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

- 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 Estados Unidos (DP_LIVE.csv): Se trata de un dataframe que por cada mes nos indica los indicadores del país. (Fuente: https://databank.worldbank.org/reports.aspx?source=world-development-indicators# (https://databank.worldbank.org/reports.aspx?source=world-development-indicators#))

Importamos librerías y Datos

In [1]:

```
######################################################
# Tratamiento de Datos
######################################################
import pandas as pd
import numpy as np
from datetime import datetime
import re
from scipy.stats import trim_mean
from sklearn.linear_model import LinearRegression
from sklearn import metrics

######################################################
# 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
economic_df_original = pd.read_csv("DP_LIVE.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]:

```
#Leemos en data set, y eliminamos los datos que sean de otros paises
df_top = pd.read_csv("charts.csv")
condicion=df_top["region"]=="United States"
df_top = df_top[condicion]
#df_top contiene un listado de canciones del top200 de spotify DIARIO
```

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                    228728
year                       284803
month                      284803
dtype: int64
```

3.- Realizamos un filtrado de US_SECONOMICS

In [7]:

```
economic_df = economic_df_original.copy()

# El data set de economia contien datos deiferentes medidos de forma diferente, por ello a
#["SUBJECT"]=="TOT"] significa que queremos la medicion total, no solo en hombres ni solo e
#["FREQUENCY"]=="M"] definimos para obtener la medida de forma mensual, A significari anual
economic_df= economic_df[(economic_df["LOCATION"]=="USA") & (economic_df["SUBJECT"]=="TOT")

economic_df['date'] = pd.to_datetime(economic_df['TIME'],format="%Y-%m")
economic_df["year"]=economic_df["date"].dt.year
economic_df["month"]=economic_df["date"].dt.month
economic_df.tail()
```

Out[7]:

	LOCATION	INDICATOR	SUBJECT	MEASURE	FREQUENCY	TIME	Value	Flag Codes	date
18904	USA	HUR	TOT	PC_LF	M	2022-08	3.7	NaN	2022-08-0
18905	USA	HUR	TOT	PC_LF	M	2022-09	3.5	NaN	2022-09-0
18906	USA	HUR	TOT	PC_LF	M	2022-10	3.7	NaN	2022-10-0
18907	USA	HUR	TOT	PC_LF	M	2022-11	3.6	NaN	2022-11-0
18908	USA	HUR	TOT	PC_LF	M	2022-12	3.5	NaN	2022-12-0

4.- Modificamos ambos dataframes para la union

In [8]:

```
# Realizamos el merge en funcion del año y mes
df_master = pd.merge(economic_df,df_merged,how="inner", on = ["year","month"])
```

In [9]:

```
# Eliminamos algunas columnas para que el dataframe se visualize mejor
df_master.drop(columns=['INDICATOR', 'SUBJECT', "MEASURE",
                        "lastfm_url","artist_x","url","chart","trend","FREQUENCY"    ,
                        "TIME","Flag Codes","LOCATION"   ,"date_x","mbid",
                        "spotify_id",   "genre" ,"date_y",
                        "number_of_emotion_tags",   "valence_tags", "arousal_tags", "domina
                        "artist_y"],inplace=True)
```

In [10]:

```
# IMPORTANTE: ahora el dataframe contiene una columna que se llama "seed" la que tiene el p
# pero esta informacion esta en formato string, asi que primero debemos crear una columna c
# estos adjetivos los defini observando el dataframe y definiendo los mas recurrentes y  ma

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_master[word]=word
    df_master[word] = df_master.apply(lambda x1: iscategory(x1[word], x1['seeds']), axis=1)

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

In [11]:

```
display(df_master.columns)
```

```
Index(['Value', 'year', 'month', 'title', 'seeds', 'rank', 'COUNTRY',
       'streams', 'angry', 'aggressive', 'romantic', 'optimistic', 'positiv
e',
       'powerful', 'light', 'sad', 'dramatic', 'bitter', 'smooth'],
      dtype='object')
```

In [12]:

```
df_master["streams"]=df_master["streams"].astype(np.float64)

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

In [13]:

```
df_master.dtypes
```

Out[13]:

```
year             int64
month            int64
angry          float64
Value          float64
aggressive     float64
romantic       float64
optimistic     float64
positive       float64
powerful       float64
light          float64
sad            float64
dramatic       float64
bitter         float64
smooth         float64
streams        float64
dtype: object
```

In [14]:

```
df_master.head(12)
```

Out[14]:

	year	month	angry	Value	aggressive	romantic	optimistic	positive	powerful	lig
0	2017	1	0.005325	4.7	0.014294	0.017377	0.004624	0.012752	0.021160	0.0407
1	2017	2	0.005842	4.6	0.029337	0.013716	0.005588	0.006477	0.017145	0.0420
2	2017	3	0.002849	4.4	0.022249	0.011260	0.010582	0.011260	0.020079	0.0132
3	2017	4	0.005139	4.4	0.016150	0.018499	0.006607	0.014535	0.024226	0.0132
4	2017	5	0.024734	4.4	0.013268	0.035545	0.016708	0.007371	0.017690	0.0150
5	2017	6	0.015459	4.3	0.027505	0.040956	0.011845	0.004417	0.013250	0.0156
6	2017	7	0.014717	4.3	0.021423	0.043405	0.012109	0.001863	0.008756	0.0102
7	2017	8	0.013544	4.4	0.030214	0.047925	0.006425	0.004688	0.016322	0.0133
8	2017	9	0.026703	4.3	0.023978	0.045232	0.003451	0.000000	0.014896	0.0136
9	2017	10	0.019469	4.2	0.021416	0.037345	0.008319	0.009204	0.018761	0.0125
10	2017	11	0.018018	4.2	0.011314	0.039807	0.008171	0.009009	0.023046	0.0159
11	2017	12	0.017788	4.1	0.007769	0.050705	0.012063	0.005520	0.020650	0.0290

