

¿Se puede medir el bienestar de un país en función de las emociones encontradas en las canciones más escuchadas? (Análisis Descriptivo Básico)

- Actividad 2 Grupal del CUA de Data Analyst, Análisis e Interpretación de Datos, UNIR 2023
 - Realizado por:
 - * David Toscano Recalde
 - * Nicolás Felipe Trujillo Montero
 - * Iris Aguado Fernández

Descripción

Nuestro objetivo es realizar un análisis tomando de muestra aleatoria de personas de EEUU para observar si existe una relación entre la canción más escuchada en un país y la situación económica del país. Para ello, partiremos de una serie de datos y realizaremos un par de análisis descriptivos, uno general y uno robusto para llegar a una conclusión.

Los datos son los siguientes:

- Top 1 de Spotify (charts.csv): Se trata de un dataframe completo de todas las canciones top 200 y virales 50 gráficos publicados globalmente por Spotify. (Fuente: <https://www.kaggle.com/datasets/dhruvildave/spotify-charts?resource=download> (<https://www.kaggle.com/datasets/dhruvildave/spotify-charts?resource=download>))
- Lista de Canciones junto con Emocion asociadas (muse_v3.csv): Se trata de un dataframe que asocia 90.000 canciones con una emoción asociada a la canción en función de la letra de la canción. (Fuente: <https://www.kaggle.com/code/cakiki/muse-dataset-getting-started/data> (<https://www.kaggle.com/code/cakiki/muse-dataset-getting-started/data>))
- Datos Macroeconómicos a nivel global (US_SECONOMICS_2.csv): Se trata de un dataframe que por cada país y año nos indica los indicadores del país. (Fuente: <https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS> (<https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS>))

Importamos librerías y Datos

In [1]:

```
#####  
# Tratamiento de Datos  
#####  
import pandas as pd  
import numpy as np  
from datetime import datetime  
import re  
  
#####  
# Gráficos  
#####  
import matplotlib.pyplot as plt  
import seaborn as sns
```

In [2]:

```
# DF Top Spotify  
df_top_original = pd.read_csv("charts.csv")  
  
# DF Etiquetas X Cancion  
df_labels_original = pd.read_csv("muse_v3.csv")  
  
# DF Variables Macroec  
socioeco_original = pd.read_csv("US_SECONOMICS_2.csv")
```

Depuración y Filtración para hacer el análisis

1.- Nos quedamos con el top 1 de solo nuestro tamaño de la muestra, es decir, Estados Unidos

NOTA: El valor de streams es NaN cuando la columna chart es "viral50".

In [3]:

```
df_top = df_top_original.copy()
_eeuuFilter=df_top_original["region"]=="United States"
df_top = df_top_original[_eeuuFilter].reset_index().drop(columns=['index'], axis=1)
df_top["streams"] = df_top["streams"].fillna("NO")
display(df_top.head(5))
```

	title	rank	date	artist	url	region	
0	Bad and Boujee (feat. Lil Uzi Vert)	1	2017-01-01	Migos	https://open.spotify.com/track/4Km5HrUvYTaSufi...	United States	t
1	Fake Love	2	2017-01-01	Drake	https://open.spotify.com/track/343YBumqHu19cGo...	United States	t
2	Starboy	3	2017-01-01	The Weeknd, Daft Punk	https://open.spotify.com/track/5aAx2yezTd8zXrk...	United States	t
3	Closer	4	2017-01-01	The Chainsmokers, Halsey	https://open.spotify.com/track/7BKLCZ1jbUBVqRi...	United States	t
4	Black Beatles	5	2017-01-01	Rae Sremmurd, Gucci Mane	https://open.spotify.com/track/6fujklziTHa8uoM...	United States	t



2.- Realizamos un filtrado para poder juntar df_top con df_labels.

In [4]:

```
df_labels = df_labels_original.copy()

# Cambiamos la columna track por title para poder juntarlo con df_top
df_labels.rename(columns = {'track':'title'}, inplace = True)

# Tenemos que ver si hay valores NA, y si los hay ver si nos merece la pena eliminarlos.
print(df_labels.count())
display(df_labels["genre"])
```

```
lastfm_url      90001
title           90001
artist          90001
seeds           90001
number_of_emotion_tags  90001
valence_tags    90001
arousal_tags    90001
dominance_tags  90001
mbid            61217
spotify_id      61630
genre           83362
dtype: int64

0          rap
1         metal
2          rap
3        hip-hop
4         metal
...
89996      NaN
89997  progressive rock
89998      NaN
89999      NaN
90000      ambient
Name: genre, Length: 90001, dtype: object
```

