LAB 4 : EDA AND DATA WRANGING

Introduction

Data analysis is a cornerstone of modern decision-making, and effective analysis begins with **Exploratory Data Analysis (EDA)** and **data wrangling**. These processes form the foundation for uncovering insights and ensuring data quality, enabling informed and accurate decision-making.

EDA: Exploratory Data Analysis

EDA is a systematic approach used by data scientists and analysts to:

- Investigate datasets and summarize their main characteristics.
- Identify patterns, spot anomalies, and test hypotheses.
- Use descriptive statistics and visualization techniques to explore data.

The primary goal of EDA is to provide an accurate understanding of the data before proceeding with further analysis or modeling. In this lab, EDA played a critical role in identifying user viewership categories and analyzing production trends across countries. These insights informed the overall understanding of global entertainment patterns.

Data Wrangling

Data wrangling involves transforming raw data into a usable, structured format. This essential step ensures that datasets are:

- Complete and consistent.
- Free from anomalies, missing values, or redundancies.
- Properly formatted for analysis.

Key tasks in data wrangling include:

- **Cleaning:** Fixing missing values, handling duplicates, and standardizing formats.
- **Integration:** Merging multiple datasets (e.g., IMDb and Netflix data) to create a unified dataset.
- **Transformation:** Normalizing data, encoding categorical variables, and creating new features for analysis.

In this lab, data wrangling was pivotal in preparing the IMDb and Netflix datasets. Tasks like merging, cleaning, and structuring data ensured a robust base for analysis, enabling the extraction of meaningful insights.

Together, EDA and data wrangling allowed us to analyze the IMDb and Netflix datasets effectively. By leveraging columns such as 'rating' and 'type' and examining production data across countries, we gained a comprehensive understanding of user preferences and production trends. These methods highlight the importance of making data reliable and actionable for answering complex analytical questions confidently.

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

In [ ]:
```
imdb_df = pd.read_csv('imdb_rating.csv')
netflix_df = pd.read_csv('netflix_data.csv')

imdb_df.head()
```

Out[ ]:

	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTE
0	Blood Red Sky	(2021)	\nAction, Horror, Thriller	6.1	\nA woman with a mysterious illness is forced ...	\n Director:\nPeter Thorwarth\n| \n Star...	21,06
1	Masters of the Universe: Revelation	(2021–)	\nAnimation, Action, Adventure	5.0	\nThe war for Eternia begins again in what may...	\n \n Stars:\nChris Wood, \nSara...	17,87
2	The Walking Dead	(2010–2022)	\nDrama, Horror, Thriller	8.2	\nSheriff Deputy Rick Grimes wakes up from a c...	\n \n Stars:\nAndrew Lincoln, \n...	885,80
3	Rick and Morty	(2013–)	\nAnimation, Adventure, Comedy	9.2	\nAn animated series that follows the exploits...	\n \n Stars:\nJustin Roiland, \n...	414,84
4	Army of Thieves	(2021)	\nAction, Crime, Horror	NaN	\nA prequel, set before the events of Army of ...	\n Director:\nMatthias Schweighöfer\n| \n ...	Na

In [ ]:

```
# dropping the columns that are not required
netflix_df.drop(columns = ['show_id', 'cast', 'date_added', 'duration', 'des
imdb_df = imdb_df.drop(columns = ['ONE-LINE', 'STARS', 'RunTime','Gross'])
```

