Practica_Muestreo

July 25, 2023

Reporte del Proceso de Muestreo

Marco Antonio Obregón Flores

Paso 1: Identificar y definir el grupo objetivo

El conjunto de datos está compuesto por diversas reseñas de anime, con información variada como el título, el género, la popularidad y las calificaciones dadas por los usuarios. Nuestro grupo objetivo es el género del anime, ya que buscamos realizar un análisis basado en estos distintos géneros.

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[2]:
```
df_anime = pd.read_csv("/Users/marcgrayson/Documents/Big Data/Practica 4␣
↪Muestreo/archive (3)/final_animedataset.csv")
```

[3]:
```
df_anime.head()
```

[3]:

	username	anime_id	my_score	user_id	gender	title	type	source	score	scored_by	rank	popularity	genre
0	karthiga	21	9	2255153	Female	One Piece	TV	Manga	8.54	423868	91.0	35	Action, Adventure, Comedy, Super Power, Drama,…
1	karthiga	59	7	2255153	Female	Chobits	TV	Manga	7.53	175388	1546.0	188	Sci-Fi, Comedy, Drama, Romance, Ecchi, Seinen
2	karthiga	74	7	2255153	Female	Gakuen Alice	TV	Manga	7.77	33244	941.0	1291	Comedy, School, Shoujo, Super Power
3	karthiga	120	7	2255153	Female	Fruits Basket	TV	Manga	7.77	167968	939.0	222	Slice of Life, Comedy, Drama, Romance, Fantasy…
4	karthiga	178	7	2255153	Female	Ultra Maniac	TV	Manga	7.26	9663	2594.0	2490	Magic, Comedy, Romance, School, Shoujo

[54]:
```
# Rows
df_anime.shape[0]
```

[54]:
```
35305695
```

Paso 2: Crear un rango específico de muestreo

Se decide utilizar una fracción del conjunto de datos original debido a su gran tamaño. Se seleccionó aleatoriamente un 10% del conjunto de datos original para facilitar el manejo de los datos.

[28]:
```
df_frac = df_anime.sample(frac=0.1)
```

[29]:
```
df_sample.shape[0]
```

[29]:
```
3530570
```

Paso 3: Seleccionar el método adecuado para los datos

Se decide utilizar el muestreo estratificado para garantizar que cada género estuviera representado en nuestra muestra. Primero, separamos los géneros, que estaban en una única columna separada por comas, en varias filas para facilitar el análisis. Luego, realizamos un muestreo estratificado basado en la popularidad de cada género.

[30]:
```
df_popularity_sample = df_frac.sample(n=1000, weights='popularity',␣
↪random_state=1)
```

[32]:
```
# Crear una nueva columna que es una lista de los géneros
df_popularity_sample2 = df_popularity_sample
df_popularity_sample2['genre_list'] = df_popularity_sample2['genre'].str.
↪split(', ')

# Explode la lista de géneros en filas separadas
df_genre_exploded = df_popularity_sample2.explode('genre_list')
```

[33]:
```
df_genre_exploded.head()
```

[33]:

	username	anime_id	my_score	user_id	gender	title	type
7278571	1st_King	3466	7	4455785	Male	Kino no Tabi: The Beautiful World - Tou no Kuni	Special
7278571	1st_King	3466	7	4455785	Male	Kino no Tabi: The Beautiful World - Tou no Kuni	Special
7278571	1st_King	3466	7	4455785	Male	Kino no Tabi: The Beautiful World - Tou no Kuni	Special
22776852	tomu	7375	0	239407	Male	Shakugan no Shana S Specials	Special
22776852	tomu	7375	0	239407	Male	Shakugan no Shana S Specials	Special

```
              source  score  scored_by    rank  popularity  \
7278571   Light novel   7.67      13521  1170.0        2320
7278571   Light novel   7.67      13521  1170.0        2320
7278571   Light novel   7.67      13521  1170.0        2320
22776852  Light novel   6.99       9162  3616.0        2671
22776852  Light novel   6.99       9162  3616.0        2671

                                      genre     genre_list
7278571   Adventure, Fantasy, Psychological      Adventure
7278571   Adventure, Fantasy, Psychological        Fantasy
7278571   Adventure, Fantasy, Psychological  Psychological
22776852                    Comedy, Parody         Comedy
22776852                    Comedy, Parody         Parody
```

Paso 4: Especificar el tamaño de la muestra

Se decide que el tamaño de la muestra sería de 1000 registros. Los tamaños de las muestras para cada estrato (género) se calcularon basándose en las proporciones de cada género en el conjunto de datos.

[38]:
```
#
sample_size = 1000

# Calcular los tamaños de las muestras para cada estrato (género)
stratum_sizes = df_genre_exploded['genre_list'].value_counts(normalize=True) *␣
 ↪sample_size

# Redondear los tamaños de las muestras a enteros y convertir a diccionario
stratum_sizes = np.round(stratum_sizes).astype(int).to_dict()
```

[39]:
```
print(stratum_sizes)
```

```
{'Comedy': 120, 'Action': 79, 'Sci-Fi': 62, 'Fantasy': 62, 'Adventure': 60,
'Drama': 59, 'Romance': 58, 'Shounen': 51, 'School': 48, 'Supernatural': 39,
'Slice of Life': 37, 'Ecchi': 27, 'Magic': 26, 'Mecha': 23, 'Seinen': 22,
'Shoujo': 19, 'Super Power': 17, 'Historical': 16, 'Hentai': 16, 'Mystery': 15,
'Military': 15, 'Harem': 13, 'Sports': 12, 'Music': 11, 'Psychological': 10,
'Parody': 10, 'Space': 9, 'Martial Arts': 9, 'Demons': 9, 'Horror': 8, 'Game':
6, 'Kids': 6, 'Samurai': 5, 'Police': 4, 'Shoujo Ai': 3, 'Thriller': 3,
'Vampire': 3, 'Josei': 2, 'Dementia': 2, 'Yaoi': 2, 'Shounen Ai': 1}
```