In [5]:

```
df_labels.drop(df_labels[df_labels['genre'].isna()].index, inplace = True)
display(df_labels.count())
```

```
lastfm_url      83362
title           83362
artist          83362
seeds           83362
number_of_emotion_tags  83362
valence_tags    83362
arousal_tags    83362
dominance_tags  83362
mbid            58559
spotify_id      58687
genre           83362
dtype: int64
```

In [6]:

```
df_merged = pd.merge(df_labels,df_top,how="inner", on = "title")
df_merged.drop(['mbid','spotify_id'], axis=1)
df_merged['date'] = pd.to_datetime(df_merged['date'],format="%Y-%m-%d")
df_merged["year"]=df_merged["date"].dt.year
df_merged["month"]=df_merged["date"].dt.month
df_merged.rename(columns = {'region':'COUNTRY'}, inplace = True)
display(df_merged.count())
```

lastfm_url	284803
title	284803
artist_x	284803
seeds	284803
number_of_emotion_tags	284803
valence_tags	284803
arousal_tags	284803
dominance_tags	284803
mbid	210823
spotify_id	247773
genre	284803
rank	284803
date	284803
artist_y	284803
url	284803
COUNTRY	284803
chart	284803
trend	284803
streams	284803
year	284803
month	284803
dtype: int64	

3.- Realizamos un filtrado de US_SECONOMICS

In [7]:

```
socioeco = pd.read_csv("US_SECONOMICS_2.csv")
socioeco = socioeco.set_index('Indicator Name')
#socioeco.dropna(inplace=True)
socioeco.drop(columns=['Country Name', 'Country Code', "Indicator Code"], inplace=True)
socioeco=socioeco.reset_index()
socioeco.set_index('Indicator Name')
socioeco.rename(columns = {'Indicator Name':'year'}, inplace = True)
socioeco.head(2)
socioeco = socioeco.melt('year').pivot('variable', 'year', 'value').rename_axis(index='year')
socioeco['year'] = socioeco['year'].astype("int64")
display(socioeco)
```

C:\Users\NicolasFTM\AppData\Local\Temp\ipykernel_1228\192668905.py:9: Future Warning: In a future version of pandas all arguments of DataFrame.pivot will be keyword-only.

```
socioeco = socioeco.melt('year').pivot('variable', 'year', 'value').rename_axis(index='year', columns=None).reset_index()
```

	year	Consumer price index (2010 = 100)	GNI per capita (constant LCU)	Inflation, GDP deflator (annual %)	Unemployment, total (% of total labor force) (national estimate)	Unemployment, youth total (% of total labor force ages 15-24) (national estimate)
0	2017	112.411557	59625.171237	1.899610	4.36	9.24
1	2018	115.157303	61024.329301	2.404059	3.90	8.61
2	2019	117.244195	62173.485113	1.793931	3.67	8.39
3	2020	118.690502	60010.506479	1.304912	8.05	14.92
4	2021	124.266414	63279.718625	4.492792	5.35	9.73

4.- Modificamos ambos dataframes para la union

In [8]:

```
df_merged.columns
```

Out[8]:

```
Index(['lastfm_url', 'title', 'artist_x', 'seeds', 'number_of_emotion_tags',
      'valence_tags', 'arousal_tags', 'dominance_tags', 'mbid', 'spotify_id',
      'genre', 'rank', 'date', 'artist_y', 'url', 'COUNTRY', 'chart', 'trend',
      'streams', 'year', 'month'],
      dtype='object')
```

In [9]:

```
df_merged.drop(columns=["lastfm_url", "url", "chart", "trend",
                        "mbid",
                        "spotify_id", "genre",
                        "number_of_emotion_tags", "valence_tags", "arousal_tags", "dominance_tags",
                        "artist_y"], inplace=True)
```

In [10]:

```
# df_top.dropna(inplace=True)
df_merged.count()
```

Out[10]:

```
title      284803
artist_x    284803
seeds       284803
rank        284803
date        284803
COUNTRY     284803
streams     284803
year        284803
month       284803
dtype: int64
```

In [11]:

```
df_merged.sample(10)
```

Out[11]:

	title	artist_x	seeds	rank	date	COUNTRY	streams	year	month
20697	Silence	Blindside	['calm']	188	2019-01-05	United States	201755.0	2019	1
249838	Promiscuous	Nelly Furtado	['sexy']	188	2020-11-15	United States	201640.0	2020	11
261357	In My Mind	SR-71	['nostalgic']	9	2018-07-21	United States	NO	2018	7
182162	GUMMO	6ix9ine	['ethereal', 'sensual']	101	2018-02-16	United States	304537.0	2018	2
177275	Believer	American Authors	['fun']	161	2018-09-30	United States	217544.0	2018	9
250202	Redbone	Childish Gambino	['sexy']	69	2017-03-19	United States	371047.0	2017	3
70166	Closer	Flint Glass	['apocalyptic', 'gloomy']	170	2018-06-28	United States	223163.0	2018	6
32293	Better	Plumb	['angry']	38	2019-03-10	United States	521393.0	2019	3
27364	Control	Control Alt Deus	['gritty']	144	2020-12-27	United States	233986.0	2020	12
145188	Heaven	Live	['sweet']	129	2018-07-17	United States	268810.0	2018	7

In [12]:

```
labels = ["angry", "aggressive",
          "romantic", "optimistic", "positive",
          "powerful",
          "light",
          "sad",
          "dramatic",
          "bitter",
          "smooth"]

def iscategory(x,y):
    return bool(re.search(x,y))

for word in labels:
    df_merged[word]=word
    df_merged[word] = df_merged.apply(lambda x1: iscategory(x1[word], x1['seeds']), axis=1)
```

In [13]:

```
df_merged.drop(df_merged[df_merged["streams"] == "NO"].index, inplace = True)
```

In [14]:

```
df_merged = df_merged.groupby(["year"]).agg(
    {
        "streams": "sum",
        "angry": 'sum',
        "aggressive": 'sum',
        "romantic": 'sum',
        "optimistic": 'sum',
        "positive": 'sum',
        "powerful": 'sum',
        "light": 'sum',
        "sad": 'sum',
        "dramatic": 'sum',
        "bitter": 'sum',
        "smooth": 'sum'
    })
```

In [15]:

```
display(df_merged.head(5))
```

	streams	angry	aggressive	romantic	optimistic	positive	powerful	light	sad	d
year										
2017	19613352139.0	714	1097	1659	412	369	959	1191	2237	
2018	21742534757.0	1283	952	2380	1375	347	2287	1306	3480	
2019	17995873982.0	974	773	1171	355	214	1334	493	2751	
2020	13534490081.0	524	80	530	801	349	859	212	2707	
2021	11252408261.0	283	208	936	436	202	852	246	1730	

In [16]:

```
labels = ["angry", "aggressive",
          "romantic", "optimistic", "positive",
          "powerful",
          "light",
          "sad",
          "dramatic",
          "bitter",
          "smooth"]
for word in labels:
    df_merged[word]=df_merged[word].astype(np.float64)
```

Se obtiene el df consolidado y depurado (df_master)

In [17]:

```
df_master = pd.merge(socioeco,df_merged,how="inner", on = ["year"])
df_master = df_master
df_master.head()
```

Out[17]:

	year	Consumer price index (2010 = 100)	GNI per capita (constant LCU)	Inflation, GDP deflator (annual %)	Unemployment, total (% of total labor force) (national estimate)	Unemployment, youth total (% of total labor force ages 15-24) (national estimate)	streams
0	2017	112.411557	59625.171237	1.899610	4.36	9.24	19613352139.0
1	2018	115.157303	61024.329301	2.404059	3.90	8.61	21742534757.0
2	2019	117.244195	62173.485113	1.793931	3.67	8.39	17995873982.0
3	2020	118.690502	60010.506479	1.304912	8.05	14.92	13534490081.0
4	2021	124.266414	63279.718625	4.492792	5.35	9.73	11252408261.0

Apartir de aqui se debe iniciar el tratamiento

In [18]:

```
corr = df_master.corr(method='pearson') #por defecto Pearson ¿existe relación lineal entre
corr = corr.iloc[1:6,7:100]
# HeatMap con tamaño ampliado, cuadrado, divergencia con colores y con anotaciones de 2 dec
plt.figure(figsize=(20,12))
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True, annot=True, fmt=".2f"
)
# Rota las etiquetas del eje horizontal
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
)
```

C:\Users\NicolasFTM\AppData\Local\Temp\ipykernel_1228\2121862967.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

corr = df_master.corr(method='pearson') #por defecto Pearson ¿existe relación lineal entre variables?

Out[18]:

```
[Text(0.5, 0, 'aggressive'),
Text(1.5, 0, 'romantic'),
Text(2.5, 0, 'optimistic'),
Text(3.5, 0, 'positive'),
Text(4.5, 0, 'powerful'),
Text(5.5, 0, 'light'),
Text(6.5, 0, 'sad'),
Text(7.5, 0, 'dramatic'),
Text(8.5, 0, 'bitter'),
Text(9.5, 0, 'smooth')]
```