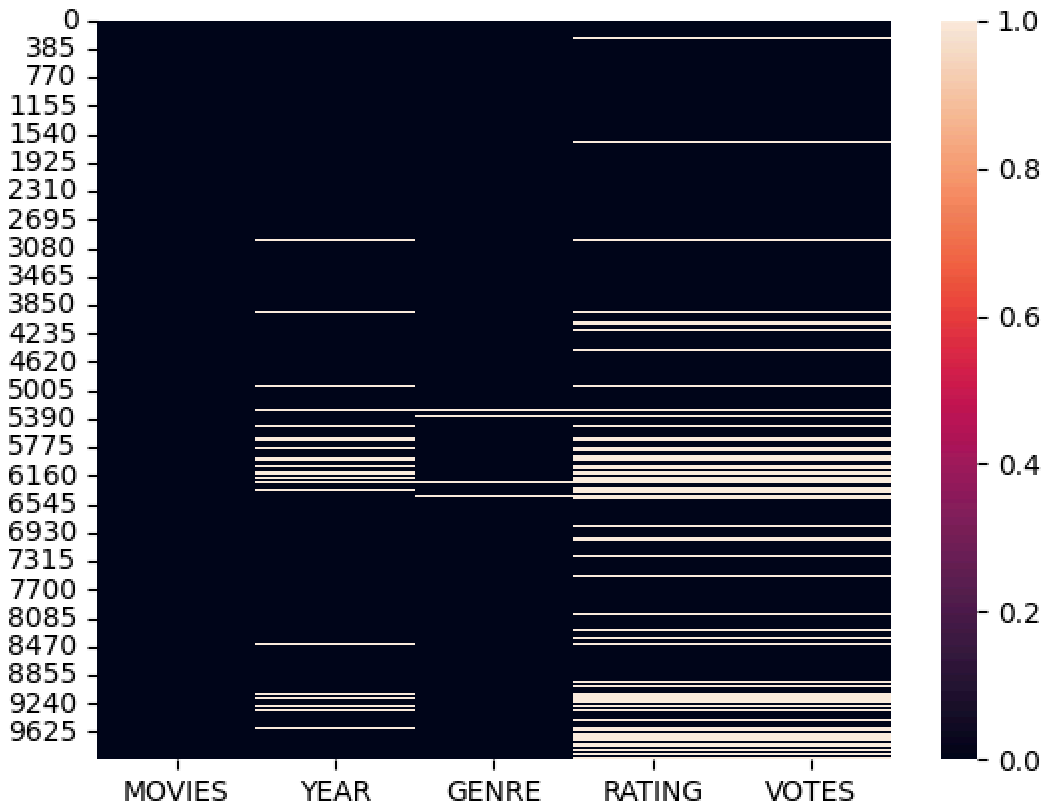
Preliminary Data Exploration

In [ ]:

```
imdb_df.info()

# plotting histplot to view null_data
sns.heatmap(imdb_df.isna())
```

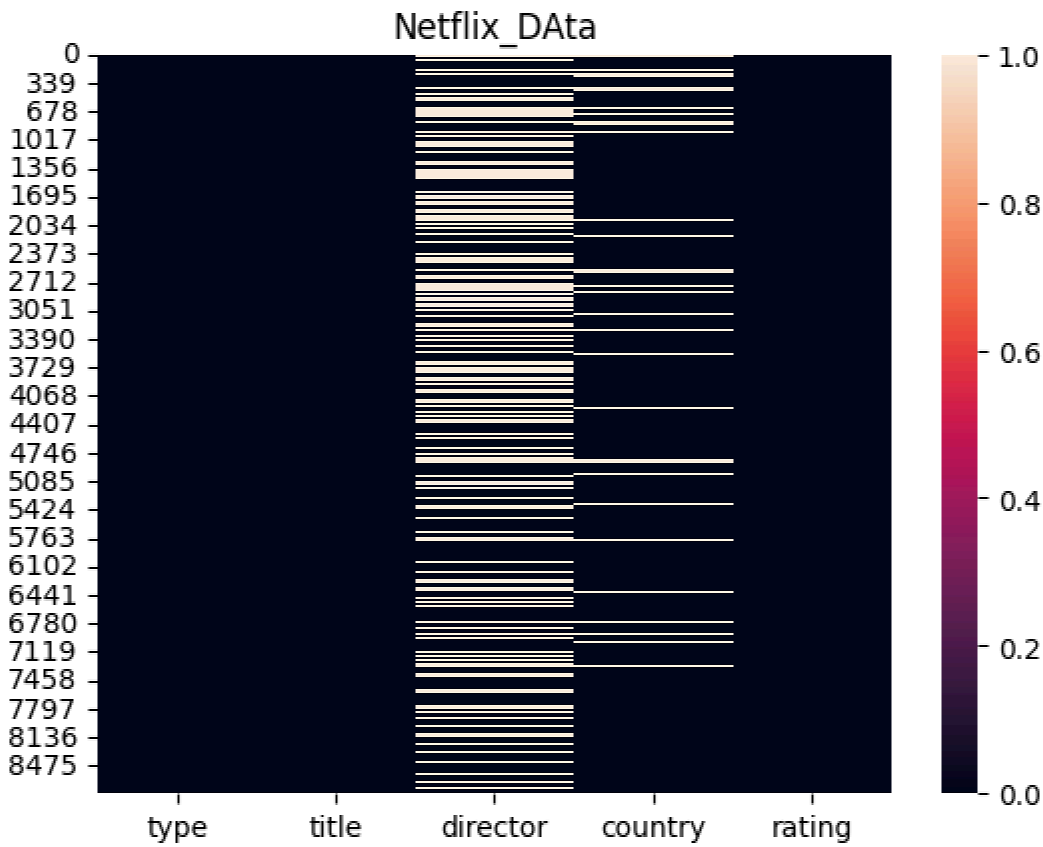
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9999 entries, 0 to 9998
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   MOVIES  9999 non-null   object 
 1   YEAR    9355 non-null   object 
 2   GENRE   9919 non-null   object 
 3   RATING  8179 non-null   float64
 4   VOTES   8179 non-null   object 
dtypes: float64(1), object(4)
memory usage: 390.7+ KB
```

Out[ ]: <Axes: >



In [ ]:
```
netflix_df.info()
sns.heatmap(netflix_df.isna())
plt.title("Netflix_DAta")
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8807 entries, 0 to 8806
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   type      8807 non-null   object
 1   title     8807 non-null   object
 2   director  6173 non-null   object
 3   country   7976 non-null   object
 4   rating    8803 non-null   object
dtypes: object(5)
memory usage: 344.1+ KB
```



In [ ]:

```
# dropping the NaN values from the database
print(f"Netflix Data \n {netflix_df.isna().sum()}")

netflix_df.dropna(inplace=True)

print(f"\n\nNetflix Data \n {netflix_df.isna().sum()}")

netflix_df.info()
```

```
Netflix Data
 type           0
title          0
director    2634
country      831
rating         4
dtype: int64


Netflix Data
 type        0
title       0
director    0
country     0
rating      0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
Index: 5750 entries, 0 to 8806
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   type      5750 non-null   object
 1   title     5750 non-null   object
 2   director  5750 non-null   object
 3   country   5750 non-null   object
 4   rating    5750 non-null   object
dtypes: object(5)
memory usage: 269.5+ KB
```

In [ ]:
```
imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9999 entries, 0 to 9998
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   MOVIES  9999 non-null   object 
 1   YEAR    9355 non-null   object 
 2   GENRE   9919 non-null   object 
 3   RATING  8179 non-null   float64
 4   VOTES   8179 non-null   object 
dtypes: float64(1), object(4)
memory usage: 390.7+ KB
```

In [ ]:
```
# dropping the NaN values form the imdb_data
print(f"Imdb_data \n\n {imdb_df.isna().sum()}")

new_df = imdb_df.dropna(how='any')

print(f"Imdb_data \n\n {imdb_df.isna().sum()}")
```

```
Imdb_data

 MOVIES              0
GENRE              0
RATING             0
VOTES              0
Released_Year      0
title           4371
type            4371
dtype: int64
Imdb_data

 MOVIES              0
GENRE              0
RATING             0
VOTES              0
Released_Year      0
title           4371
type            4371
dtype: int64
```

In [ ]:
```
# imdb_df.info()
imdb_df = new_df
```

In [ ]:
```
imdb_df.info()
netflix_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9999 entries, 0 to 9998
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   MOVIES  9999 non-null   object 
 1   YEAR    9355 non-null   object 
 2   GENRE   9919 non-null   object 
 3   RATING  8179 non-null   float64
 4   VOTES   8179 non-null   object 
dtypes: float64(1), object(4)
memory usage: 390.7+ KB
<class 'pandas.core.frame.DataFrame'>
Index: 5750 entries, 0 to 8806
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   type      5750 non-null   object
 1   title     5750 non-null   object
 2   director  5750 non-null   object
 3   country   5750 non-null   object
 4   rating    5750 non-null   object
dtypes: object(5)
memory usage: 269.5+ KB
```

In [ ]:
```
imdb_df.drop_duplicates(subset=['MOVIES'],inplace=True)
print(imdb_df.duplicated().sum())
imdb_df.info()
```

```
0
<class 'pandas.core.frame.DataFrame'>
Index: 5507 entries, 0 to 5788
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MOVIES         5507 non-null   object
 1   GENRE          5507 non-null   object
 2   RATING         5507 non-null   float64
 3   VOTES          5507 non-null   int64
 4   Released_Year  5507 non-null   object
 5   title          1416 non-null   object
 6   type           1416 non-null   object
dtypes: float64(1), int64(1), object(5)
memory usage: 344.2+ KB
```

In [ ]:

```
# dropping the duplicate from the netflix data
netflix_df.drop_duplicates(subset=['title'],inplace=True)
netflix_df.duplicated().sum()
```

Out[ ]:

```
0
```

In [ ]:

```
netflix_df.head()
imdb_df.head()
# imdb_df.YEAR.unique() # viewing the unique years in the database


imdb_df['Released_Year'] = (imdb_df.YEAR.str.extract(r'(\d{4})')) # extracin


imdb_df.drop('YEAR', inplace=True, axis=1) # deleting the year column

imdb_df


#
```

Out[ ]:

	MOVIES	GENRE	RATING	VOTES	Released_Year	title	type
0	blood red sky	Action, Horror, Thriller	6.1	21062	2021	NaN	NaN
1	masters of the universe: revelation	Animation, Action, Adventure	5.0	17870	2021	NaN	NaN
2	the walking dead	Drama, Horror, Thriller	8.2	885805	2010	NaN	NaN
3	rick and morty	Animation, Adventure, Comedy	9.2	414849	2013	NaN	NaN
4	outer banks	Action, Crime, Drama	7.6	25858	2020	NaN	NaN
...	...	...	...	...	...	...	...
5550	alex	Action, Crime, Thriller	7.3	30	2017	NaN	NaN
5653	the drew barrymore show	Talk-Show	6.8	14	2020	NaN	NaN
5733	nbc sunday night football	Sport	6.6	11	2006	NaN	NaN
5776	dad stop embarrassing me	Comedy, Family	5.7	98	2021	NaN	NaN
5788	kajko i kokosz	Animation, Action, Adventure	7.1	34	2021	NaN	NaN

5507 rows × 7 columns

In [ ]:

```
# transforming the the VOTES columns to numericmel column
imdb_df['VOTES'] = imdb_df.VOTES.str.replace(",", "" ,regex=True)
#
imdb_df.VOTES = pd.to_numeric(imdb_df['VOTES'])
imdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5507 entries, 0 to 5788
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MOVIES         5507 non-null   object
 1   GENRE          5507 non-null   object
 2   RATING         5507 non-null   float64
 3   VOTES          5507 non-null   int64
 4   Released_Year  5507 non-null   object
 5   title          1416 non-null   object
 6   type           1416 non-null   object
dtypes: float64(1), int64(1), object(5)
memory usage: 473.2+ KB
```

In [ ]:

```
# replacing the \n characters
imdb_df['GENRE'] = imdb_df.GENRE.str.strip().str.replace(r'\n','', regex=Tru
imdb_df['GENRE']
```

Out[ ]:

	GENRE
0	Action, Horror, Thriller
1	Animation, Action, Adventure
2	Drama, Horror, Thriller
3	Animation, Adventure, Comedy
4	Action, Crime, Drama
...	...
5550	Action, Crime, Thriller
5653	Talk-Show
5733	Sport
5776	Comedy, Family
5788	Animation, Action, Adventure

5507 rows × 1 columns

dtype: object

In [ ]:

```
# merging the two databases netflix_df and imdb_df
# merged_data = pd.merge(left=imdb_data, right=netflix_data, how='inner', le
merged_df = pd.merge(left=imdb_df, right=netflix_df, how='inner', left_on='M

merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1436 entries, 0 to 1435
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MOVIES         1436 non-null   object 
 1   GENRE          1436 non-null   object 
 2   RATING         1436 non-null   float64
 3   VOTES          1436 non-null   int64  
 4   Released_Year  1436 non-null   object 
 5   type           1436 non-null   object 
 6   title          1436 non-null   object 
 7   director       1436 non-null   object 
 8   country        1436 non-null   object 
 9   rating         1436 non-null   object 
dtypes: float64(1), int64(1), object(8)
memory usage: 112.3+ KB
```

Find for each year the 5 most popular shows and movies separately (i.e. use the information from ‘type’ column of netflix data to find if it is a show or a movie and rank the shows and movies separately)

In [ ]:

```
# movies_df
# # Create a mapping of 'title' to 'type' from netflix_df
# title_to_type = dict(zip(netflix_df['title'], netflix_df['type']))

# # Map the 'type' values to the 'MOVIES' column in imdb_df
# imdb_df['type'] = imdb_df['MOVIES'].map(title_to_type)

# sort the database by the year and votes
# top_100_per_year = imdb_df.sort_values(['Released_Year', 'VOTES'], ascendi
movie_df = merged_df[merged_df['type']=='Movie']

top_5movie_per_year = movie_df.sort_values(['Released_Year', 'VOTES'], ascen


top_5movie_per_year[['Released_Year', 'MOVIES', 'RATING', 'rating', 'type', 
```

Out[ ]:

	Released_Year	MOVIES	RATING	rating	type	VOTES
4	2021	army of the dead	5.8	R	Movie	132378
33	2021	the dig	7.1	PG-13	Movie	60598
16	2021	the woman in the window	5.7	R	Movie	57048
135	2021	the white tiger	7.1	R	Movie	51960
115	2021	outside the wire	5.4	R	Movie	37342
...	...	...	...	...	...	...
87	1968	rosemary's baby	8.0	R	Movie	201472
22	1966	star trek	8.3	PG-13	Movie	76213
803	1945	nazi concentration camps	8.3	TV-MA	Movie	1358
1254	1945	know your enemy - japan	6.0	TV-14	Movie	764
1276	1944	the negro soldier	5.9	TV-14	Movie	690

111 rows × 6 columns

In [ ]:

```
# Shows Df
merged_df.head()