In [15]:

```
def calcul_tps_medianv2(x, column):
    a=x[column].values.tolist()
    if len(a)%2==1:
        a = np.median(a)
    elif len(a)==0:
        a=0
    else:
        a= a[np.argpartition(a,int((len(a)/2)-1))[int((len(a)/2)-1)]]
    return a
```

In [16]:

```
columns_aux = list(set(df_master.columns)-set(['year', 'month', 'streams']))
df_master_filtered = []
for _year in range(2017,2022):
    df_aux = df_master[df_master['year'] == _year]
    value_median = calcul_tps_medianv2(df_aux, 'Value')
    df_aux = df_aux[df_aux['Value'] == value_median].iloc[0]
    df_aux = df_aux[columns_aux].values.ravel()
    df_master_filtered.append(df_aux)
```

In [17]:

```
df_master_res = pd.DataFrame(df_master_filtered, columns = columns_aux)
```

In [18]:

```
df_master_res.index=range(2017,2022)
df_master_res.head()
```

Out[18]:

	optimistic	angry	powerful	romantic	dramatic	bitter	smooth	Value	sad
2017	0.011845	0.015459	0.013250	0.040956	0.019474	0.032323	0.026902	4.3	0.043365
2018	0.026576	0.023344	0.038068	0.031604	0.009337	0.009337	0.028192	3.8	0.064644
2019	0.004535	0.012956	0.036493	0.017491	0.004319	0.025696	0.036277	3.6	0.058087
2020	0.017938	0.009396	0.018508	0.012244	0.002278	0.008257	0.006549	6.9	0.051253
2021	0.010523	0.010204	0.014031	0.025191	0.000000	0.006059	0.036671	5.4	0.049426

El dataframe queda listo, usar df_master para el analisis

A continuacion realizo unas graficas basicas exploratorias

In [19]:

```
display(df_master_res[['angry','sad','positive', 'optimistic','aggressive','Value']])
# sns.scatterplot(data=df_master_res,x= df_master_res.index ,y=  'happy' )
# sns.scatterplot(data=df_master_res,x= df_master_res.index ,y=  'Value' )
# #plt.legend(loc='center',bbox_to_anchor=(1.12,0.5))
# plt.show()
```

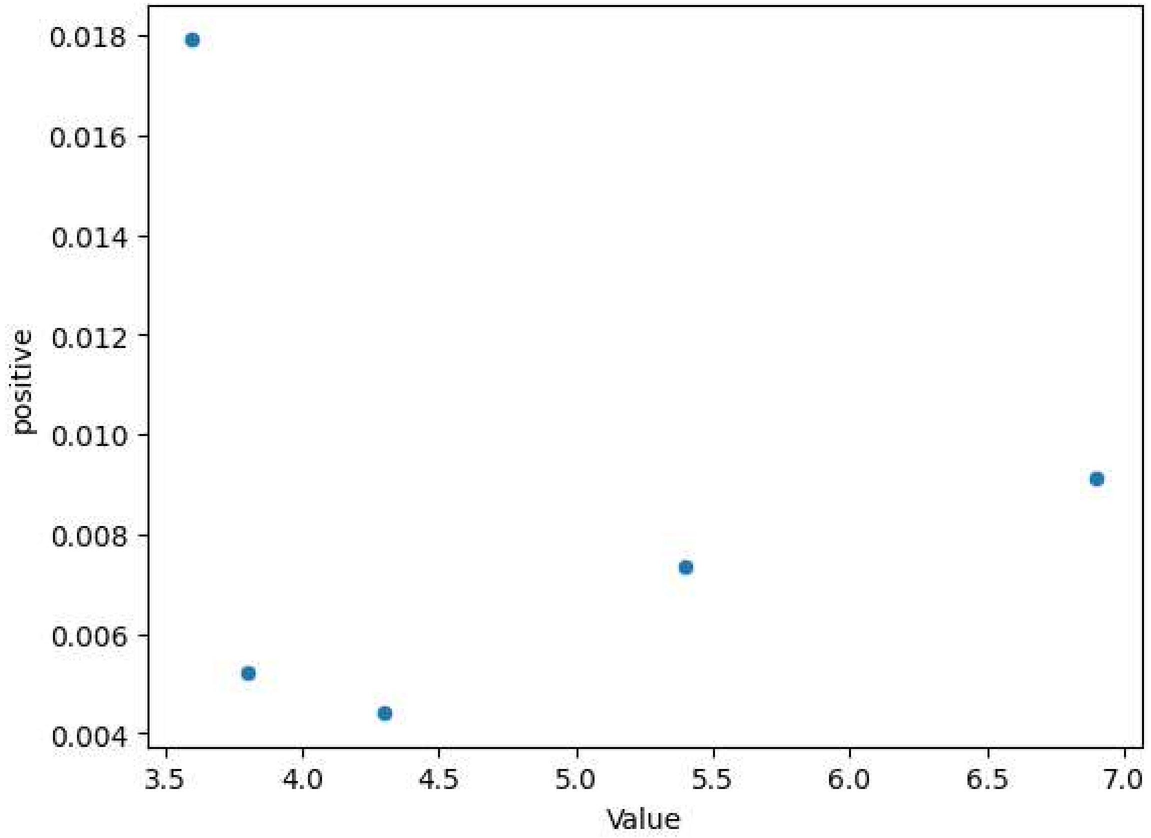
	angry	sad	positive	optimistic	aggressive	Value
2017	0.015459	0.043365	0.004417	0.011845	0.027505	4.3
2018	0.023344	0.064644	0.005207	0.026576	0.021907	3.8
2019	0.012956	0.058087	0.017923	0.004535	0.016195	3.6
2020	0.009396	0.051253	0.009112	0.017938	0.005125	6.9
2021	0.010204	0.049426	0.007334	0.010523	0.019452	5.4