Paso 5: Recolectar los datos muestreados

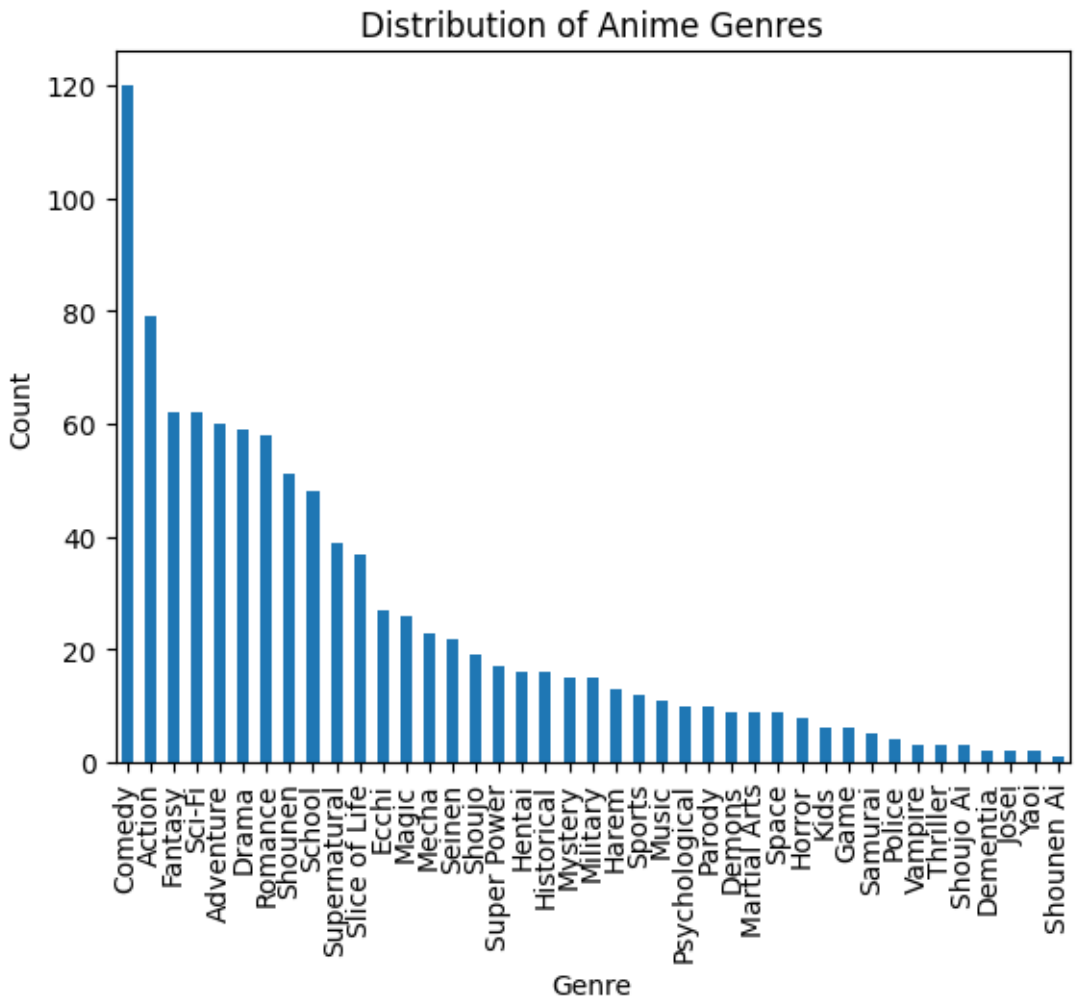
Aplicamos la función de muestreo estratificado a nuestro conjunto de datos y obtuvimos una muestra estratificada. En esta muestra, cada género estaba representado en proporción a su prevalencia en el conjunto de datos original.

Finalmente, se realizó un análisis de las calificaciones medias por género y se descubrió que los géneros con las calificaciones promedio más altas eran Thriller, Dementia y Vampire. Esto propor-

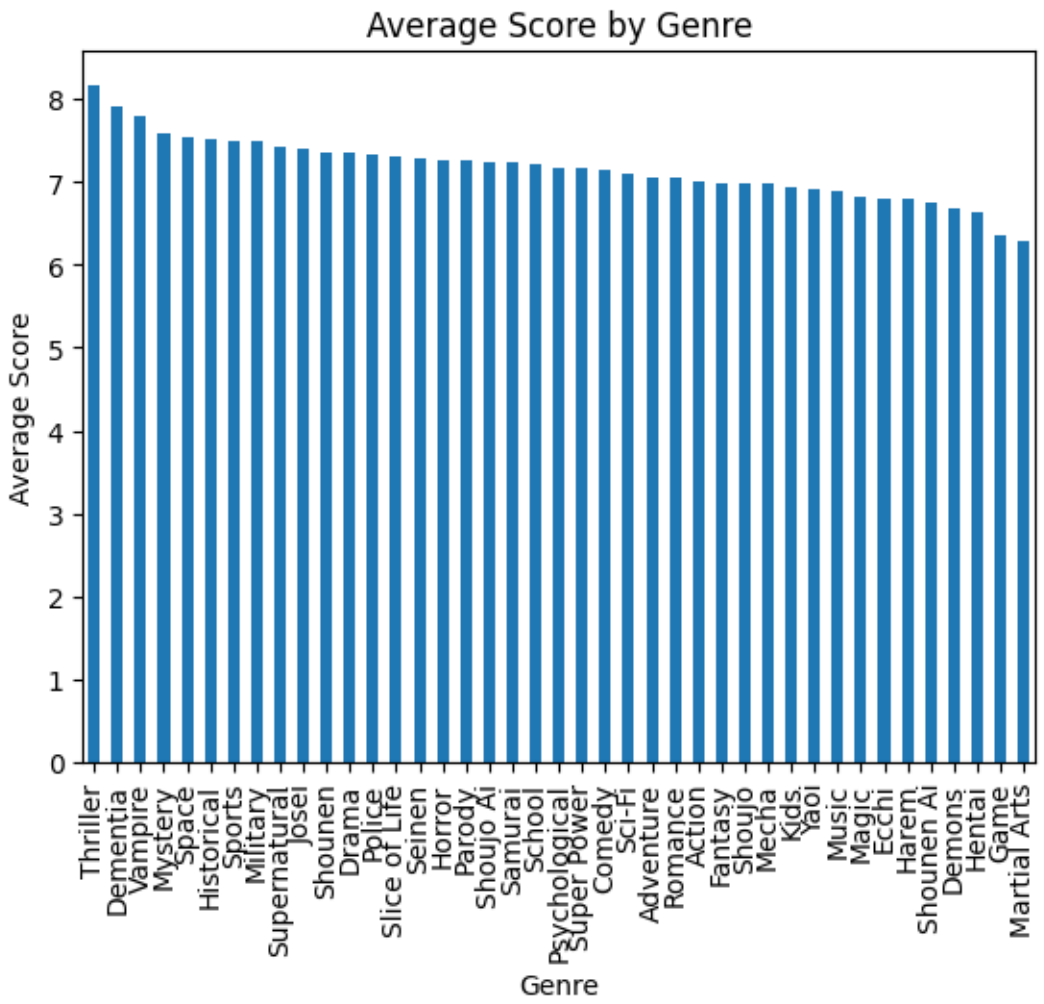
ciona un insight valioso para los creadores de contenido de anime y los aficionados al anime, ya que muestra qué géneros tienden a ser mejor valorados por los espectadores. Además, la visualización de los datos a través de gráficos de barras y boxplots permitió entender mejor la distribución y el rango de las calificaciones para cada género.