# TV Show df
show_df = merged_df[merged_df['type']=='TV Show']

top_5show_per_year = show_df.sort_values(['Released_Year', 'VOTES'], ascendi


top_5show_per_year[['Released_Year', 'MOVIES', 'RATING', 'rating', 'type', '
```

Out[ ]:

	Released_Year	MOVIES	RATING	rating	type	VOTES
220	2021	night stalker: the hunt for a serial killer	7.5	TV-MA	TV Show	20124
389	2021	crime scene: the vanishing at the cecil hotel	5.9	TV-MA	TV Show	15072
65	2021	halston	7.5	TV-MA	TV Show	10460
453	2021	murder among the mormons	7.0	TV-14	TV Show	4914
182	2021	trese	7.1	TV-MA	TV Show	2521
317	2020	tiger king: murder, mayhem and madness	7.5	TV-MA	TV Show	70207
50	2020	feel good	7.5	TV-MA	TV Show	7949
419	2020	the ripper	7.1	TV-MA	TV Show	7810
131	2020	julie and the phantoms	8.5	TV-G	TV Show	7576
547	2020	the pharmacist	7.7	TV-MA	TV Show	6140
233	2019	don't f**k with cats: hunting an internet killer	8.0	TV-MA	TV Show	42827
3	2019	kingdom	8.4	TV-MA	TV Show	34906
269	2019	to the lake	7.3	TV-MA	TV Show	10507
495	2019	the confession killer	7.4	TV-14	TV Show	7618
6	2019	kingdom	7.1	TV-MA	TV Show	6388
12	2018	you	7.7	TV-MA	TV Show	157666
151	2018	sacred games	8.6	TV-MA	TV Show	80715
416	2018	ghoul	7.1	TV-MA	TV Show	13031
402	2018	watership down	7.2	TV-PG	TV Show	5587
1220	2018	ellen degeneres: relatable	6.5	TV-MA	TV Show	4482

	Released_Year	MOVIES	RATING	rating	type	VOTES
10	2017	riverdale	6.8	TV-14	TV Show	126112
1097	2017	dave chappelle	8.7	TV-MA	TV Show	2224
361	2017	hot girls wanted: turned on	6.6	TV-MA	TV Show	2061
1420	2017	riverdale	7.5	TV-14	TV Show	908
1006	2017	daughters of destiny	8.6	TV-14	TV Show	822
526	2016	cheese in the trap	7.4	TV-14	TV Show	3348
372	2016	degrassi: next class	6.9	TV-14	TV Show	2876
640	2016	kuromukuro	7.2	TV-14	TV Show	1165
1022	2016	ari shaffir: double negative	6.8	TV-MA	TV Show	667
829	2016	world of winx	6.8	TV-Y7	TV Show	642
11	2015	supergirl	6.2	TV-14	TV Show	115373
18	2015	miraculous: tales of ladybug & cat noir	7.7	TV-Y7	TV Show	8300
1417	2015	supergirl	7.5	TV-14	TV Show	1025
1	2014	the flash	7.6	TV-14	TV Show	320264
7	2014	gotham	7.8	TV-MA	TV Show	216458
1418	2014	the flash	7.9	TV-14	TV Show	1881
1296	2014	dealer	6.3	TV-MA	TV Show	536
112	2013	hemlock grove	7.1	TV-MA	TV Show	37861
1260	2013	brave miss world	7.1	TV-14	TV Show	546
1213	2013	monty don's french gardens	7.9	TV-G	TV Show	186
9	2012	arrow	7.5	TV-14	TV Show	414712

	Released_Year	MOVIES	RATING	rating	type	VOTES
355	2012	comedians in cars getting coffee	8.1	TV-14	TV Show	11473
1419	2012	comedians in cars getting coffee	8.2	TV-14	TV Show	360
1342	2012	los tiempos de pablo escobar	6.8	TV-14	TV Show	268
527	2011	frozen planet	9.0	TV-PG	TV Show	27986
765	2010	the trial	5.6	TV-MA	TV Show	1462
2	2005	supernatural	8.4	TV-14	TV Show	404273
37	2002	naruto	8.3	TV-14	TV Show	79832

In [ ]:

```
netflix_df.head()
```

Out[ ]:

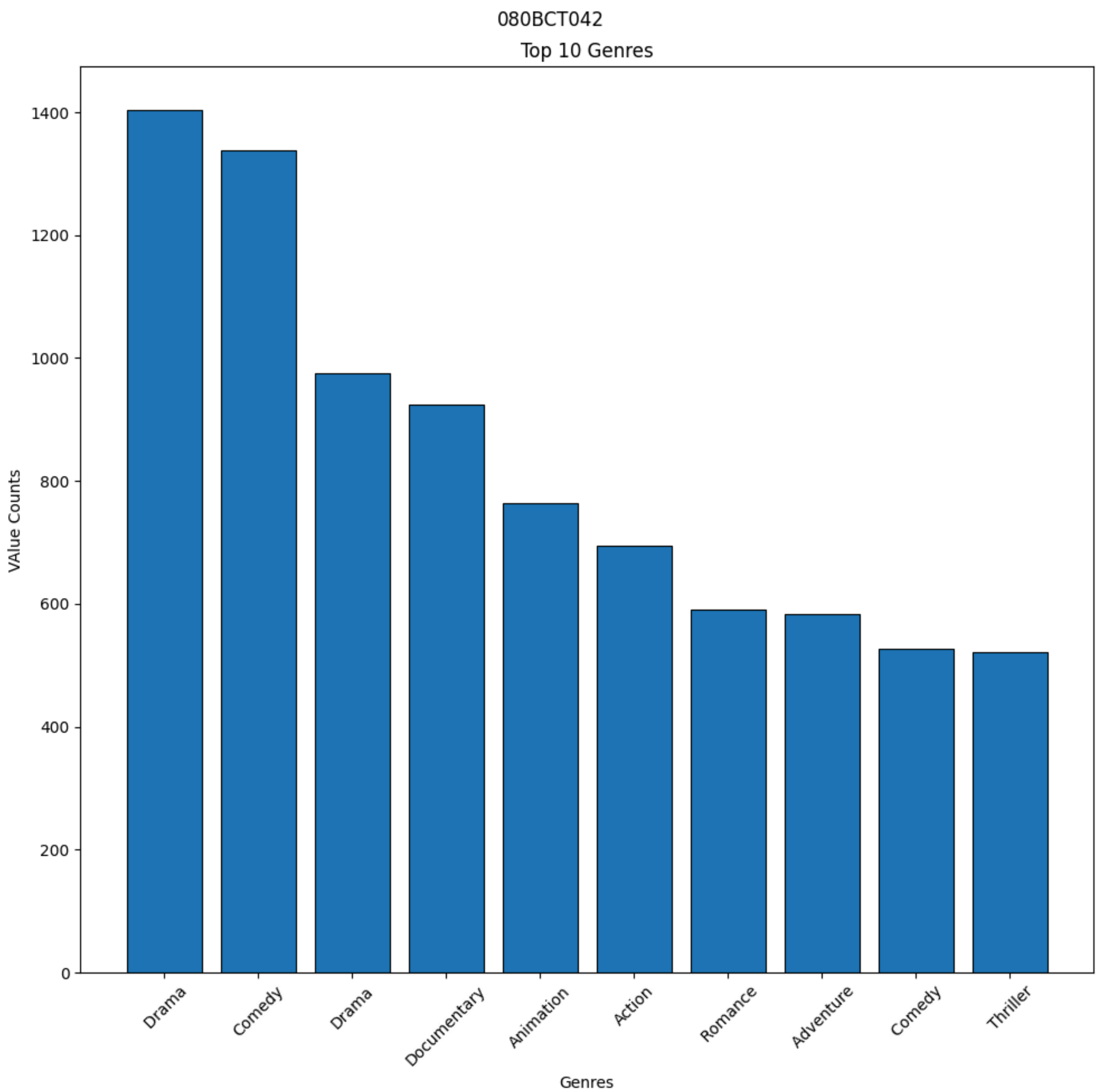
	type	title	director	country	rating
0	Movie	dick johnson is dead	Kirsten Johnson	United States	PG-13
7	Movie	sankofa	Haile Gerima	United States, Ghana, Burkina Faso, United Kin...	TV-MA
8	TV Show	the great british baking show	Andy Devonshire	United Kingdom	TV-14
9	Movie	the starling	Theodore Melfi	United States	PG-13
12	Movie	je suis karl	Christian Schwochow	Germany, Czech Republic	TV-MA

□ Find what genre of movies are most popular (top 10) and show in a bar graph.

In [ ]:

```
# using .stack() method to split and stack the the strings
stack = imdb_df.GENRE.str.split(',', expand=True).stack()
genre_count = stack.value_counts()

top_10_genre = genre_count.head(10)



top_10_genre
```

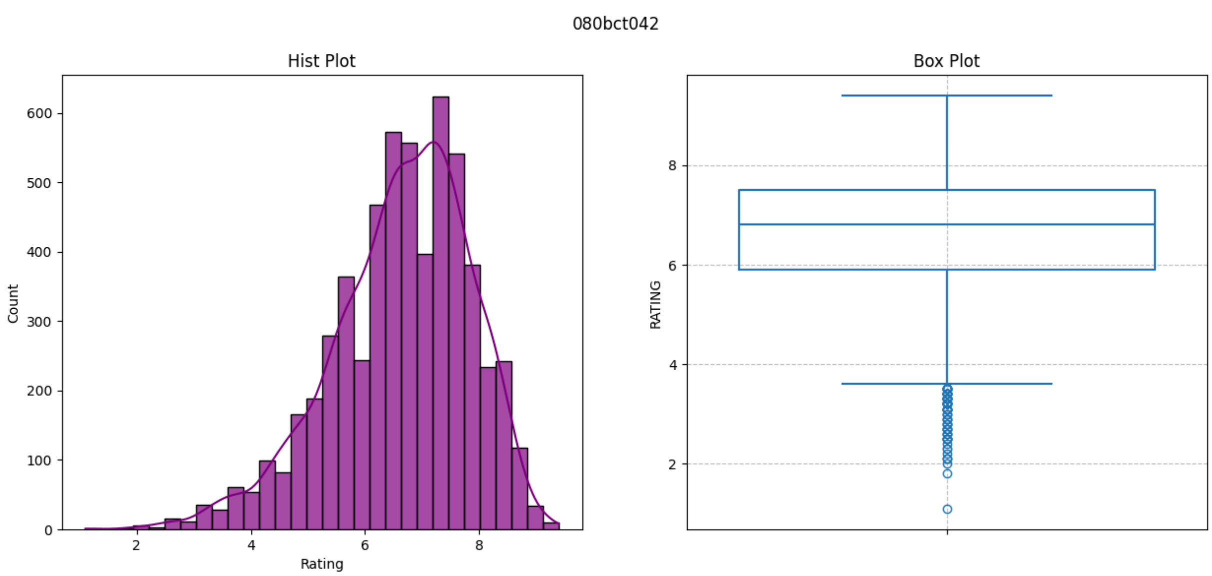
```
fig, ax = plt.subplots(figsize=(10,10))
plt.suptitle("080BCT042")
ax.set_title("Top 10 Genres")
ax.set_ylabel("VAlue Counts")
ax.set_xlabel("Genres")