In [20]:

```
sns.scatterplot(data=df_master_res,x= 'Value',y= 'positive')
```

Out[20]:

```
<AxesSubplot: xlabel='Value', ylabel='positive'>
```



In [21]:

```
model = LinearRegression()

# Eliminamos el outlier
df_master_res_pos = df_master_res.drop(index=(2019))
model.fit(np.array(df_master_res_pos['Value']).reshape(-1,1), df_master_res_pos['positive']
```

Out[21]:

```
▾ LinearRegression

LinearRegression()
```

In [22]:

```
prediccion = model.predict(np.array(df_master_res_pos['Value']).reshape(-1,1))
print(metrics.r2_score(df_master_res_pos['positive'], prediccion))
```

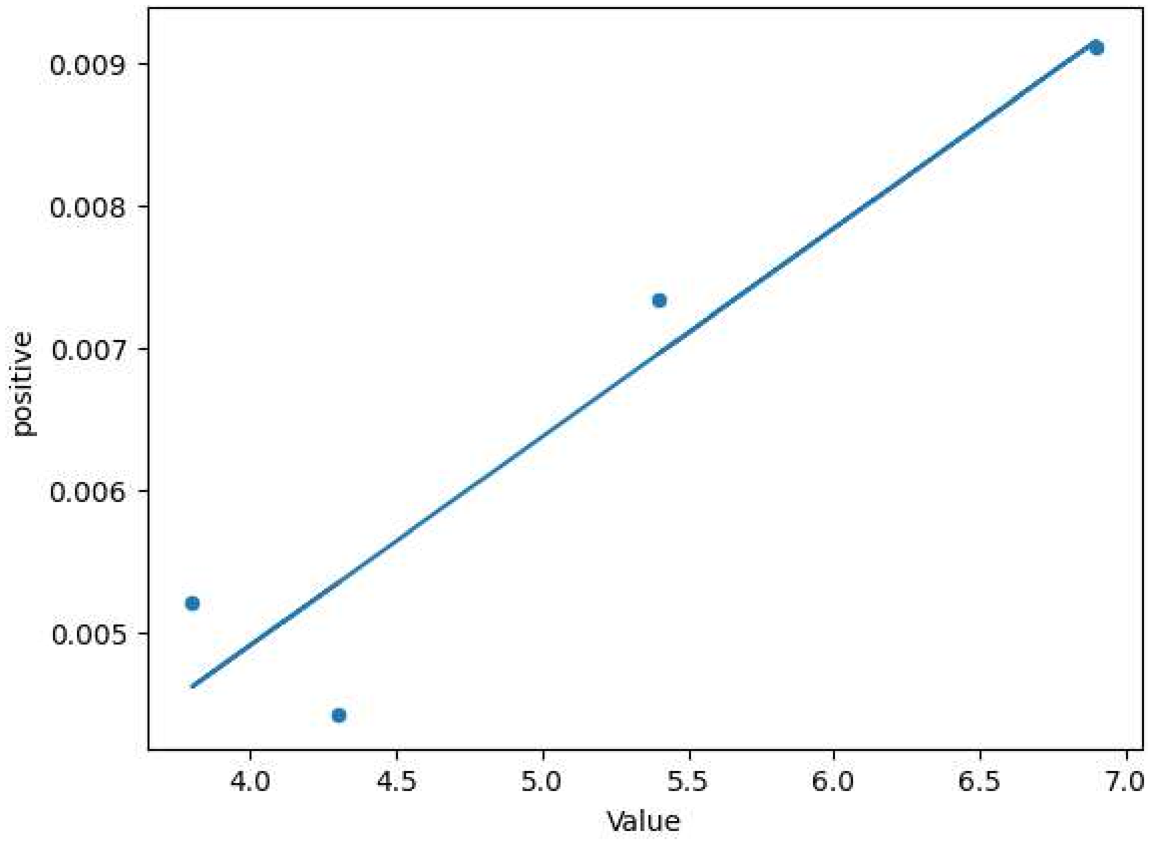
```
0.8994570907722056
```

In [23]:

```
sns.scatterplot(data=df_master_res_pos,x= 'Value',y= 'positive')
plt.plot(df_master_res_pos['Value'], prediccion)
```