[40]:
```
# Definir una función para hacer el muestreo estratificado
def stratified_sample(group):
    genre = group.name
    n = stratum_sizes.get(genre, 0)
    return group.sample(n=n)

# Aplicar el muestreo estratificado
df_stratified_sample = df_genre_exploded.groupby('genre_list',␣
 ↪group_keys=False).apply(stratified_sample)
```

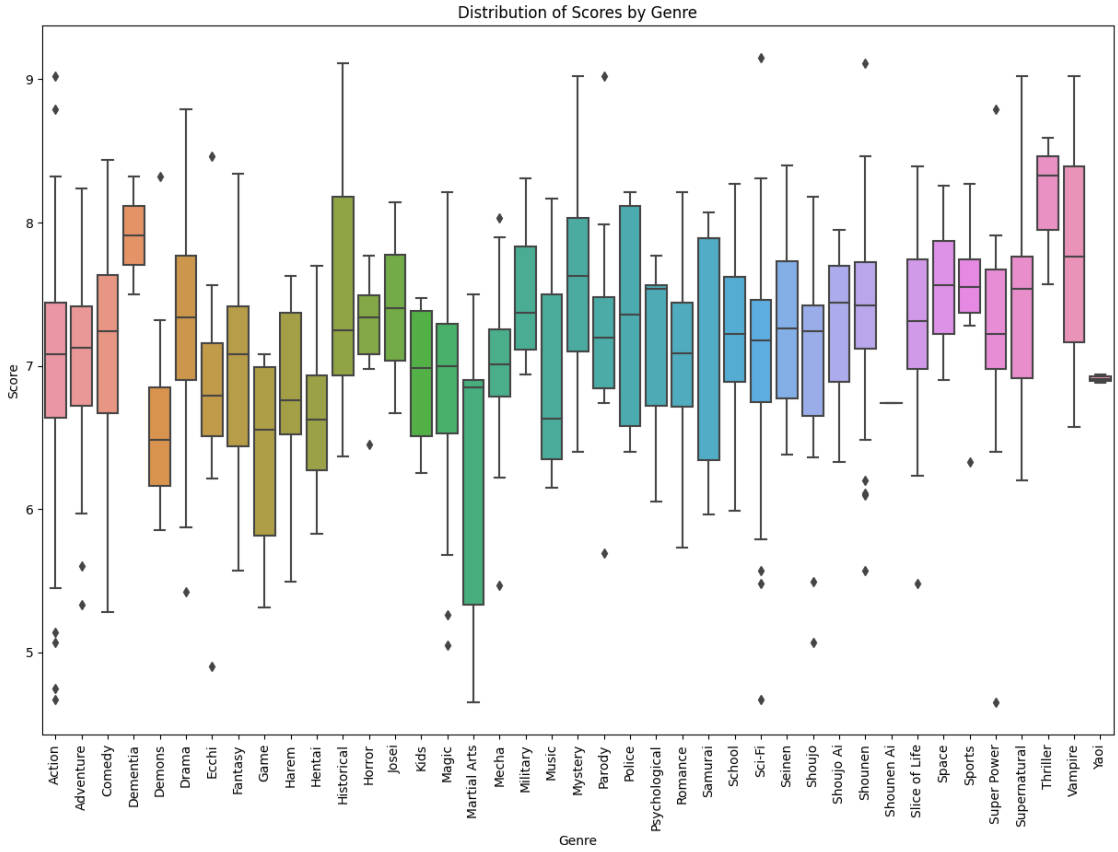
[44]:
```
import matplotlib.pyplot as plt
df_stratified_sample['genre_list'].value_counts().plot(kind='bar')
plt.xlabel('Genre')
plt.ylabel('Count')
plt.title('Distribution of Anime Genres')
plt.show()
```



[48]:
```
mean_scores = df_stratified_sample.groupby('genre_list')['score'].mean().
  ↪sort_values(ascending=False)
mean_scores.plot(kind='bar')
plt.xlabel('Genre')
plt.ylabel('Average Score')
plt.title('Average Score by Genre')
plt.show()
```



[49]:
```
import seaborn as sns
plt.figure(figsize=(15, 10))
sns.boxplot(x='genre_list', y='score', data=df_stratified_sample)
plt.xlabel('Genre')
plt.ylabel('Score')
plt.title('Distribution of Scores by Genre')
plt.xticks(rotation=90)
plt.show()
```



[52]:
```
# Calcular las calificaciones promedio por género
mean_scores = df_stratified_sample.groupby('genre_list')['score'].mean().
  ↪sort_values(ascending=False)

# Convertir el resultado en un DataFrame
mean_scores_df = mean_scores.reset_index()

# Cambiar el nombre de las columnas
mean_scores_df.columns = ['Genre', 'Average Score']

print(mean_scores_df)
```

```
           Genre  Average Score
0       Thriller       8.163333
1       Dementia       7.910000
2        Vampire       7.783333
3        Mystery       7.593333
4          Space       7.550000
5     Historical       7.509375
6         Sports       7.503333
```

```
7        Military       7.491333
8    Supernatural       7.417692
9           Josei       7.405000
10        Shounen       7.365294
11          Drama       7.342373
12         Police       7.332500
13  Slice of Life       7.301081
14         Seinen       7.285455
15         Horror       7.261250
16         Parody       7.253000
17      Shoujo Ai       7.240000
18        Samurai       7.230000
19         School       7.222500
20  Psychological       7.174000
21    Super Power       7.170588
22         Comedy       7.142167
23         Sci-Fi       7.088548
24      Adventure       7.060500
25        Romance       7.050172
26         Action       6.994430
27        Fantasy       6.991613
28         Shoujo       6.990526
29          Mecha       6.977391
30           Kids       6.926667
31           Yaoi       6.910000
32          Music       6.888182
33          Magic       6.828077
34          Ecchi       6.806667
35          Harem       6.803077
36     Shounen Ai       6.740000
37         Demons       6.673333
38         Hentai       6.642500
39           Game       6.366667
40   Martial Arts       6.296667
```