bar = ax.bar(top_10_genre.index, top_10_genre.values, edgecolor='black', lir

# Display the plot
plt.xticks(rotation=45)  # Rotate x-axis labels if needed
plt.tight_layout()
plt.show()
```



Plot the distribution of values of ‘RATING’ column of imdb dataset using histogram plot and in a box plot. Also

identify outlier values using the box plot.

In [ ]:
```
#  creating the subplots
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(15, 6))
plt.suptitle("080bct042")


sns.histplot(data=imdb_df,
                       x='RATING',
                      kde=True,
                      ax=ax[0],
                      bins=30,
                      color='purple',
                      edgecolor='black',
                      alpha=0.7
                       )
ax[0].set_title("Hist Plot")

ax[0].set_xlabel('Rating')

sns.boxplot(data=imdb_df,
            y= imdb_df.RATING,
            ax= ax[1],
            fill=False
            )

ax[1].set_title("Box Plot")


plt.grid(linestyle='--', alpha=0.8)
plt.show()
```



Explore which country produces the most shows and movies (separately) and how popular they are (find the rating of top movies and shows for the country producing most shows and movies).

In [ ]:
```
# transforming the the VOTES columns to numericmel column
merged_df['VOTES'] = merged_df.VOTES.str.replace(",", "" ,regex=True)

merged_df.VOTES = pd.to_numeric(merged_df['VOTES'])

merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1351 entries, 0 to 1350
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MOVIES         1351 non-null   object 
 1   GENRE          1351 non-null   object 
 2   RATING         1351 non-null   float64
 3   VOTES          1351 non-null   int64  
 4   Released_Year  1351 non-null   object 
 5   type           1351 non-null   object 
 6   title          1351 non-null   object 
 7   director       1351 non-null   object 
 8   country        1351 non-null   object 
 9   rating         1351 non-null   object 
dtypes: float64(1), int64(1), object(8)
memory usage: 105.7+ KB
```

In [ ]:
```
# finding the country  with highest movie produced
movie_df = merged_df[merged_df['type']=='Movie']
country_df = movie_df.country.str.split(',', expand=True).stack()
country_df = country_df.value_counts()

top_movies = movie_df[movie_df['country'] == country_df.index[0]]
top_movies = top_movies.sort_values(by='RATING', ascending=False)[0:10]

# top movies of USA
print(f"Top Movies for the {country_df.index[0]}")
top_movies[['MOVIES', 'RATING', 'country']]
```

```
Top Movies for the United States
```

Out[ ]:

	MOVIES	RATING	country
750	In Our Mothers' Gardens	8.9	United States
17	Bo Burnham: Inside	8.7	United States
953	Springsteen on Broadway	8.5	United States
625	Dave Chappelle: Sticks & Stones	8.5	United States
380	Bo Burnham: what.	8.4	United States
1244	Bill Hicks: Sane Man	8.4	United States
352	Bo Burnham: Make Happy	8.4	United States
833	Ben Platt Live from Radio City Music Hall	8.4	United States
776	Nazi Concentration Camps	8.3	United States
492	Kiss the Ground	8.3	United States

In [ ]:

```
# finding the country  with highest TV Show produced
movie_df = merged_df[merged_df['type']=='TV Show']
country_df = movie_df.country.str.split(',', expand=True).stack()
country_df = country_df.value_counts()

top_movies = movie_df[movie_df['country'] == country_df.index[0]]
top_movies = top_movies.sort_values(by='RATING', ascending=False)[0:10]

# top TV show of USA
print(f"Top TV Show for the {country_df.index[0]}")
top_movies[['MOVIES', 'RATING', 'country', 'type']].reset_index()
```

```
Top TV Show for the United States
```

Out[ ]:

	index	MOVIES	RATING	country	type
0	1059	Dave Chappelle	8.7	United States	TV Show
1	971	Daughters of Destiny	8.6	United States	TV Show
2	566	Middleditch & Schwartz	8.6	United States	TV Show
3	126	Julie and the Phantoms	8.5	United States	TV Show
4	344	Comedians in Cars Getting Coffee	8.1	United States	TV Show
5	5	Gotham	7.8	United States	TV Show
6	528	The Pharmacist	7.7	United States	TV Show
7	10	You	7.7	United States	TV Show
8	0	The Flash	7.6	United States	TV Show
9	1150	Move	7.6	United States	TV Show

Shows/Movies by which director is popular (Find top 10 directors) and all genres for the movies or shows that they made.

In [ ]:

```
# Split multiple directors into separate rows
exploded_df = merged_df.assign(director=merged_df['director'].str.split(', '

# Group by directors and calculate the mean rating and sum of genres
director_df = exploded_df.groupby(['director'], as_index=False).agg({'RATING