Out[23]:

```
[<matplotlib.lines.Line2D at 0x2101afe2390>]
```

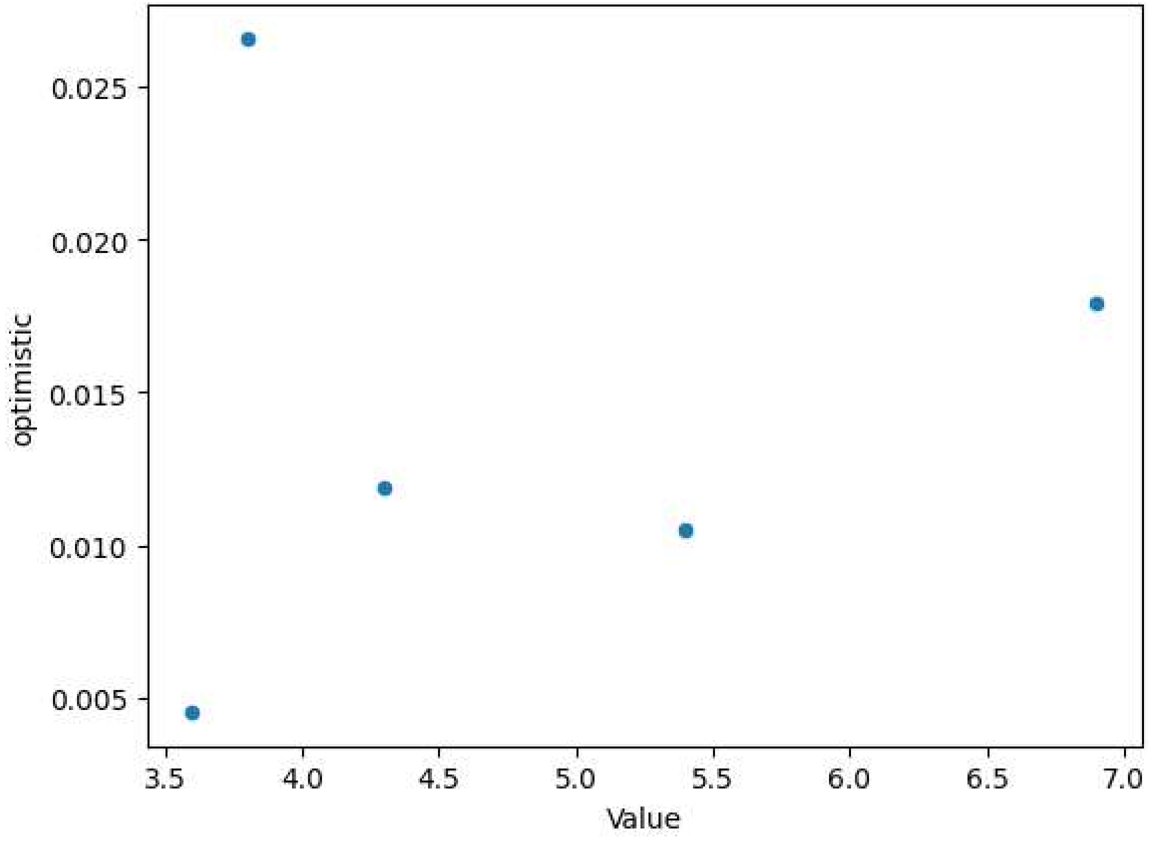


In [24]:

```
sns.scatterplot(data=df_master_res,x= 'Value',y= 'optimistic')
```

Out[24]:

```
<AxesSubplot: xlabel='Value', ylabel='optimistic'>
```



In [25]:

```
df_master_res_opt = df_master_res.drop(index=(2018))

model.fit(np.array(df_master_res_opt['Value']).reshape(-1,1), df_master_res_opt['optimistic
prediccion = model.predict(np.array(df_master_res_opt['Value']).reshape(-1,1))
print(metrics.r2_score(df_master_res_opt['optimistic'], prediccion))
```