[53]:
```python
# Calcular estadísticas descriptivas por género
boxplot_stats = df_stratified_sample.groupby('genre_list')['score'].describe()

# Convertir el resultado en un DataFrame
boxplot_stats_df = boxplot_stats.reset_index()

print(boxplot_stats_df)
```

```
       genre_list  count      mean       std   min     25%    50%     75%  \
0          Action   79.0  6.994430  0.848839  4.67  6.6400  7.080  7.4400
1       Adventure   60.0  7.060500  0.610775  5.33  6.7200  7.125  7.4125
2          Comedy  120.0  7.142167  0.697848  5.28  6.6700  7.240  7.6350
3        Dementia    2.0  7.910000  0.579828  7.50  7.7050  7.910  8.1150
```

4	Demons	9.0	6.673333	0.766355	5.85	6.1600	6.480	6.8500
5	Drama	59.0	7.342373	0.649021	5.42	6.9000	7.340	7.7700
6	Ecchi	27.0	6.806667	0.619839	4.90	6.5100	6.790	7.1600
7	Fantasy	62.0	6.991613	0.692975	5.57	6.4375	7.080	7.4175
8	Game	6.0	6.366667	0.747922	5.31	5.8150	6.555	6.9875
9	Harem	13.0	6.803077	0.590768	5.49	6.5200	6.760	7.3700
10	Hentai	16.0	6.642500	0.501750	5.83	6.2700	6.625	6.9350
11	Historical	16.0	7.509375	0.807552	6.37	6.9325	7.245	8.1775
12	Horror	8.0	7.261250	0.421271	6.45	7.0775	7.340	7.4950
13	Josei	2.0	7.405000	1.039447	6.67	7.0375	7.405	7.7725
14	Kids	6.0	6.926667	0.533392	6.25	6.5100	6.985	7.3850
15	Magic	26.0	6.828077	0.735929	5.05	6.5275	6.995	7.2950
16	Martial Arts	9.0	6.296667	1.079977	4.65	5.3300	6.850	6.9000
17	Mecha	23.0	6.977391	0.554578	5.47	6.7850	7.010	7.2550
18	Military	15.0	7.491333	0.484869	6.94	7.1150	7.370	7.8350
19	Music	11.0	6.888182	0.703503	6.15	6.3500	6.630	7.5000
20	Mystery	15.0	7.593333	0.685072	6.40	7.1000	7.630	8.0300
21	Parody	10.0	7.253000	0.871449	5.69	6.8400	7.195	7.4800
22	Police	4.0	7.332500	0.944788	6.40	6.5800	7.360	8.1125
23	Psychological	10.0	7.174000	0.594590	6.05	6.7175	7.540	7.5650
24	Romance	58.0	7.050172	0.564715	5.73	6.7150	7.090	7.4400
25	Samurai	5.0	7.230000	0.997722	5.96	6.3400	7.890	7.8900
26	School	48.0	7.222500	0.542577	5.99	6.8875	7.220	7.6225
27	Sci-Fi	62.0	7.088548	0.700494	4.67	6.7450	7.180	7.4625
28	Seinen	22.0	7.285455	0.598910	6.38	6.7750	7.260	7.7300
29	Shoujo	19.0	6.990526	0.741826	5.07	6.6500	7.240	7.4200
30	Shoujo Ai	3.0	7.240000	0.828312	6.33	6.8850	7.440	7.6950
31	Shounen	51.0	7.365294	0.636350	5.57	7.1200	7.420	7.7250
32	Shounen Ai	1.0	6.740000	NaN	6.74	6.7400	6.740	6.7400
33	Slice of Life	37.0	7.301081	0.647837	5.48	6.9800	7.310	7.7400
34	Space	9.0	7.550000	0.449694	6.90	7.2200	7.560	7.8700
35	Sports	12.0	7.503333	0.460481	6.33	7.3700	7.550	7.7425
36	Super Power	17.0	7.170588	0.872951	4.65	6.9800	7.220	7.6700
37	Supernatural	39.0	7.417692	0.633937	6.20	6.9150	7.540	7.7650
38	Thriller	3.0	8.163333	0.530031	7.57	7.9500	8.330	8.4600
39	Vampire	3.0	7.783333	1.225167	6.57	7.1650	7.760	8.3900
40	Yaoi	2.0	6.910000	0.042426	6.88	6.8950	6.910	6.9250

	max
0	9.02
1	8.24
2	8.44
3	8.32
4	8.32
5	8.79
6	8.46
7	8.34
8	7.08

```
9   7.63
10  7.70
11  9.11
12  7.77
13  8.14
14  7.47
15  8.21
16  7.50
17  8.03
18  8.31
19  8.17
20  9.02
21  9.02
22  8.21
23  7.77
24  8.21
25  8.07
26  8.27
27  9.15
28  8.40
29  8.18
30  7.95
31  9.11
32  6.74
33  8.39
34  8.26
35  8.27
36  8.79
37  9.02
38  8.59
39  9.02
40  6.94
```

[206]:
```
df_anime_unique = df_anime.drop_duplicates(subset='title')
```

[207]:
```
df_anime_unique.head()
```

[207]:

	username	anime_id	my_score	user_id	gender	title	type	source	score	scored_by	rank	popularity
0	karthiga	21	9	2255153	Female	One Piece	TV	Manga	8.54	423868	91.0	35
1	karthiga	59	7	2255153	Female	Chobits	TV	Manga	7.53	175388	1546.0	188
2	karthiga	74	7	2255153	Female	Gakuen Alice	TV	Manga				
3	karthiga	120	7	2255153	Female	Fruits Basket	TV	Manga				
4	karthiga	178	7	2255153	Female	Ultra Maniac	TV	Manga				

```
2   7.77      33244   941.0        1291
3   7.77     167968   939.0         222
4   7.26       9663  2594.0        2490

                                                 genre
0  Action, Adventure, Comedy, Super Power, Drama,…
1      Sci-Fi, Comedy, Drama, Romance, Ecchi, Seinen
2                 Comedy, School, Shoujo, Super Power
3  Slice of Life, Comedy, Drama, Romance, Fantasy…
4              Magic, Comedy, Romance, School, Shoujo
```