# Top 10 directors based on average RATING
top_10_directors = director_df.sort_values(by='RATING', ascending=False).hea

# Showing the most popular TV shows/movies of the director
most_popular_titles = []
types = []

# Iterate over top_10_directors to get the most popular title and type
for director in top_10_directors['director']:
    # Get the row with the highest RATING for the director
    popular_row = exploded_df[exploded_df['director'] == director].nlargest(

    # Extract the most popular movie/show and its type
    most_popular_titles.append(popular_row['MOVIES'].values[0])
    types.append(popular_row['type'].values[0])

# Add the new columns to top_10_directors
top_10_directors['popular_work'] = most_popular_titles
top_10_directors['type'] = types

# View the updated top_10_directors
top_10_directors
```

Out[ ]:

	director	RATING	GENRE	popular_work	type
1248	Tim Van Someren	9.1	Documentary, Music	Hans Zimmer: Live in Prague	Movie
625	Jonnie Hughes	9.0	Documentary, Biography	David Attenborough: A Life on Our Planet	Movie
36	Alastair Fothergill	9.0	Documentary, BiographyDocumentary	David Attenborough: A Life on Our Planet	Movie
1151	Shantrelle P. Lewis	8.9	Documentary	In Our Mothers' Gardens	Movie
998	Peter Jackson	8.8	Action, Adventure, DramaAction, Adventure, Drama	The Lord of the Rings: The Return of the King	Movie
918	Nguyen Thanh Tung	8.7	Documentary, Music	Sky Tour: The Movie	Movie
221	Chris Bould	8.6	Documentary, ComedyDocumentary, Comedy	Bill Hicks: Revelations	Movie
1285	Vanessa Roth	8.6	Documentary	Daughters of Destiny	TV Show
748	Lilibet Foster	8.6	Documentary, Biography, Drama	Be Here Now	Movie
1239	Thom Zimny	8.5	Documentary, Music	Springsteen on Broadway	Movie

In [ ]:

```
top_10_directors

# exploded_df.loc[625]
# exploded_df[exploded_df['director']=='Jonnie Hughes']['MOVIES']
```

Out[ ]:

	director	RATING	GENRE	popular_work	type
1248	Tim Van Someren	9.1	Documentary, Music	Hans Zimmer: Live in Prague	Movie
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Find the most occurring user viewership category (i.e. ‘rating’ column of the imdb dataset) for the 100 highest voted movies/shows of each year and for each top 10 countries (top countries based on number of shows produced).

In [ ]:

```
# sort the database by the year and votes
top_100_per_year = imdb_df.sort_values(['Released_Year', 'VOTES'], ascending

# Count the number of movies/shows by country
top_countries = netflix_df['country'].value_counts().head(10).index.tolist()
top_countries
```

```
# Clean titles for merging
imdb_df['MOVIES'] = imdb_df['MOVIES'].str.strip().str.lower()
netflix_df['title'] = netflix_df['title'].str.strip().str.lower()

# Merge IMDb and Netflix datasets
merged_df = top_100_per_year.merge(netflix_df, left_on='MOVIES', right_on='t


# Filter by top countries
filtered_df = merged_df[merged_df['country'].isin(top_countries)]
```

In [ ]:

```
most_frequent_ratings = (
    filtered_df.groupby(['Released_Year', 'country'])['rating']
    .agg(lambda x: x.value_counts().idxmax())
    .reset_index()
)


most_frequent_ratings = (
    filtered_df.groupby(['Released_Year', 'country'])['rating'].agg(lambda x
)

# renaming the columns
most_frequent_ratings.columns = ['Year', 'Country', 'Most_Popular_Viewershi

most_frequent_ratings
```

Out[ ]:

	Year	Country	Most_Popular_Viewership_Category
0	1944	United States	TV-14
1	1945	United States	TV-MA
2	1968	United States	R
3	1973	India	TV-14
4	1975	United Kingdom	PG
...	...	...	...
62	2020	United States	R
63	2021	France	TV-MA
64	2021	India	TV-MA
65	2021	United Kingdom	PG-13
66	2021	United States	TV-MA

67 rows × 3 columns

Discussion

This lab explored user viewership trends and production patterns using the IMDb and Netflix datasets. Key findings include:

- **User Ratings:** Certain rating categories consistently dominated among the top 100 highly voted movies and shows, reflecting global audience preferences.
- **Country Trends:** The top 10 content-producing countries displayed significant differences in output, influenced by regional preferences and resources.
- **Movies vs. Shows:** Movies catered to broad, one-time audiences, while shows engaged viewers with serialized storytelling.
- **Data Challenges:** Merging and cleaning datasets highlighted the importance of data wrangling for reliable results.

These insights illustrate the power of data analysis in understanding global entertainment trends.

Conclusion

This lab highlighted the role of **EDA** and **data wrangling** in uncovering patterns in user ratings and production trends. We identified key viewership categories, analyzed top content-producing countries, and distinguished differences between movies and shows.

The results emphasize the importance of clean, structured data for meaningful analysis. Future work could explore genre-specific trends or audience demographics for deeper insights.