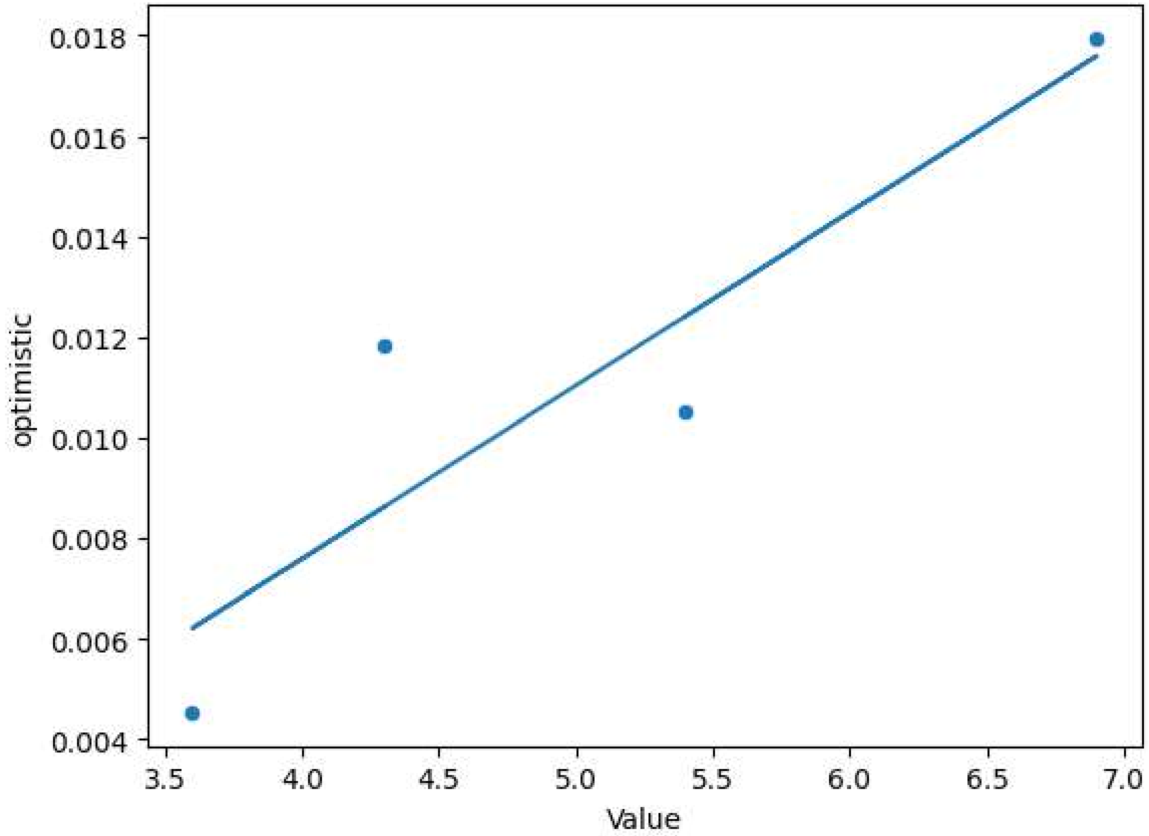
```
0.8137769438783127
```

In [26]:

```
sns.scatterplot(data=df_master_res_opt,x= 'Value',y= 'optimistic')
plt.plot(df_master_res_opt['Value'], prediccion)
```

Out[26]:

```
[<matplotlib.lines.Line2D at 0x21019d54190>]
```

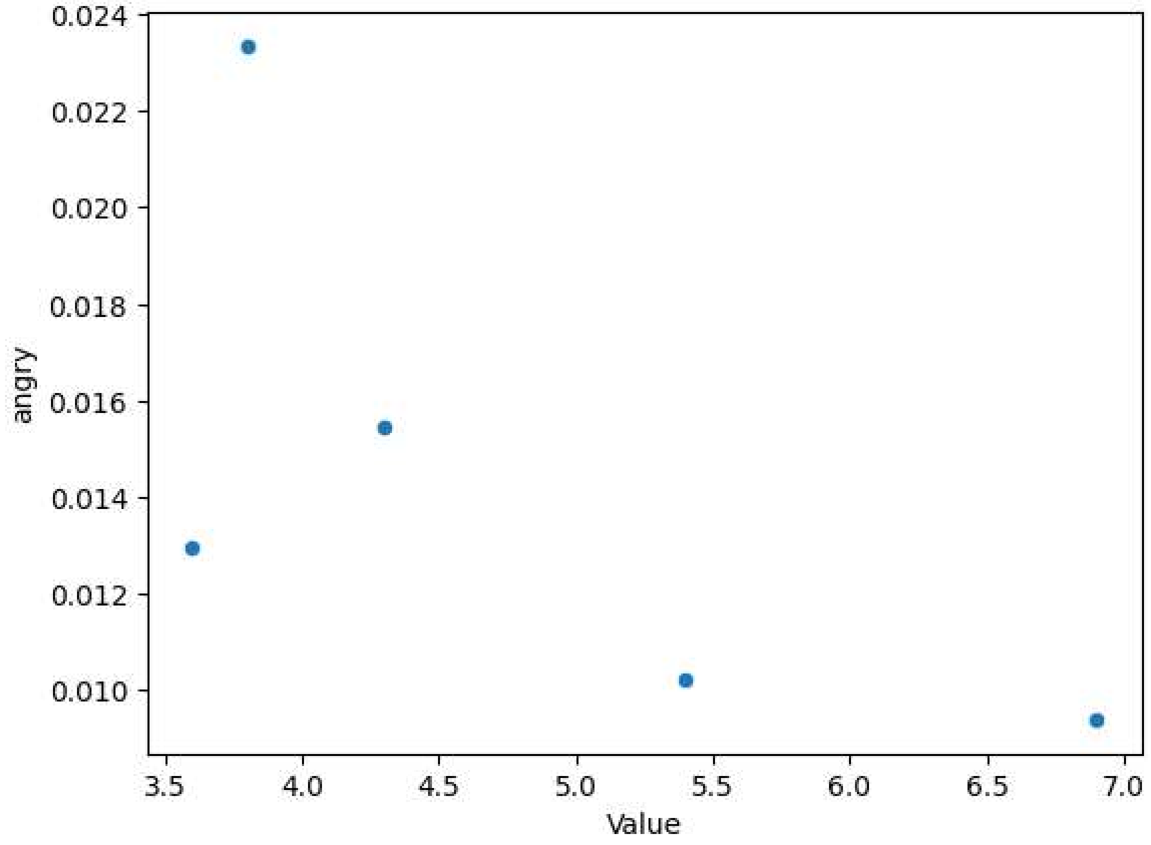


In [27]:

```
sns.scatterplot(data=df_master_res,x= 'Value',y= 'angry')
```

Out[27]:

```
<AxesSubplot: xlabel='Value', ylabel='angry'>
```



In [29]:

```
df_master_res_ang = df_master_res.drop(index=(2018))

model.fit(np.array(df_master_res_ang['Value']).reshape(-1,1), df_master_res_ang['angry'])
prediccion = model.predict(np.array(df_master_res_ang['Value']).reshape(-1,1))
print(metrics.r2_score(df_master_res_ang['angry'], prediccion))
```