[208]:
```
df_anime_ls = df_anime_unique.copy()
df_anime_ls['genre_list'] = df_anime_ls['genre'].str.split(', ')
```

[209]:
```
df_anime_ls
```

[209]:
```
              username  anime_id  my_score  user_id  gender  \
0              karthiga        21         9  2255153  Female
1              karthiga        59         7  2255153  Female
2              karthiga        74         7  2255153  Female
3              karthiga       120         7  2255153  Female
4              karthiga       178         7  2255153  Female
…                   …         …         …        …       …
942083    DeadlyKizuna     19925         0  1237755    Male
977569    AtomskLevent     36876         0   407248    Male
1067114   LeoneTheKing     36254        10  5481345    Male
1474125       niepokon     36790         5  5475906    Male
15789900       uemmega     37863         0  4561255    Male

                         title   type        source  score  scored_by    rank  \
0                    One Piece     TV         Manga   8.54     423868    91.0
1                      Chobits     TV         Manga   7.53     175388  1546.0
2                 Gakuen Alice     TV         Manga   7.77      33244   941.0
3                Fruits Basket     TV         Manga   7.77     167968   939.0
4                  Ultra Maniac     TV         Manga   7.26       9663  2594.0
…                           …    …           …    …       …     …
942083    KY-kei JC Kuuki-chan    ONA      Original   5.60        209  8196.0
977569               Furifure 2    OVA  Visual novel   6.44        252     NaN
1067114          Jukujo Shigan    OVA      Original   5.80        226     NaN
1474125     Ling Yu 2nd Season    ONA         Novel   6.93        215  3814.0
15789900        Diamond Fusion  Music          Game   7.27        240  2514.0

          popularity                                          genre  \
0                 35  Action, Adventure, Comedy, Super Power, Drama,…
1                188      Sci-Fi, Comedy, Drama, Romance, Ecchi, Seinen
2               1291                 Comedy, School, Shoujo, Super Power
3                222  Slice of Life, Comedy, Drama, Romance, Fantasy…
```

```
4               2490             Magic, Comedy, Romance, School, Shoujo
…                …                                                    …
942083          9596                                      Comedy, School
977569          7892                                              Hentai
1067114         8520                                              Hentai
1474125         9338                                             Fantasy
15789900        9237                                               Music

                                                  genre_list
0          [Action, Adventure, Comedy, Super Power, Drama…
1            [Sci-Fi, Comedy, Drama, Romance, Ecchi, Seinen]
2                      [Comedy, School, Shoujo, Super Power]
3          [Slice of Life, Comedy, Drama, Romance, Fantas…
4                    [Magic, Comedy, Romance, School, Shoujo]
…                                                          …
942083                                      [Comedy, School]
977569                                              [Hentai]
1067114                                             [Hentai]
1474125                                            [Fantasy]
15789900                                            [Music]

[8746 rows x 14 columns]
```

[210]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import MultiLabelBinarizer
```

[211]:
```
df_anime_ls['genre_list'] = df_anime_ls['genre_list'].apply(lambda x: x if␣
 ↪isinstance(x, list) else [])
# One-hot encoding for genre_list
mlb = MultiLabelBinarizer()
encoded_genres = pd.DataFrame(mlb.
 ↪fit_transform(df_anime_ls['genre_list']),columns=mlb.classes_,␣
 ↪index=df_anime_ls.index)
df_encoded = pd.concat([df_anime_ls, encoded_genres], axis=1)
```

[212]:
```
df_encoded = df_encoded.drop(columns=['username',␣
 ↪'title','genre_list','anime_id', 'user_id', 'my_score', 'scored_by'])
```

[213]:
```
df_encoded
```

[213]:
```
          gender   type        source  score    rank  popularity  \
0         Female     TV         Manga   8.54    91.0          35
1         Female     TV         Manga   7.53  1546.0         188
2         Female     TV         Manga   7.77   941.0        1291
3         Female     TV         Manga   7.77   939.0         222
4         Female     TV         Manga   7.26  2594.0        2490
…          …     …           …     …      …           …
```

```
942083      Male    ONA      Original   5.60  8196.0        9596
977569      Male    OVA  Visual novel   6.44     NaN        7892
1067114     Male    OVA      Original   5.80     NaN        8520
1474125     Male    ONA         Novel   6.93  3814.0        9338
15789900    Male  Music          Game   7.27  2514.0        9237

                                                  genre  Action  \
0          Action, Adventure, Comedy, Super Power, Drama,…       1
1              Sci-Fi, Comedy, Drama, Romance, Ecchi, Seinen       0
2                        Comedy, School, Shoujo, Super Power       0
3          Slice of Life, Comedy, Drama, Romance, Fantasy…       0
4                    Magic, Comedy, Romance, School, Shoujo       0
…                                                      …     …
942083                                    Comedy, School       0
977569                                            Hentai       0
1067114                                           Hentai       0
1474125                                          Fantasy       0
15789900                                           Music       0

           Adventure  Cars  …  Shounen Ai  Slice of Life  Space  Sports  \
0                  1     0  …           0              0      0       0
1                  0     0  …           0              0      0       0
2                  0     0  …           0              0      0       0
3                  0     0  …           0              1      0       0
4                  0     0  …           0              0      0       0
…                …   …   …  …         …             …    …      …
942083             0     0  …           0              0      0       0
977569             0     0  …           0              0      0       0
1067114            0     0  …           0              0      0       0
1474125            0     0  …           0              0      0       0
15789900           0     0  …           0              0      0       0

           Super Power  Supernatural  Thriller  Vampire  Yaoi  Yuri
0                    1             0         0        0     0     0
1                    0             0         0        0     0     0
2                    1             0         0        0     0     0
3                    0             0         0        0     0     0
4                    0             0         0        0     0     0
…                  …             …       …       …   …   …
942083               0             0         0        0     0     0
977569               0             0         0        0     0     0
1067114              0             0         0        0     0     0
1474125              0             0         0        0     0     0
15789900             0             0         0        0     0     0

