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1649 - accuracy: 0.4215 - val_loss: 0.1654 - val_accuracy: 0.3956
Epoch 17/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1638 - accuracy: 0.4325 - val_loss: 0.1641 - val_accuracy: 0.3956
Epoch 18/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1625 - accuracy: 0.4490 - val_loss: 0.1628 - val_accuracy: 0.4176
Epoch 19/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1613 - accuracy: 0.4628 - val_loss: 0.1616 - val_accuracy: 0.4176
Epoch 20/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1601 - accuracy: 0.4545 - val_loss: 0.1604 - val_accuracy: 0.4176
Epoch 21/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1589 - accuracy: 0.4793 - val_loss: 0.1592 - val_accuracy: 0.4176
Epoch 22/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1578 - accuracy: 0.4738 - val_loss: 0.1581 - val_accuracy: 0.4066
Epoch 23/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1566 - accuracy: 0.4876 - val_loss: 0.1570 - val_accuracy: 0.4066
Epoch 24/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1556 - accuracy: 0.4959 - val_loss: 0.1559 - val_accuracy: 0.4505
Epoch 25/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1545 - accuracy: 0.4986 - val_loss: 0.1548 - val_accuracy: 0.4615
Epoch 26/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1534 - accuracy: 0.5152 - val_loss: 0.1538 - val_accuracy: 0.4725
Epoch 27/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1523 - accuracy: 0.5234 - val_loss: 0.1531 - val_accuracy: 0.4615
Epoch 28/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1516 - accuracy: 0.5124 - val_loss: 0.1519 - val_accuracy: 0.4945
Epoch 29/200
363/363 [==============================] - 0s 1ms/step - loss: 0.1506 - accuracy: 0.5234 - val_loss: 0.1510 - val_accuracy: 0.5165
```

Visualize Model Performances

```python
plt.rcParams.update({'font.size': 14})
fig2, axes = plt.subplots(2, 1, figsize=(11, 6.5))
axes[0].plot(history.epoch,history.history['loss'], label='Train')
axes[0].plot(history.epoch,history.history['val_loss'], label='Valid')
axes[0].set_ylabel('loss', fontsize=14)
axes[0].set_title('Loss Function', fontsize=14)
axes[0].xaxis.set_tick_params(labelsize=14)
axes[0].yaxis.set_tick_params(labelsize=14)
axes[0].legend(fontsize=14)
axes[1].plot(history.epoch,history.history['accuracy'], label='Train')
axes[1].plot(history.epoch,history.history['val_accuracy'], label='Valid')
#axes[1].scatter(x=129, y=0.8097,'r*', label='0.8097')
axes[1].set_ylabel('Accuracy', fontsize=14)
axes[1].set_xlabel('Iteration number', fontsize=14)
axes[1].set_title('Accuracy', fontsize=14)
axes[1].xaxis.set_tick_params(labelsize=14)
axes[1].yaxis.set_tick_params(labelsize=14)
axes[1].legend(fontsize=14)
# fig2.suptitle('MLP with SGD')
fig2.tight_layout()
fig2.subplots_adjust(top=0.88)
fig2.show()
```



Test Prediction Model

```python
y_pred = model.predict(x_test)
y_pred_class = np.argmax(y_pred, axis=1)
```

```
5/5 [==============================] - 0s 1ms/step
```

```python
y_pred_class
```

```
array([0, 1, 2, 0, 1, 0, 3, 3, 0, 1, 0, 1, 2, 0, 3, 0, 0, 0, 1, 1, 0, 1,
       2, 2, 1, 0, 3, 0, 1, 2, 3, 1, 1, 2, 2, 0, 2, 0, 0, 3, 3, 2, 3, 1,
       3, 2, 0, 0, 3, 3, 0, 0, 0, 2, 0, 3, 3, 0, 1, 2, 2, 0, 0, 0, 1, 3,
       0, 2, 3, 1, 1, 0, 3, 0, 2, 0, 2, 2, 0, 2, 1, 0, 2, 0, 0, 3, 2, 0,
       0, 0, 1, 0, 0, 1, 1, 2, 2, 0, 0, 2, 1, 1, 2, 3, 3, 0, 1, 0, 2, 0,
```

```
        0, 3, 0, 2, 2, 3, 3, 3, 0, 0, 0, 0, 1, 3, 0, 3, 1, 0, 1, 3, 1, 2,
        0, 0, 0, 2, 2, 2, 1, 2, 0, 1, 2, 3, 1, 0, 3, 2, 2, 3, 1, 0])
```

```
keys = encoder.classes_
values = encoder.transform(encoder.classes_)
dictionary = dict(zip(keys, values))
print(dictionary)
```