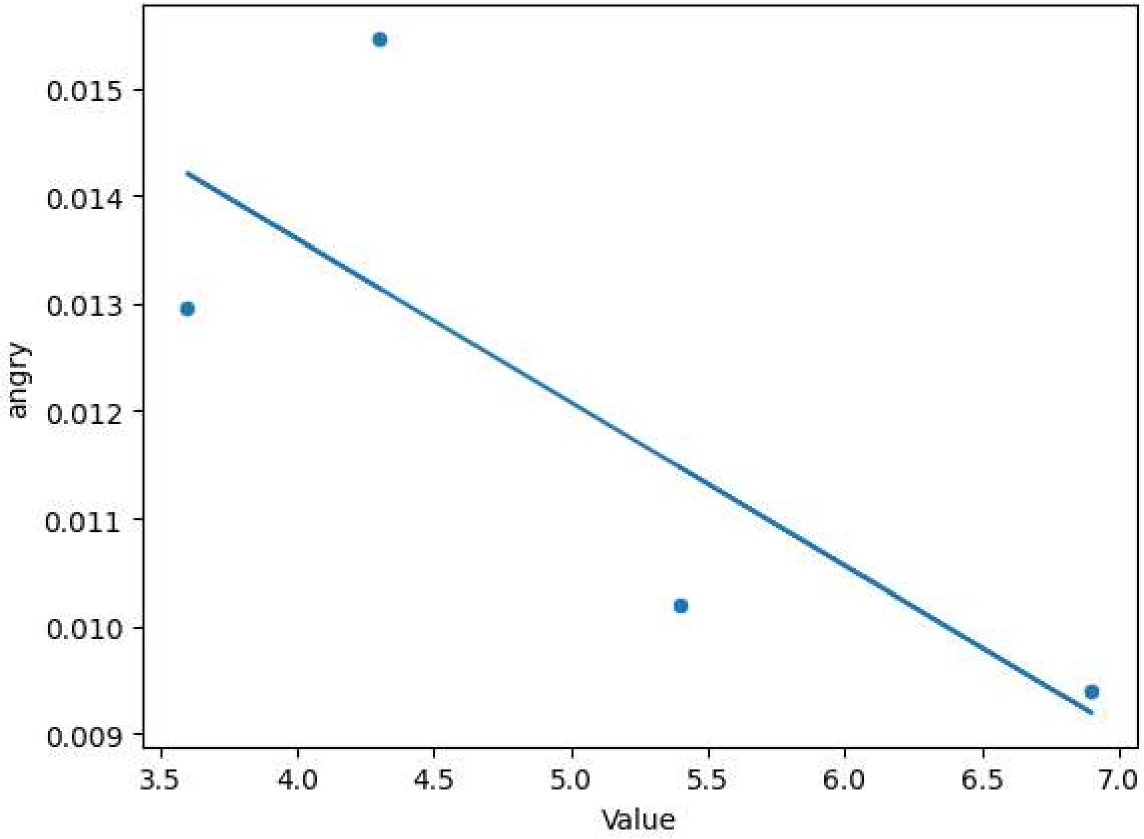
```
0.6252641152419298
```

In [30]:

```
sns.scatterplot(data=df_master_res_ang,x= 'Value',y= 'angry')
plt.plot(df_master_res_ang['Value'], prediccion)
```