[8746 rows x 50 columns]
```

[219]:
```
# Exclude non-numeric columns for K-means
df_kmeans = df_encoded.select_dtypes(include=[np.number])
```

[220]:
```
from sklearn.impute import SimpleImputer

# Crea un imputador que rellenará los valores faltantes con la media
imputer = SimpleImputer(strategy='mean')

# Ajusta el imputador y transforma df_kmeans con los valores imputados
df_kmeans_imputed = pd.DataFrame(imputer.fit_transform(df_kmeans),␣
 ↪columns=df_kmeans.columns)
```

[221]:
```
# Apply KMeans
kmeans = KMeans(n_clusters=5, random_state=0)  # Change n_clusters accordingly
kmeans.fit(df_kmeans_imputed)
```

[221]:
```
KMeans(n_clusters=5, random_state=0)
```

[222]:
```
# Add the cluster labels for each data point to the dataframe
df_encoded['cluster'] = kmeans.labels_
```

[223]:
```
print(df_encoded['cluster'].value_counts())
```

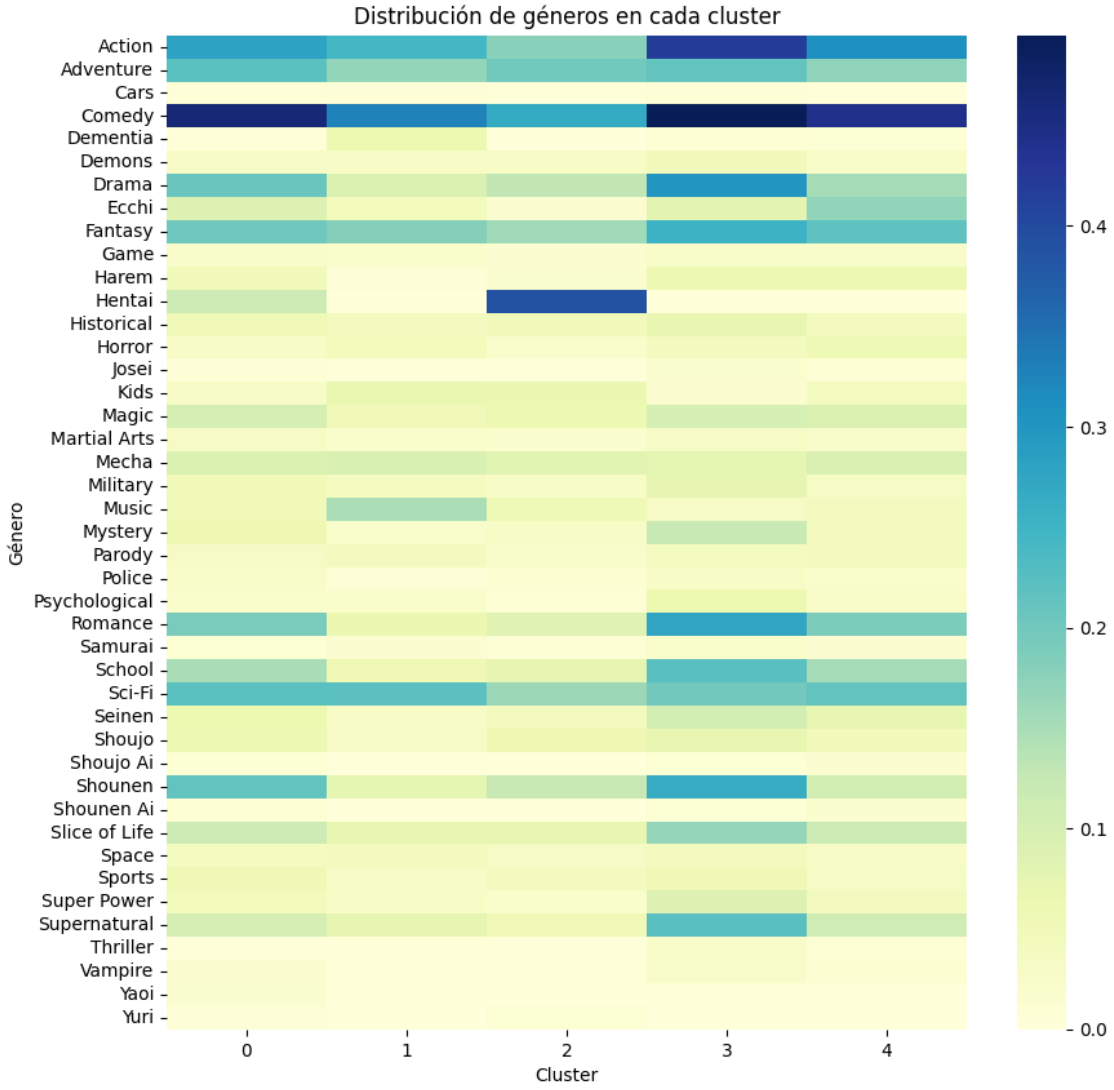
```
2    2183
3    2053
0    1978
1    1401
4    1131
Name: cluster, dtype: int64
```

[224]:
```
cluster_summary_df = df_encoded.groupby('cluster').mean()
print(cluster_summary_df)
```

```
           gender      type     source     score         rank   popularity  \
cluster
0        0.442872  3.438827   8.264408  7.097260  3086.569106  3462.549545
1        0.737330  2.388294   9.890079  5.612448  7779.312634  7929.535332
2        0.741182  3.008704  10.108566  6.595731  4029.776108  6770.591388
3        0.237214  3.724793   6.881637  7.747146  1289.730638  1271.660010
4        0.422635  3.761273   8.372237  6.203192  6455.588859  3657.138815

                genre    Action  Adventure      Cars  …  Shounen Ai  \
cluster                                               …
0        1993.504550  0.281092   0.221941  0.005056  …    0.009606
1        2110.474661  0.244111   0.169879  0.007138  …    0.001428
2        2277.875859  0.176363   0.199725  0.003665  …    0.001374
3        1800.863614  0.418899   0.214321  0.006332  …    0.011203
4        1943.030062  0.308576   0.172414  0.003537  …    0.017683
```

```
         Slice of Life     Space    Sports  Super Power  Supernatural  \
cluster
0             0.115774  0.036906  0.056117     0.046006      0.104146
1             0.072091  0.041399  0.027837     0.029265      0.073519
2             0.071919  0.034356  0.041228     0.020156      0.051306
3             0.167073  0.041890  0.056503     0.088651      0.224062
4             0.114058  0.028294  0.033599     0.042440      0.113174