```
{'Energetic': 0, 'Happy': 1, 'Relaxing': 2, 'Sad': 3}
```

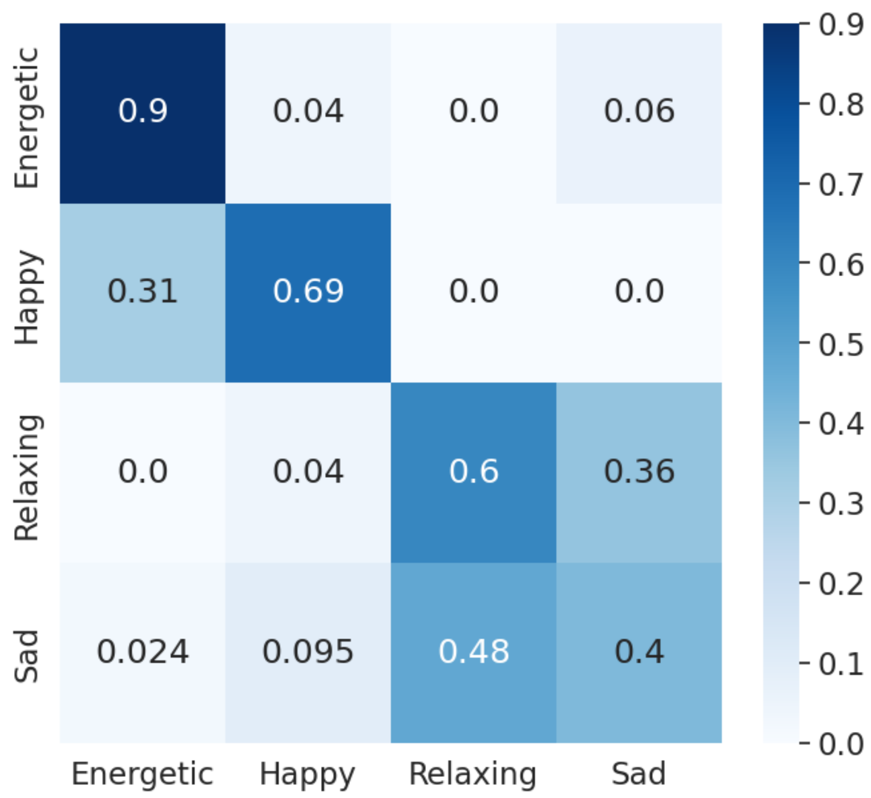
Model Evaluations

```
from sklearn.metrics import accuracy_score, precision_score
acc_score = accuracy_score(y_pred=y_pred_class, y_true = test['mood'])
pc_score = precision_score(average=None, y_pred=y_pred_class, y_true = test['mood'])
print(f'Accuracy score is {acc_score}, Precision score is {pc_score} ')
```

```
Accuracy score is 0.6644736842105263, Precision score is [0.78947368 0.77419355 0.42857143 0.5862069 ]
```

```
from sklearn.metrics import confusion_matrix, classification_report
from matplotlib import pyplot as plt
import seaborn as sns

def plot_confusion_matrix(y_test,y_scores, classNames):
    y_test=np.argmax(y_test, axis=1)
    y_scores=np.argmax(y_scores, axis=1)
    classes = len(classNames)
    cm = confusion_matrix(y_test, y_scores)
    print("**** Confusion Matrix ****")
    print(cm)
    print("**** Classification Report ****")
    print(classification_report(y_test, y_scores, target_names=classNames))
    con = np.zeros((classes,classes))
    for x in range(classes):
        for y in range(classes):
            con[x,y] = cm[x,y]/np.sum(cm[x,:])

    plt.figure(figsize=(8,7))
    sns.set(font_scale=1.5) # for label size
    df = sns.heatmap(con, annot=True,fmt='.2', cmap='Blues',xticklabels= classNames , yticklabels= classNames)
    df.figure.savefig("image2.png")

classNames = ['Energetic', 'Happy', 'Relaxing', 'Sad']
plot_confusion_matrix(y_test,y_pred, classNames)
```

```
**** Confusion Matrix ****
[[45  2  0  3]
 [11 24  0  0]
 [ 0  1 15  9]
 [ 1  4 20 17]]
**** Classification Report ****
              precision    recall  f1-score   support

   Energetic       0.79      0.90      0.84        50
       Happy       0.77      0.69      0.73        35
    Relaxing       0.43      0.60      0.50        25
         Sad       0.59      0.40      0.48        42

    accuracy                           0.66       152
   macro avg       0.64      0.65      0.64       152
weighted avg       0.67      0.66      0.66       152
```




```
pred_class_y = pd.DataFrame(y_pred_class.astype(np.float32), columns=['class'])
track_test = x_test.copy()
track_test.drop(["danceability","energy","loudness", "speechiness","instrumentalness","liveness","valence","tempo"], axis=1, inplace=True)
track_test = pd.DataFrame(track_test)
track_test = track_test.reset_index()
pred_trackclass = pd.concat([track_test,pred_class_y], axis =1)
pred_trackclass.set_index('track_name', inplace=True)
pred_trackclass
```

	class
track_name	
Bad Habits	0.0
Cake By The Ocean	1.0
Thousand (feat. Lisa Hannigan)	2.0

Discussion

Feature on metadata

- Artist names and other datas might be able to used as a feature to improve the model accuracy.
- Neglecting some features (i.e., instrumentalness) might improve the model accuracy.

References

- Mikemoschitto. (2022, May 18). Deep learning and music: Mood Classification of spotify songs. Medium. Retrieved December 21, 2022, from https://mikemoschitto.medium.com/deep-learning-and-music-mood-classification-of-spotify-songs-b2dda2bf455
- Singh, K. (2021, May 29). Music mood classification using neural networks and Spotify's web api. Medium. Retrieved December 21, 2022, from https://medium.com/codex/music-mood-classification-using-neural-networks-and-spotifys-web-api-d73b391044a4

Double-click (or enter) to edit

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