Out[30]:

```
[<matplotlib.lines.Line2D at 0x21016a692d0>]
```

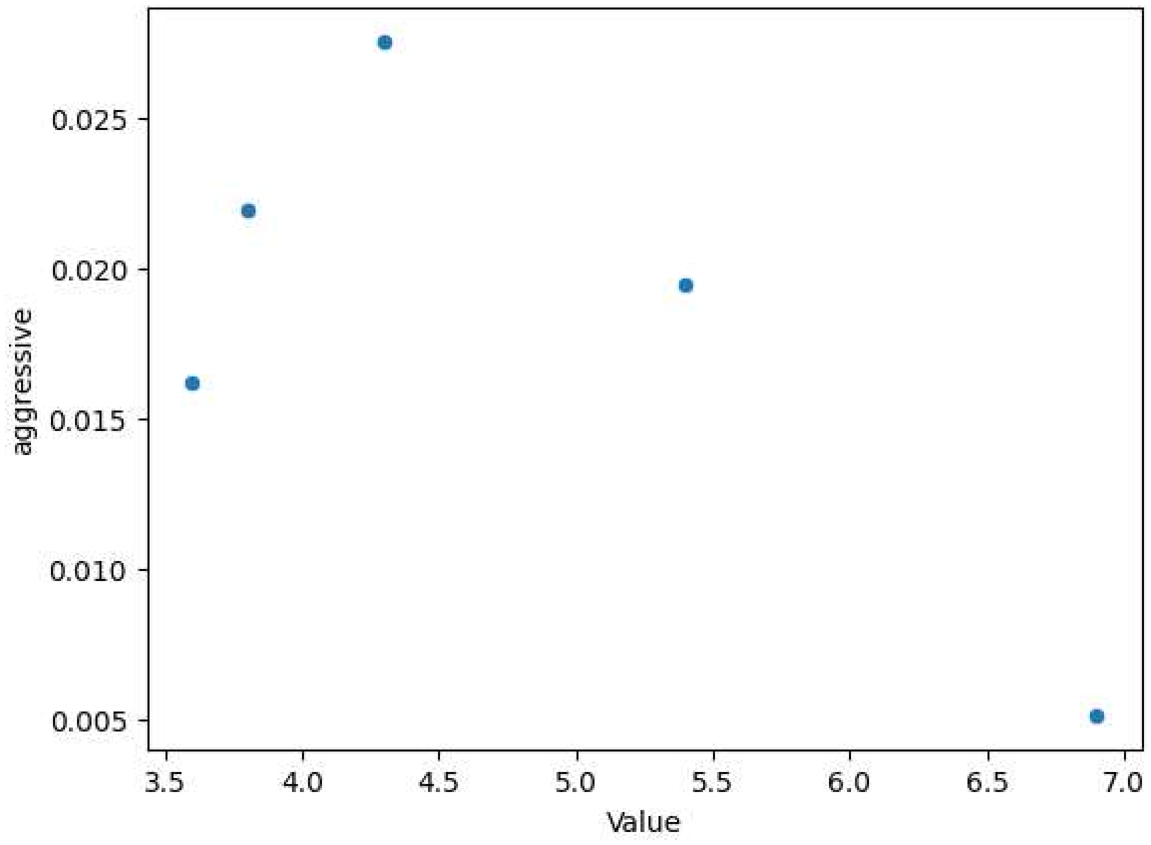


In [31]:

```
sns.scatterplot(data=df_master_res,x= 'Value',y= 'aggressive')
```

Out[31]:

```
<AxesSubplot: xlabel='Value', ylabel='aggressive'>
```



In [32]:

```
df_master_res_ang = df_master_res.drop(index=(2020))

model.fit(np.array(df_master_res_ang['Value']).reshape(-1,1), df_master_res_ang['aggressive
prediccion = model.predict(np.array(df_master_res_ang['Value']).reshape(-1,1))
print(metrics.r2_score(df_master_res_ang['aggressive'], prediccion))
```

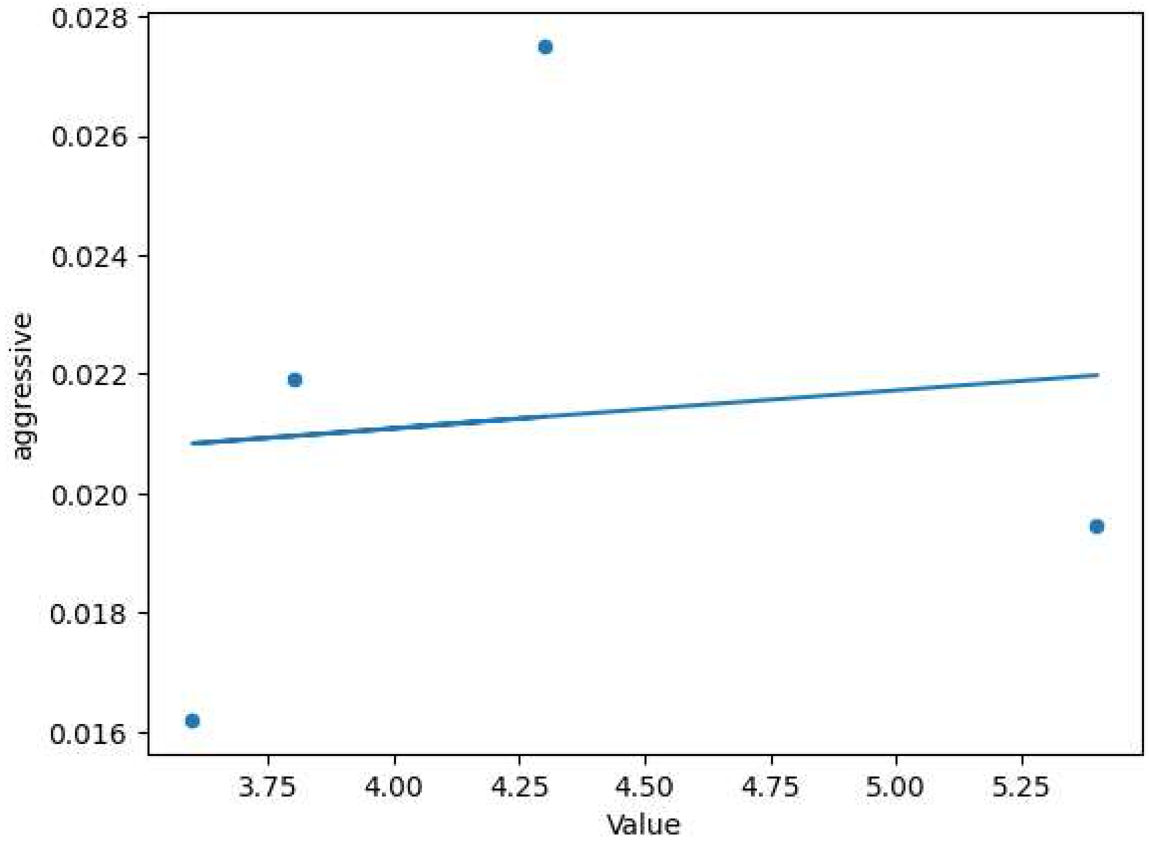
```
0.011423683490765613
```

In [33]:

```
sns.scatterplot(data=df_master_res_ang,x= 'Value',y= 'aggressive')
plt.plot(df_master_res_ang['Value'], prediccion)
```

Out[33]:

```
[<matplotlib.lines.Line2D at 0x2101ae0cc50>]
```



Año 2020

In [34]:

```
df_master1 = df_master[df_master['year']==2020]
df_master1.head()
```