         Thriller   Vampire      Yaoi      Yuri
cluster
0        0.002528  0.013650  0.016684  0.007078
1        0.005710  0.005710  0.000000  0.000000
2        0.002290  0.004581  0.001374  0.011452
3        0.026303  0.024355  0.000000  0.000000
4        0.008842  0.012378  0.000000  0.000000

[5 rows x 50 columns]
```

[225]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Vamos a seleccionar solo las columnas de los géneros
genre_cols = cluster_summary_df.columns[cluster_summary_df.columns.
  ↪get_loc("Action"):]

# Gráfico de barras de los géneros en cada cluster
plt.figure(figsize=(10,10))
sns.heatmap(cluster_summary_df[genre_cols].T, cmap='YlGnBu')

plt.title('Distribución de géneros en cada cluster')
plt.xlabel('Cluster')
plt.ylabel('Género')
plt.show()
```



[226]:
```python
# Supongamos que df_encoded es tu DataFrame
# Convertimos todas las columnas no numéricas a numéricas
for col in df_encoded.columns:
    if df_encoded[col].dtype == 'object':
        df_encoded[col] = df_encoded[col].astype('category').cat.codes
```

[227]:
```python
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Normalizamos los datos antes de aplicar DBSCAN
scaler = StandardScaler()
df_normalized = scaler.fit_transform(df_encoded)
```

```python
# Ajustamos DBSCAN a los datos normalizados
dbscan = DBSCAN(eps=0.5, min_samples=5)
dbscan.fit(df_normalized)

# Añadimos las etiquetas de cluster a df_encoded
df_encoded['cluster'] = dbscan.labels_
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[227], line 11
      9 # Ajustamos DBSCAN a los datos normalizados
     10 dbscan = DBSCAN(eps=0.5, min_samples=5)
---> 11 dbscan.fit(df_normalized)
     13 # Añadimos las etiquetas de cluster a df_encoded
     14 df_encoded['cluster'] = dbscan.labels_

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/
 ↪site-packages/sklearn/cluster/_dbscan.py:347, in DBSCAN.fit(self, X, y,␣
 ↪sample_weight)
    322 def fit(self, X, y=None, sample_weight=None):
    323     """Perform DBSCAN clustering from features, or distance matrix.
    324
    325     Parameters
   (…)
    345         Returns a fitted instance of self.
    346     """
--> 347     X = self._validate_data(X, accept_sparse="csr")
    349     if sample_weight is not None:
    350         sample_weight = _check_sample_weight(sample_weight, X)

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/
 ↪site-packages/sklearn/base.py:577, in BaseEstimator._validate_data(self, X, y ␣
 ↪reset, validate_separately, **check_params)
    575     raise ValueError("Validation should be done on X, y or both.")
    576 elif not no_val_X and no_val_y:
--> 577     X = check_array(X, input_name="X", **check_params)
    578     out = X
    579 elif no_val_X and not no_val_y:

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/
 ↪site-packages/sklearn/utils/validation.py:899, in check_array(array,␣
 ↪accept_sparse, accept_large_sparse, dtype, order, copy, force_all_finite,␣
 ↪ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator,␣
 ↪input_name)
    893         raise ValueError(
    894             "Found array with dim %d. %s expected <= 2."
    895             % (array.ndim, estimator_name)
```

```
    896         )
    898     if force_all_finite:
--> 899         _assert_all_finite(
    900             array,
    901             input_name=input_name,
    902             estimator_name=estimator_name,
    903             allow_nan=force_all_finite == "allow-nan",
    904         )
    906 if ensure_min_samples > 0:
    907     n_samples = _num_samples(array)

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/
 ↪site-packages/sklearn/utils/validation.py:146, in _assert_all_finite(X,␣
 ↪allow_nan, msg_dtype, estimator_name, input_name)
    124         if (
    125             not allow_nan
    126             and estimator_name
   (…)
    130             # Improve the error message on how to handle missing values
 ↪in
    131             # scikit-learn.
    132             msg_err += (
    133                 f"\n{estimator_name} does not accept missing values"
    134                 " encoded as NaN natively. For supervised learning, you
 ↪might want"
   (…)
    144                 "#estimators-that-handle-nan-values"
    145             )
--> 146         raise ValueError(msg_err)
    148 # for object dtype data, we only check for NaNs (GH-13254)
    149 elif X.dtype == np.dtype("object") and not allow_nan:

ValueError: Input X contains NaN.
DBSCAN does not accept missing values encoded as NaN natively. For supervised␣
 ↪learning, you might want to consider sklearn.ensemble.
 ↪HistGradientBoostingClassifier and Regressor which accept missing values␣
 ↪encoded as NaNs natively. Alternatively, it is possible to preprocess the␣
 ↪data, for instance by using an imputer transformer in a pipeline or drop␣
 ↪samples with missing values. See https://scikit-learn.org/stable/modules/
 ↪impute.html You can find a list of all estimators that handle NaN values at␣
 ↪the following page: https://scikit-learn.org/stable/modules/impute.
 ↪html#estimators-that-handle-nan-values
```

[228]:
```
from sklearn.preprocessing import StandardScaler

# Normalizamos los datos antes de aplicar DBSCAN
scaler = StandardScaler()
df_normalized = scaler.fit_transform(df_encoded_clean)
```

```
# Ajustamos PCA a los datos normalizados
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(df_normalized)

# Creamos un DataFrame con las componentes principales
principalDf = pd.DataFrame(data = principalComponents, columns = ['principal␣
 ↪component 1', 'principal component 2'])

# Añadimos las etiquetas de cluster a principalDf
principalDf['cluster'] = dbscan.labels_

# Visualizamos los clusters
plt.figure(figsize=(10,10))
sns.scatterplot(data=principalDf, x='principal component 1', y='principal␣
 ↪component 2', hue='cluster', palette='viridis')

plt.title('Visualización de los clusters en 2D usando PCA')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[228], line 15
     12 principalDf = pd.DataFrame(data = principalComponents, columns =␣
 ↪['principal component 1', 'principal component 2'])
     14 # Añadimos las etiquetas de cluster a principalDf
---> 15 principalDf['cluster'] = dbscan.labels_
     17 # Visualizamos los clusters
     18 plt.figure(figsize=(10,10))

AttributeError: 'DBSCAN' object has no attribute 'labels_'
```