Out[34]:

	year	month	angry	Value	aggressive	romantic	optimistic	positive	powerful	lig
36	2020	1	0.024111	3.5	0.001871	0.015174	0.023072	0.004781	0.014966	0.0002
37	2020	2	0.021570	3.5	0.004765	0.017055	0.026336	0.017808	0.019313	0.0025
38	2020	3	0.013183	4.4	0.008878	0.019101	0.016680	0.008071	0.022868	0.0000
39	2020	4	0.007899	14.7	0.007159	0.018761	0.016786	0.008887	0.033572	0.0004
40	2020	5	0.008796	13.2	0.003848	0.020616	0.017592	0.009071	0.034360	0.0005

In [35]:

```
display(df_master1.sort_values('Value')[['angry','sad','positive', 'optimistic','aggressive
```

	angry	sad	positive	optimistic	aggressive	Value
36	0.024111	0.080649	0.004781	0.023072	0.001871	3.5
37	0.021570	0.090043	0.017808	0.026336	0.004765	3.5
38	0.013183	0.082863	0.008071	0.016680	0.008878	4.4
46	0.011820	0.053323	0.006042	0.021539	0.000263	6.7
47	0.015573	0.038933	0.001888	0.017933	0.001652	6.7
45	0.009396	0.051253	0.009112	0.017938	0.005125	6.9
44	0.013618	0.058805	0.011142	0.020427	0.008976	7.9
43	0.027602	0.064117	0.008913	0.021564	0.002300	8.4
42	0.017827	0.058574	0.009055	0.021222	0.003679	10.2
41	0.015982	0.059361	0.007864	0.017504	0.008625	11.0
40	0.008796	0.065421	0.009071	0.017592	0.003848	13.2
39	0.007899	0.069612	0.008887	0.016786	0.007159	14.7

In [36]:

```
model.fit(np.array(df_master1['Value']).reshape(-1,1), df_master1['aggressive'])
predicion = model.predict(np.array(df_master1['Value']).reshape(-1,1))
print(metrics.r2_score(df_master1['aggressive'], predicion))
```

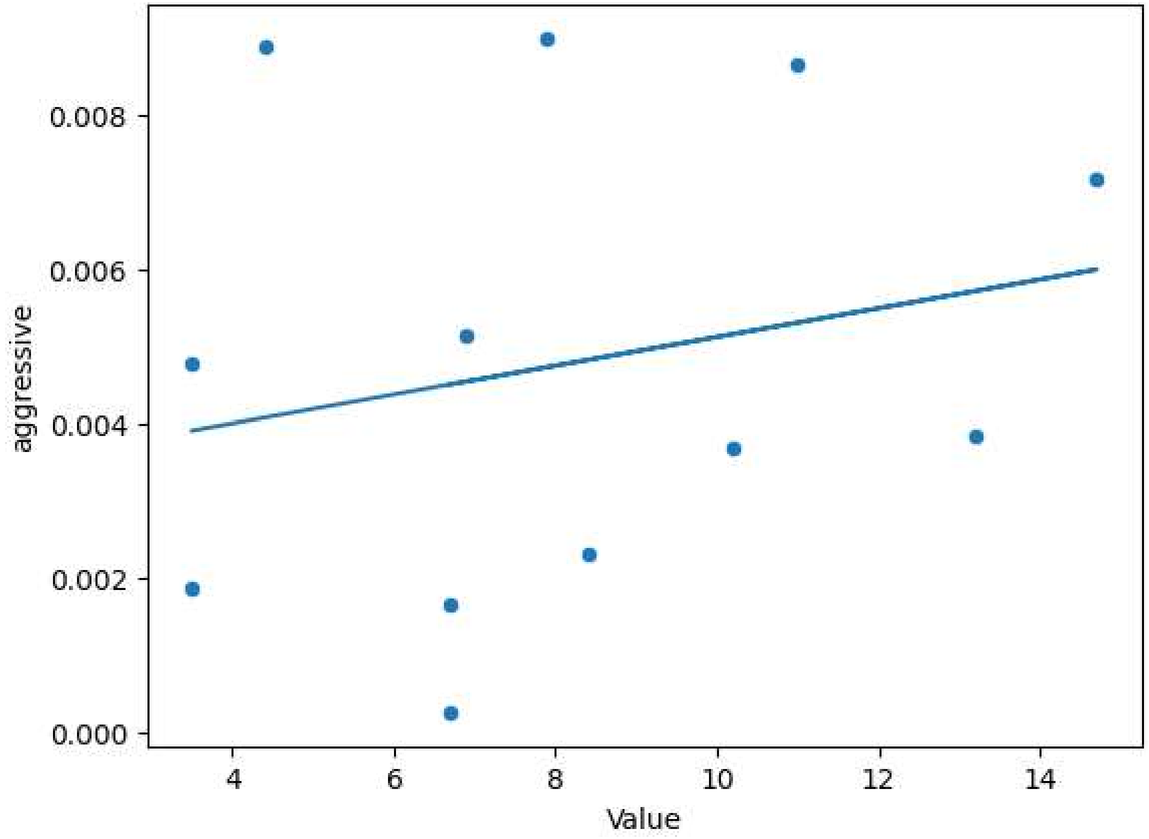
```
0.04892682641845125
```

In [37]:

```
sns.scatterplot(data=df_master1,x= 'Value',y= 'aggressive')
plt.plot(df_master1['Value'], predicion)
```

Out[37]:

```
[<matplotlib.lines.Line2D at 0x210155b1550>]
```


aggressive
Value