[235]:
```
print(df_encoded)
```

```
          gender  type  source  score    rank  popularity  genre  Action  \
0              0     5       6   8.54    91.0          35    101       1
1              0     5       6   7.53  1546.0         188   3409       0
2              0     5       6   7.77   941.0        1291   2266       0
3              0     5       6   7.77   939.0         222   3535       0
4              0     5       6   7.26  2594.0        2490   3007       0
…            …   …     …       …     …          …    …     …
942083         1     2       9   5.60  8196.0        9596   2254       0
977569         1     3      14   6.44     NaN        7892   2847       0
1067114        1     3       9   5.80     NaN        8520   2847       0
1474125        1     2       8   6.93  3814.0        9338   2641       0
```

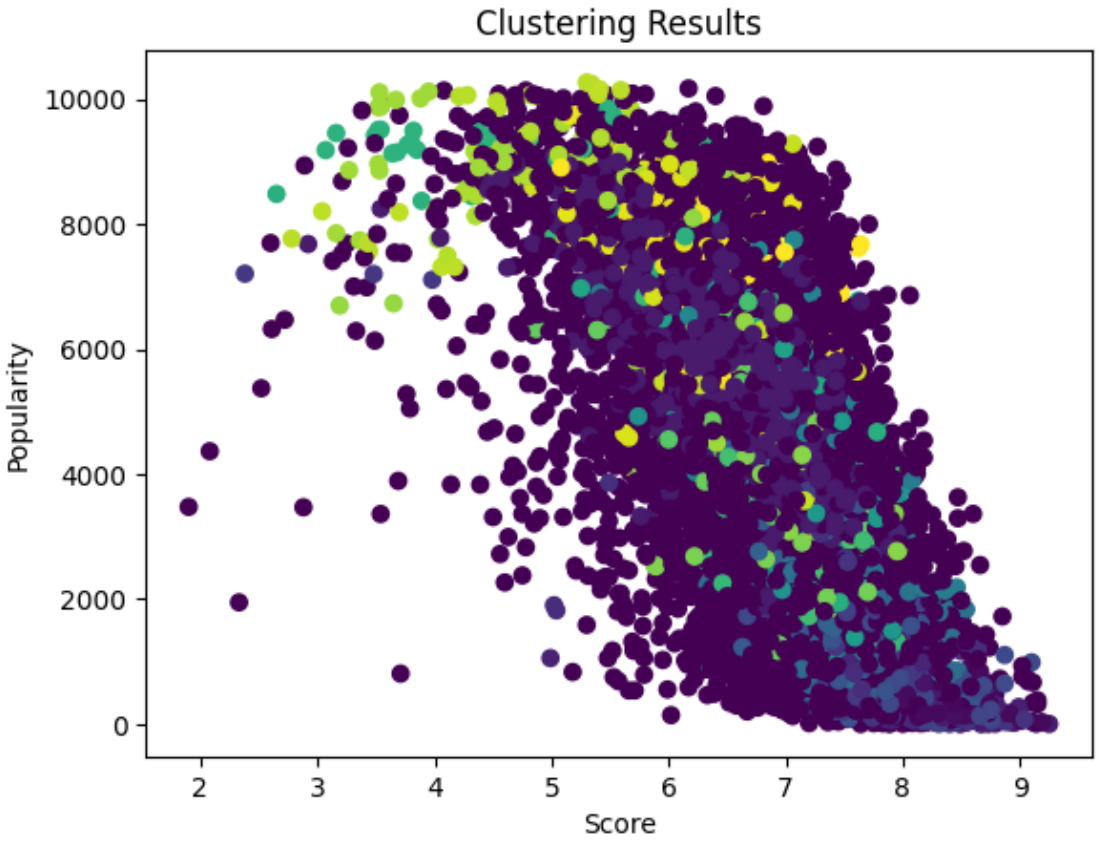
```
15789900       1     1       4   7.27  2514.0        9237   3104       0

          Adventure  Cars  …  Slice of Life  Space  Sports  Super Power  \
0                 1     0  …              0      0       0            1
1                 0     0  …              0      0       0            0
2                 0     0  …              0      0       0            1
3                 0     0  …              1      0       0            0
4                 0     0  …              0      0       0            0
…               …   …   …  …            …    …      …          …
942083            0     0  …              0      0       0            0
977569            0     0  …              0      0       0            0
1067114           0     0  …              0      0       0            0
1474125           0     0  …              0      0       0            0
15789900          0     0  …              0      0       0            0

          Supernatural  Thriller  Vampire  Yaoi  Yuri  cluster
0                    0         0        0     0     0        3
1                    0         0        0     0     0        3
2                    0         0        0     0     0        3
3                    0         0        0     0     0        3
4                    0         0        0     0     0        0
…                  …       …       …   …   …      …
942083               0         0        0     0     0        1
977569               0         0        0     0     0        2
1067114              0         0        0     0     0        2
1474125              0         0        0     0     0        2
15789900             0         0        0     0     0        2

[8746 rows x 51 columns]
```

[230]:
```python
# Crear una copia de df_encoded para no modificar el DataFrame original
df_encoded_clean = df_encoded.copy()

# Eliminar columnas innecesarias

from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')  # puedes cambiar 'mean' por 'median' o 'most_frequent' si lo prefieres
data_imputed = imputer.fit_transform(df_encoded_clean)
df_encoded_clean = pd.DataFrame(data_imputed, columns=df_encoded_clean.columns, index=df_encoded_clean.index)

# Ejecutar DBSCAN en df_encoded_clean
dbscan = DBSCAN(eps=120, min_samples=2)
dbscan.fit(df_encoded_clean)
```

[230]:
```
DBSCAN(eps=120, min_samples=2)
```

[233]:
```
df_encoded_clean['cluster'] = dbscan.labels_
```

[234]:
```
import matplotlib.pyplot as plt

# Crear un gráfico de dispersión de dos características (por ejemplo, 'score' y␣
 ↪'popularity')
plt.scatter(df_encoded_clean['score'], df_encoded_clean['popularity'],␣
 ↪c=df_encoded_clean['cluster'])
plt.xlabel('Score')
plt.ylabel('Popularity')
plt.title('Clustering Results')
plt.show()
```



[ ]:

[ ]: