NETFLIX DATA ANALYSIS

by Siddhesh M

Netflix is one of the most popular media and video streaming platforms. They have over 10000 movies or tv shows available on their platform, as of mid-2021, they have over 222M Subscribers globally. This tabular dataset consists of listings of all the movies and tv shows available on Netflix, along with details such as - cast, directors, ratings, release year, duration, etc.

BUSINESS PROBLEM

As Netflix continues to experience growth in a competitive streaming market, it faces challenges related to subscriber retention and content differentiation. With the rise of numerous alternatives offering diverse content, Netflix must address the potential for increased churn rates. The key business problem is to develop effective strategies that enhance user engagement through personalized content recommendations.

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import os
from datetime import datetime

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [ ]:
```
path = '/content/drive/MyDrive/MY_LEARNING/Netflix_Analysis/Data/netflix.csv'
```

In [ ]:
```
df = pd.read_csv(path,delimiter=',')
```

In [ ]:
```
print(f'Netflix dataset has {df.shape[0]} rows and {df.shape[1]} columns')
```

```
Netflix dataset has 8807 rows and 12 columns
```

In [ ]:
```
df.head()
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	release_year
0	s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	NaN	United States	September 25, 2021	2020
1	s2	TV Show	Blood & Water	NaN	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...	South Africa	September 24, 2021	2021
2	s3	TV Show	Ganglands	Julien Leclercq	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...	NaN	September 24, 2021	2021
3	s4	TV Show	Jailbirds New Orleans	NaN	NaN	NaN	September 24, 2021	2021
4	s5	TV Show	Kota Factory	NaN	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...	India	September 24, 2021	2021

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['show_id', 'type', 'title', 'director', 'cast', 'country', 'date_added',
       'release_year', 'rating', 'duration', 'listed_in', 'description'],
      dtype='object')
```

The dataset provided to you consists of a list of all the TV shows/movies available on Netflix:

- Show_id: Unique ID for every Movie / Tv Show
- Type: Identifier - A Movie or TV Show
- Title: Title of the Movie / Tv Show
- Director: Director of the Movie
- Cast: Actors involved in the movie/show
- Country: Country where the movie/show was produced
- Date_added: Date it was added on Netflix
- Release_year: Actual Release year of the movie/show
- Rating: TV Rating of the movie/show
- Duration: Total Duration - in minutes or number of seasons
- Listed_in: Genre
- Description: The summary description

In [ ]:
```
df.describe()
```

Out[ ]:

	release_year
count	8807.000000
mean	2014.180198
std	8.819312
min	1925.000000
25%	2013.000000
50%	2017.000000
75%	2019.000000
max	2021.000000

PREPARE THE DATA

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8807 entries, 0 to 8806
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   show_id       8807 non-null   object
 1   type          8807 non-null   object
 2   title         8807 non-null   object
 3   director      6173 non-null   object
 4   cast          7982 non-null   object
 5   country       7976 non-null   object
 6   date_added    8797 non-null   object
 7   release_year  8807 non-null   int64 
 8   rating        8803 non-null   object
 9   duration      8804 non-null   object
 10  listed_in     8807 non-null   object
 11  description   8807 non-null   object
dtypes: int64(1), object(11)
memory usage: 825.8+ KB
```

In [ ]:
```
df.dtypes
```

Out[ ]:

	0
show_id	object
type	object
title	object
director	object
cast	object
country	object
date_added	object
release_year	int64
rating	object
duration	object
listed_in	object
description	object

dtype: object

In [ ]:
```
df.describe()
```

Out[ ]:

	release_year
count	8807.000000
mean	2014.180198
std	8.819312
min	1925.000000
25%	2013.000000
50%	2017.000000
75%	2019.000000
max	2021.000000

The dataset contains only one numerical column, release_year, which indicates the timeframe of content availability. It ranges from 1925 to 2021. All other columns consist of categorical data.

Data Cleaning

Examination of missing value by column

In [ ]:

```
df.isna().sum()
```

Out[ ]:

	0
show_id	0
type	0
title	0
director	2634
cast	825
country	831
date_added	10
release_year	0
rating	4
duration	3
listed_in	0
description	0

dtype: int64

The dataset reveals missing values in several key columns:

- Director: 2,634 missing entries, indicating a significant gap that could impact analyses of directorial influence.
- Cast: 825 missing entries, which may affect insights on star power and viewer preferences.
- Country: 831 missing entries, potentially limiting regional market analysis.
- Date Added: 10 missing entries, which could affect release timing evaluations.
- Rating: 4 missing entries, important for understanding content quality.
- Duration: 3 missing entries, relevant for viewer engagement analysis.

Addressing these missing values is crucial for ensuring comprehensive insights and informed decision-making.

In [ ]:
```
print(f"Total number of missing values: {df.isna().sum().sum()}")
```

```
Total number of missing values: 4307
```

Managing Missing values

In [ ]:
```
df.director.fillna('Not Specified', inplace=True)
```

We are labeling missing Director names in the dataset as "Not Specified".

In [ ]:
```
df.cast.fillna('Not Availble', inplace=True)
```

We are labeling missing Cast in the dataset as "Not Available"

In [ ]:
```
df.country.fillna('Unknown', inplace=True)
```

We are labeling missing Country in the dataset as "Unknown".

In [ ]:
```
df.rating.fillna('NR', inplace=True)
```

We are labeling missing Rating in the dataset as "NR" which stands for "Not Rated."

In [ ]:
```
df.dropna(subset=['date_added'], inplace=True)
```

We are removing rows with missing values in the date_added column to ensure accurate analysis of content release timelines.

In [ ]:
```
duration_index = df[df.duration.isna()].index
```

In [ ]:
```
df.loc[duration_index]
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	release_year	rat
5541	s5542	Movie	Louis C.K. 2017	Louis C.K.	Louis C.K.	United States	April 4, 2017	2017	
5794	s5795	Movie	Louis C.K.: Hilarious	Louis C.K.	Louis C.K.	United States	September 16, 2016	2010	
5813	s5814	Movie	Louis C.K.: Live at the Comedy Store	Louis C.K.	Louis C.K.	United States	August 15, 2016	2015	

In this case, the duration information has been incorrectly placed under the rating column. We need to correct this by shifting the values back to their appropriate column (duration) and address any missing values in the rating column to maintain data accuracy and integrity.

In [ ]:
```
df.loc[duration_index, 'duration'] = df.loc[duration_index, 'rating']
df.loc[duration_index,'rating'] = 'NR'
```

In [ ]:
```
df.isna().sum()
```

Out[ ]:

	0
show_id	0
type	0
title	0
director	0
cast	0
country	0
date_added	0
release_year	0
rating	0
duration	0
listed_in	0
description	0

dtype: int64

Identifying Redundant Records in the Dataset

In [ ]:
```
print(f"Total number of duplicates in the dataset {df.duplicated(subset=['title'
```

```
Total number of duplicates in the dataset 0
```

Standardizing Date Format

In [ ]:
```
df.date_added = pd.to_datetime(df.date_added, format='mixed')
```

In [ ]:
```
df.date_added = df.date_added.dt.strftime('%d-%m-%Y')
```

Creating New Columns for 'Month Added' and 'Year Added' for Detailed Analysis

In [ ]:
```
df['date_added_year'] = pd.to_datetime(df.date_added).dt.year
df['date_added_month'] = pd.to_datetime(df.date_added).dt.strftime('%B')
```

Statistical Summary After Data Cleaning

In [ ]:
```
df.describe()
```

Out[ ]:

	release_year	date_added_year
count	8797.000000	8797.000000
mean	2014.183472	2018.871888
std	8.822191	1.574243
min	1925.000000	2008.000000
25%	2013.000000	2018.000000
50%	2017.000000	2019.000000
75%	2019.000000	2020.000000
max	2021.000000	2021.000000

In [ ]:
```
df.describe(include='object')
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	rating	durat
count	8797	8797	8797	8797	8797	8797	8797	8797	8
unique	8797	2	8797	4529	7683	749	1714	14	
top	s8807	Movie	Zubaan	Not Specified	Not Availble	United States	01-01-2020	TV-MA	1 Sea
freq	1	6131	1	2624	825	2812	110	3205	1

Exploring Data and Conducting Non-Graphical Analysis

Unique Values, Count of Unique Values and Frequency of Unique Values in the Dataset.

In [ ]:

```
print(f"Total number of Unique Title in the dataset: {df.title.nunique()}")
print("-"*45)
print(f"Unique value in the dataset:\n{df.title.unique()}")
```

```
Total number of Unique Title in the dataset: 8797
---------------------------------------------
Unique value in the dataset:
['Dick Johnson Is Dead' 'Blood & Water' 'Ganglands' ... 'Zombieland'
 'Zoom' 'Zubaan']
```

The dataset contains a total of 8,797 unique titles.

In [ ]:

```
print(f"Total Number of Unique Director in the Dataset: {df['director'].nunique(
print("-"*30)
print(f"Unique Values in the Dataset:\n {df['director'].unique()}")
print("-"*30)
print(f"Available frequency Values in the Dataset:\n {df['director'].value_count
```

```
Total Number of Unique Director in the Dataset: 4529
------------------------------
Unique Values in the Dataset:
 ['Kirsten Johnson' 'Not Specified' 'Julien Leclercq' ... 'Majid Al Ansari'
 'Peter Hewitt' 'Mozez Singh']
------------------------------
Available frequency Values in the Dataset:
 director
Not Specified             2624
Rajiv Chilaka               19
Raúl Campos, Jan Suter      18
Suhas Kadav                 16
Marcus Raboy                16
Name: count, dtype: int64
```

The dataset contains a total of 4529 unique Director.

In [ ]:

```
print(f"Total Number of Unique Type in the Dataset: {df['type'].nunique()}")
print("-"*30)
print(f"Unique Values in the Dataset:\n {df['type'].unique()}")
print("-"*30)
print(f"Available frequency in the Dataset:\n {df['type'].value_counts().head(5)
```

```
Total Number of Unique Type in the Dataset: 2
------------------------------
Unique Values in the Dataset:
 ['Movie' 'TV Show']
------------------------------
Available frequency in the Dataset:
 type
Movie      6131
TV Show    2666
Name: count, dtype: int64
```

The dataset includes a total of 2 unique types, comprising 6,131 movies and 2,666 TV shows.

In [ ]:

```
movie = df.loc[df['type'] == 'Movie']
movie
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	rele
0	s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	Not Availble	United States	25-09-2021	
6	s7	Movie	My Little Pony: A New Generation	Robert Cullen, José Luis Ucha	Vanessa Hudgens, Kimiko Glenn, James Marsden, ...	Unknown	24-09-2021	
7	s8	Movie	Sankofa	Haile Gerima	Kofi Ghanaba, Oyafunmike Ogunlano, Alexandra D...	United States, Ghana, Burkina Faso, United Kin...	24-09-2021	
9	s10	Movie	The Starling	Theodore Melfi	Melissa McCarthy, Chris O'Dowd, Kevin Kline, T...	United States	24-09-2021	
12	s13	Movie	Je Suis Karl	Christian Schwochow	Luna Wedler, Jannis Niewöhner, Milan Peschel, ...	Germany, Czech Republic	23-09-2021	
...	...	...	...	...	...	...	...	
8801	s8802	Movie	Zinzana	Majid Al Ansari	Ali Suliman, Saleh Bakri, Yasa, Ali Al-Jabri, ...	United Arab Emirates, Jordan	09-03-2016	
8802	s8803	Movie	Zodiac	David Fincher	Mark Ruffalo, Jake Gyllenhaal, Robert Downey J...	United States	20-11-2019	
8804	s8805	Movie	Zombieland	Ruben Fleischer	Jesse Eisenberg, Woody Harrelson, Emma Stone, ...	United States	01-11-2019	

	show_id	type	title	director	cast	country	date_added	rele
8805	s8806	Movie	Zoom	Peter Hewitt	Tim Allen, Courteney Cox, Chevy Chase, Kate Ma...	United States	11-01-2020	
8806	s8807	Movie	Zubaan	Mozez Singh	Vicky Kaushal, Sarah-Jane Dias, Raaghav Chanan...	India	02-03-2019	

6131 rows × 14 columns

In [ ]:
```
tv_shows = df.loc[df['type'] == 'TV Show']
tv_shows
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	release_
1	s2	TV Show	Blood & Water	Not Specified	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...	South Africa	24-09-2021	
2	s3	TV Show	Ganglands	Julien Leclercq	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...	Unknown	24-09-2021	
3	s4	TV Show	Jailbirds New Orleans	Not Specified	Not Availble	Unknown	24-09-2021	
4	s5	TV Show	Kota Factory	Not Specified	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...	India	24-09-2021	
5	s6	TV Show	Midnight Mass	Mike Flanagan	Kate Siegel, Zach Gilford, Hamish Linklater, H...	Unknown	24-09-2021	
...	...	...	...	...	...	...	...	
8795	s8796	TV Show	Yu-Gi-Oh! Arc-V	Not Specified	Mike Liscio, Emily Bauer, Billy Bob Thompson, ...	Japan, Canada	01-05-2018	
8796	s8797	TV Show	Yunus Emre	Not Specified	Gökhan Atalay, Payidar Tüfekçioglu, Baran Akbu...	Turkey	17-01-2017	
8797	s8798	TV Show	Zak Storm	Not Specified	Michael Johnston, Jessica Gee-George, Christin...	United States, France, South Korea, Indonesia	13-09-2018	

	show_id	type	title	director	cast	country	date_added	release_
8800	s8801	TV Show	Zindagi Gulzar Hai	Not Specified	Sanam Saeed, Fawad Khan, Ayesha Omer, Mehreen ...	Pakistan	15-12-2016	
8803	s8804	TV Show	Zombie Dumb	Not Specified	Not Availble	Unknown	01-07-2019	

2666 rows × 14 columns

In [ ]:
```
print(f"Available frequency in the Dataset:\n {movie['duration'].value_counts().
```

```
Available frequency in the Dataset:
 duration
90 min    152
97 min    146
94 min    146
93 min    146
91 min    144
Name: count, dtype: int64
```

In [ ]:
```
print(f"Available frequency in the Dataset:\n {tv_shows['duration'].value_counts
```

```
Available frequency in the Dataset:
 duration
1 Season     1793
2 Seasons     421
3 Seasons     198
4 Seasons      94
5 Seasons      64
Name: count, dtype: int64
```

Available Frequency of Duration in Minutes for Movies and in Seasons for TV Shows

In [ ]:
```
movie['duration'] = movie['duration'].str.split(' ').str[0].astype(int)
tv_shows['duration'] = tv_shows['duration'].str.split(' ').str[0].astype(int)
```

In [ ]:
```
movie.head()
```

Out[ ]:

	show_id	type	title	director	cast	country	date_added	release
0	s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	Not Availble	United States	25-09-2021	
6	s7	Movie	My Little Pony: A New Generation	Robert Cullen, José Luis Ucha	Vanessa Hudgens, Kimiko Glenn, James Marsden, ...	Unknown	24-09-2021	
7	s8	Movie	Sankofa	Haile Gerima	Kofi Ghanaba, Oyafunmike Ogunlano, Alexandra D...	United States, Ghana, Burkina Faso, United Kin...	24-09-2021	
9	s10	Movie	The Starling	Theodore Melfi	Melissa McCarthy, Chris O'Dowd, Kevin Kline, T...	United States	24-09-2021	
12	s13	Movie	Je Suis Karl	Christian Schwochow	Luna Wedler, Jannis Niewöhner, Milan Peschel, ...	Germany, Czech Republic	23-09-2021	

Oldest and Most Recent Movies and TV Shows Released on OTT Platforms

In [ ]:

```
print(f"Oldest Movie Released: {movie['release_year'].min()}")
print(f"Oldest TV Show Released: {tv_shows['release_year'].min()}")
```

```
Oldest Movie Released: 1942
Oldest TV Show Released: 1925
```

The oldest movie was released in 1942, while the oldest TV show premiered in 1925

In [ ]:

```
print(f"Most Recent Movie Released: {movie['release_year'].max()}")
print(f"Most Recent TV Show Released: {tv_shows['release_year'].max()}")
```

```
Most Recent Movie Released: 2021
Most Recent TV Show Released: 2021
```

The latest movie was released in 1942, while the oldest TV show premiered in 1925.

In [ ]:
```
df.groupby(['type','rating'])['show_id'].count().reset_index(name='count')
```

Out[ ]:

	type	rating	count
0	Movie	G	41
1	Movie	NC-17	3
2	Movie	NR	80
3	Movie	PG	287
4	Movie	PG-13	490
5	Movie	R	797
6	Movie	TV-14	1427
7	Movie	TV-G	126
8	Movie	TV-MA	2062
9	Movie	TV-PG	540
10	Movie	TV-Y	131
11	Movie	TV-Y7	139
12	Movie	TV-Y7-FV	5
13	Movie	UR	3
14	TV Show	NR	6
15	TV Show	R	2
16	TV Show	TV-14	730
17	TV Show	TV-G	94
18	TV Show	TV-MA	1143
19	TV Show	TV-PG	321
20	TV Show	TV-Y	175
21	TV Show	TV-Y7	194
22	TV Show	TV-Y7-FV	1

Total Count of Rating Categories Available for Movies and TV Shows.

In [ ]:
```
df['country'] = df['country'].astype(str).str.replace('^,|,$', ' ', regex=True)
unnested_country=unnested_genre=unnested_dir=unnested_cast=df
unnested_country['country']=unnested_country['country'].str.split(",")
unnested_country=unnested_country.explode(['country'])
unnested_country['country']=unnested_country.country.str.strip()
```

Unpaking Country Data

In [ ]:
```
unnested_genre['listed_in']=unnested_genre['listed_in'].str.split(",")
unnested_genre=unnested_genre.explode(['listed_in'])
```

Unpacking Genre Data

In [ ]:
```
unnested_dir['director']=unnested_dir['director'].str.split(",")
unnested_dir=unnested_dir.explode(['director'])
```

Unpacking director data

In [ ]:
```
unnested_cast['cast']=unnested_cast['cast'].str.split(",")
unnested_cast=unnested_cast.explode(['cast'])
```

In [ ]:
```
print(f"Total Number of Unique Countries in the Dataset: {unnested_country['coun
print("-"*30)
print(f"Unique Values in the Dataset:\n {unnested_country['country'].value_count
```

```
Total Number of Unique Countries in the Dataset: 123
------------------------------
Unique Values in the Dataset:
 country
United States     3684
India             1046
Unknown            830
United Kingdom     805
Canada             445
France             393
Japan              317
Spain              232
South Korea        231
Germany            226
Name: count, dtype: int64
```

Total Number of Unique Countries in the Dataset, Along with the Count of Titles for Each Country.

In [ ]:
```
print(f"Total Number of Unique Genres in the Dataset: {unnested_genre['listed_in
print("-"*30)
print(f"Unique Values in the Dataset:\n {unnested_genre['listed_in'].value_count
```

```
Total Number of Unique Genres in the Dataset: 73
------------------------------
Unique Values in the Dataset:
 listed_in
 International Movies     2624
Dramas                    1600
Comedies                  1210
Action & Adventure         859
Documentaries              829
 Dramas                    827
International TV Shows     773
 Independent Movies        736
 TV Dramas                 695
 Romantic Movies           613
Name: count, dtype: int64
```

Total Number of Genre in the Dataset, Along with the Count of Titles for Each Genre.

In [ ]:
```
print(f"Total Number of Unique Directors in the Dataset: {unnested_dir['director
print("-"*30)
print(f"Unique Values in the Dataset:\n {unnested_dir['director'].value_counts()
```

```
Total Number of Unique Directors in the Dataset: 5121
------------------------------
Unique Values in the Dataset:
 director
Not Specified          2624
Rajiv Chilaka            22
 Jan Suter               18
Raúl Campos              18
Suhas Kadav              16
Marcus Raboy             16
Jay Karas                15
Cathy Garcia-Molina      13
Youssef Chahine          12
Martin Scorsese          12
Name: count, dtype: int64
```

Total Number of director in the Dataset, Along with the Count of Titles for Each director.

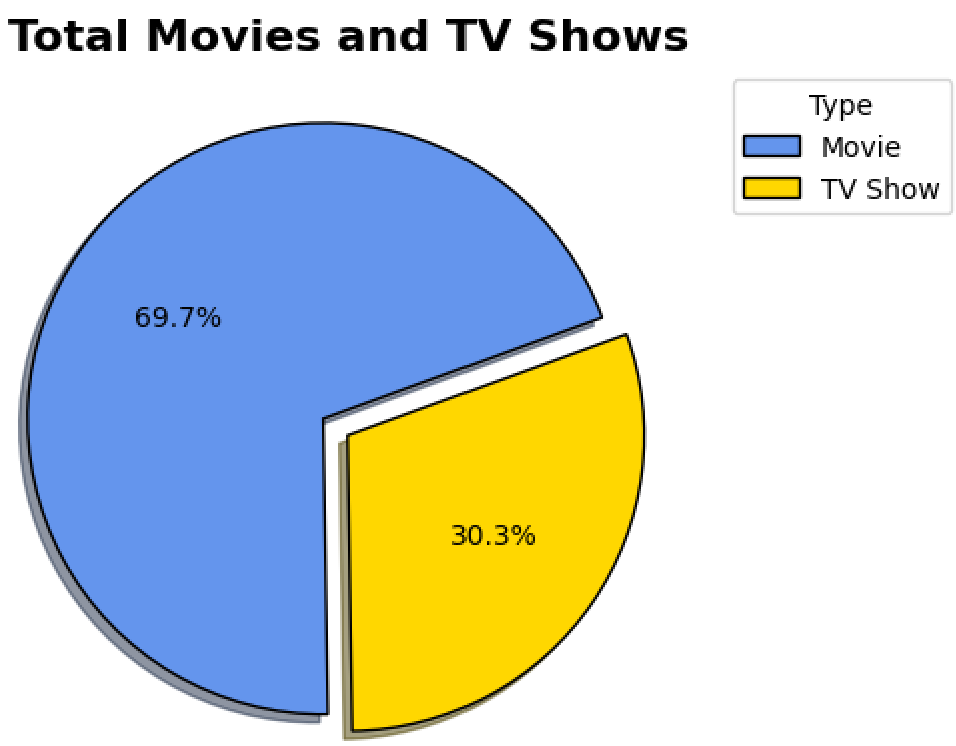
In [ ]:
```
print(f"Total Number of Unique Cast in the Dataset: {unnested_cast['cast'].nuniq
print("-"*30)
print(f"Unique Values in the Dataset:\n {unnested_cast['cast'].value_counts().he
```

```
Total Number of Unique Cast in the Dataset: 39261
------------------------------
Unique Values in the Dataset:
 cast
Not Availble         825
 Anupam Kher          39
 Rupa Bhimani         31
 Takahiro Sakurai     30
 Julie Tejwani        28
 Om Puri              27
 Rajesh Kava          26
Shah Rukh Khan        26
 Andrea Libman        25
 Paresh Rawal         25
Name: count, dtype: int64
```

Total Number of Cast in the Dataset, Along with the Count of Titles for Each Cast

Data Exploration and Conducting Graphical Analysis

In [ ]:
```
types = df.type.value_counts()
plt.pie(types, autopct='%1.1f%%' , colors = ['cornflowerblue','gold'],
startangle=20,
explode=(0.1, 0),
shadow=True,
wedgeprops={'edgecolor': 'black'})
plt.legend(types.index, title="Type", loc="upper left", bbox_to_anchor=(1, 0, 0.
plt.title('Total Movies and TV Shows',fontsize=16, fontweight='bold')
plt.show()
```



Observations from the Pie Chart

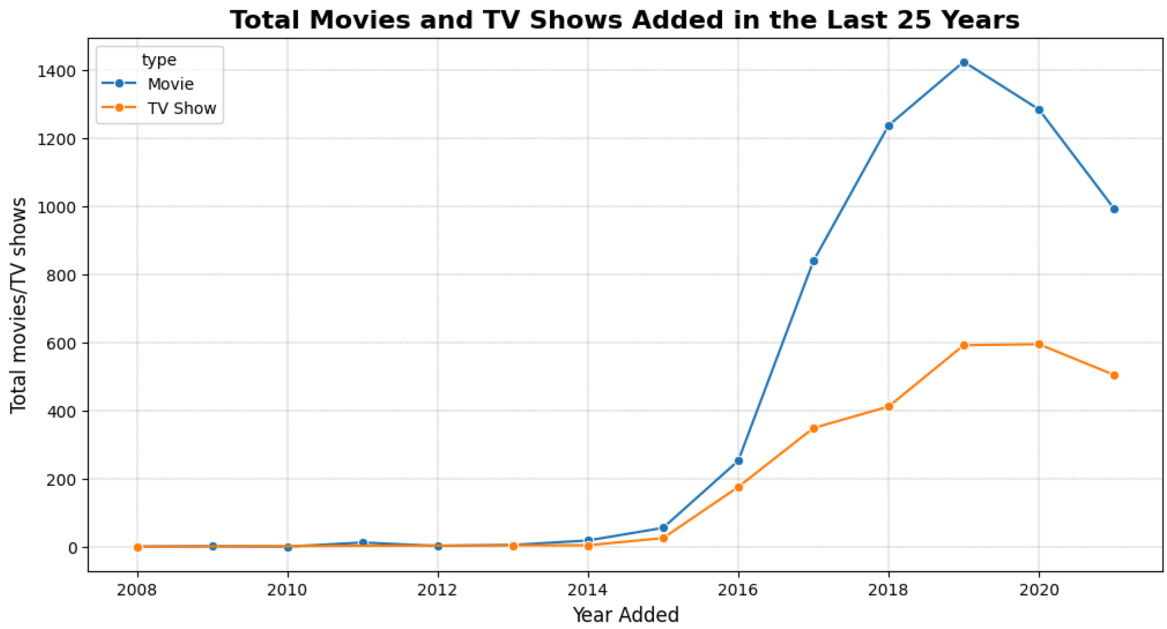
Content Type Distribution:

Movies Dominate: 69.7% of the total content consists of movies, indicating a significant preference or availability for movies compared to TV shows. TV Shows Represent a Minority: 30.3% of the content is made up of TV shows, suggesting that while they are still a popular category, they are less prevalent than movies in the dataset.

In [ ]:

```
plt.figure(figsize = (12,6))
current_year = datetime.now().year
filtered_df = df[df['date_added_year'] >= current_year-25]
filterData=filtered_df.groupby(['date_added_year','type']).size().reset_index(na

sns.lineplot(data = filterData , x = 'date_added_year' , y = 'Content_Count' , h
plt.xlabel('Year Added' , fontsize = 12)
plt.ylabel('Total movies/TV shows' , fontsize = 12)
plt.title('Total Movies and TV Shows Added in the Last 25 Years' ,fontsize=16, f
plt.grid(True, linestyle='--', linewidth=0.3, color='gray')
plt.show()
```



Observations

Overall Trend:

Both movies and TV shows have seen a significant increase in the number of releases over the past 25 years. The growth in releases has accelerated in recent years, particularly from 2016 onwards. Specific Trends:

- Movies: The number of movies released has experienced a steady and consistent increase throughout the period. There was a particularly sharp rise between 2016 and 2018.
- TV Shows: TV shows saw a slower initial growth compared to movies. However, there has been a significant surge in TV show releases in recent years, with a peak around 2019. The growth rate of TV shows has slowed down in the last couple of years.

Comparison:

- Movies vs. TV Shows: Movies have consistently outnumbered TV shows in terms of releases throughout the 25-year period. Growth Rate: While both have seen significant growth, movies have generally experienced a slightly higher growth rate compared to TV shows.
- Potential Implications: The increasing number of movies and TV shows released suggests a growing demand for content among viewers. The rapid rise in TV show releases might indicate a shift in viewer preferences or changes in production costs and distribution channels. The data could be further analyzed to explore factors driving the growth in content releases, such as technological advancements, changes in consumer behavior, or industry trends.

In [ ]:

```
filtered_df = unnested_genre[unnested_genre['date_added_year'] >= current_year-2
filterData=filtered_df.groupby(['listed_in','type']).size().reset_index(name='Co
filterData.sort_values(by='Content_Count', ascending=False, inplace=True)
filterData.head(3)
```

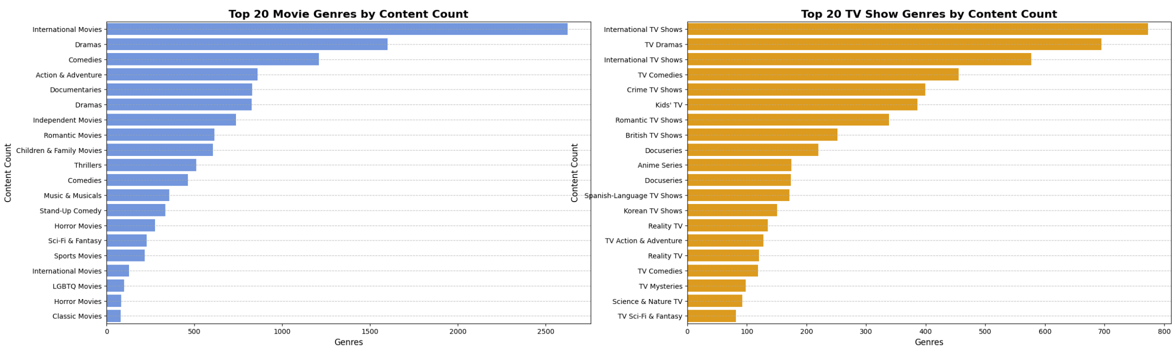
Out[ ]:

	listed_in	type	Content_Count
13	International Movies	Movie	2624
49	Dramas	Movie	1600
44	Comedies	Movie	1210

In [ ]:

```
plt.figure(figsize=(28, 8), )
plt.subplot(1, 2, 1)
sns.barplot(data=filterData[filterData['type'] == 'Movie'][0:20],
            y="listed_in",
            x="Content_Count",
            color='cornflowerblue',
)
plt.title('Top 20 Movie Genres by Content Count', fontsize=16, fontweight='bold'
plt.xlabel('Genres', fontsize=12)
plt.ylabel('Content Count', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.subplot(1, 2, 2)
sns.barplot(data=filterData[filterData['type'] == 'TV Show'][0:20],
            y="listed_in",
            x="Content_Count",
            color='orange',
)
plt.title('Top 20 TV Show Genres by Content Count', fontsize=16, fontweight='bol
plt.xlabel('Genres', fontsize=12)
plt.ylabel('Content Count', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Observations

Top 20 Movie Genres:

Dominant Genres: International Movies, Dramas, and Action & Adventure are the top three genres in terms of content count, indicating a significant preference for these categories. Diverse Genres: The chart shows a wide range of movie genres, suggesting a diverse content library. Niche Genres: Genres like Classic Movies, LGBT Movies, and Stand-Up Comedy have lower content counts, suggesting they might be niche categories with fewer offerings.

Top 20 TV Show Genres:

Dominant Genres: International TV Shows, TV Dramas, and TV Comedies are the most popular TV show genres, reflecting similar preferences to movies. Variety: TV shows also exhibit a diverse range of genres, although the distribution may differ slightly from movies.

Niche Genres: Genres like Anime Series, Korean TV Shows, and TV Sci-Fi & Fantasy have lower content counts in the TV show category.

Comparison: Genre Overlap: There is some overlap between the top genres for movies and TV shows, particularly International Movies, Dramas, and Comedies. Genre Differences: Other genres, such as Action & Adventure, Documentaries, and Independent Movies, are more prominent in the movie category, while genres like TV Mysteries, Reality TV, and British TV Shows are more prevalent in the TV show category.

Overall: The charts provide insights into the popularity and diversity of movie and TV show genres. While some genres are common to both categories, there are distinct preferences for certain genres within each category. This information can be valuable for understanding content trends, making recommendations, and tailoring content offerings to specific audience preferences.

In [ ]:
```
filtered_df = unnested_dir[(unnested_dir['date_added_year'] >= current_year-25)&
filterData=filtered_df.groupby(['director','type']).size().reset_index(name='Con
filterData.sort_values(by='Content_Count', ascending=False, inplace=True)
filterData.head(3)
```

Out[ ]:

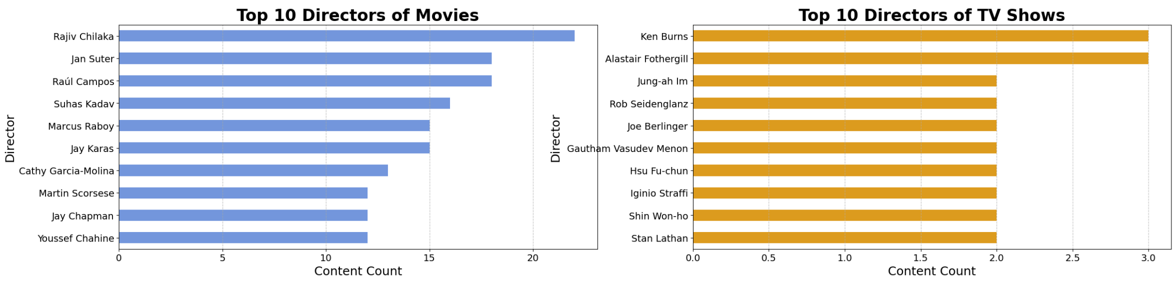
	director	type	Content_Count
4072	Rajiv Chilaka	Movie	22
265	Jan Suter	Movie	18
4119	Raúl Campos	Movie	18

In [ ]:
```
plt.figure(figsize=(28, 6), )

plt.subplot(1, 2, 1)
sns.barplot(data=filterData[filterData['type'] == 'Movie'][0:10],
y="director",
x="Content_Count",
color='cornflowerblue',width=0.5)
plt.title('Top 10 Directors of Movies', fontsize=24, fontweight='bold')
plt.xlabel('Content Count', fontsize=18)
plt.ylabel('Director', fontsize=18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.grid(axis='x', linestyle='--', alpha=0.7)

plt.subplot(1, 2, 2)
sns.barplot(data=filterData[filterData['type'] == 'TV Show'][0:10],
y="director",
x="Content_Count",
color='orange',width=0.5)
plt.title('Top 10 Directors of TV Shows', fontsize=24, fontweight='bold')
plt.xlabel('Content Count', fontsize=18)
```

```
plt.ylabel('Director', fontsize=18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```



Observation Top 10 Directors of Movies:

Rajiv Chilaka and Jan Suter are the top two movie directors based on content count, indicating their significant contributions to the movie industry.

Diverse Directors: The list includes directors from various regions, including India, the United States, and Spain, suggesting a diverse range of filmmakers.

Established Directors: Renowned directors like Martin Scorsese and Youssef Chahine are also included, highlighting their continued influence.

Top 10 Directors of TV Shows: Alastair Fothergill and Ken Burns are the leading directors in the TV show category, known for their documentary work. Diverse

Range: TV show directors also come from different backgrounds, with names like Shin Won-ho and Hsu Fu-chun representing Asian television.

Focus on Documentary and Scripted Series: Many of the top TV show directors specialize in documentary series or scripted dramas.

Comparison:

Director Overlap: There is no overlap between the top directors for movies and TV shows, suggesting that directors tend to specialize in either film or television.

Content Focus: The top movie directors may have a broader range of genres, while TV show directors often focus on specific genres like documentaries or scripted series.

Overall:

The charts provide insights into the prominent directors in the movie and TV show industries. While there is no overlap between the top directors for each category, both categories showcase a diverse range of filmmakers from different regions and backgrounds.

In [ ]:

```
filtered_df = unnested_country[
    (unnested_country['date_added_year'] >= current_year - 25) &
    (unnested_country['director'].notna()) &
    (unnested_country['director'].str.strip() != '')]
filterData=filtered_df.groupby(['country','type']).size().reset_index(name='Cont
```

```python
filterData.sort_values(by='Content_Count', ascending=False, inplace=True)
filterData.head(3)
```

Out[ ]:

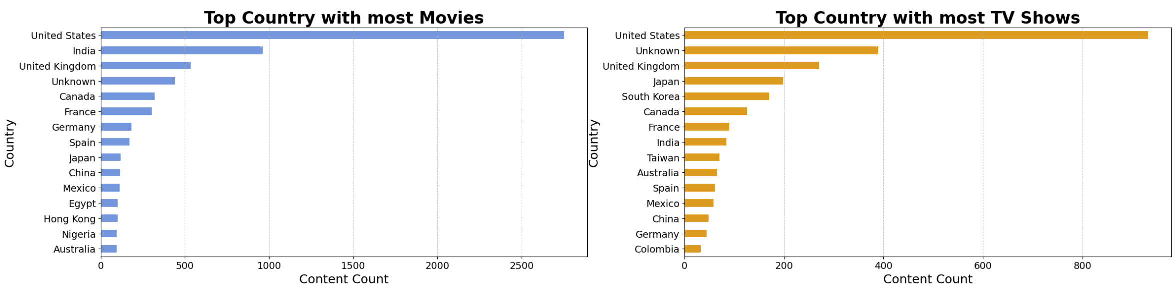
	country	type	Content_Count
172	United States	Movie	2752
65	India	Movie	962
173	United States	TV Show	932

In [ ]:

```python
plt.figure(figsize=(28, 6), )

plt.subplot(1, 2, 1)
sns.barplot(data=filterData[filterData['type'] == 'Movie'][0:15],
y="country",
x="Content_Count",
color='cornflowerblue',width=0.5)
plt.title('Top Country with most Movies', fontsize=24, fontweight='bold')
plt.xlabel('Content Count', fontsize=18)
plt.ylabel('Country', fontsize=18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.grid(axis='x', linestyle='--', alpha=0.7)

plt.subplot(1, 2, 2)
sns.barplot(data=filterData[filterData['type'] == 'TV Show'][0:15],
y="country",
x="Content_Count",
color='orange',width=0.5)
plt.title('Top Country with most TV Shows', fontsize=24, fontweight='bold')
plt.xlabel('Content Count', fontsize=18)
plt.ylabel('Country', fontsize=18)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```



Observation Top Country with Most Movies:

United States: The United States dominates the list of countries with the most movies, indicating a significant portion of the content is produced domestically.

India and Unknown: India and Unknown follow closely behind, suggesting a strong presence of Indian and international content.

Western Dominance: The majority of countries in the top 10 are Western countries, reflecting the global influence of Western cinema.

Top Country with Most TV Shows: United States: The United States also leads in the production of TV shows, although the dominance is less pronounced compared to movies.

United Kingdom and Unknown: The United Kingdom and Unknown follow closely behind, suggesting a significant contribution from these regions.

Diverse Countries: The list includes countries from various regions, including Asia, Europe, and North America, indicating a more diverse landscape for TV show production.

Comparison: Movie Production: The United States has a stronger presence in movie production compared to TV shows.

TV Show Production: While the United States is still a major producer of TV shows, other countries like the United Kingdom and Unknown have a more significant share in this category.

Regional Diversity: The top countries for TV shows exhibit more regional diversity compared to movies, suggesting a broader range of production hubs.

In [ ]:

```
# Top 10 countries producing Movies (excluding 'Unknown')
top_10_movie_countries = (
    unnested_country[(unnested_country['type'] == 'Movie') & (unnested_country['
    .groupby('country').size().sort_values(ascending=False).head(10).index)

# Filter country column in Movie data to include only top 10 countries
country_movie_data = unnested_country[unnested_country['type'] == 'Movie']['coun
    lambda x: x if x in top_10_movie_countries else 'Other')

# Top 10 countries producing TV Shows (excluding 'Unknown')
top_10_tv_countries = (
    unnested_country[(unnested_country['type'] == 'TV Show') & (unnested_country
    .groupby('country').size().sort_values(ascending=False).head(10).index)

# Filter country column in TV Show data to include only top 10 countries
country_tv_show_data = unnested_country[unnested_country['type'] == 'TV Show']['
    lambda x: x if x in top_10_tv_countries else 'Other')
```

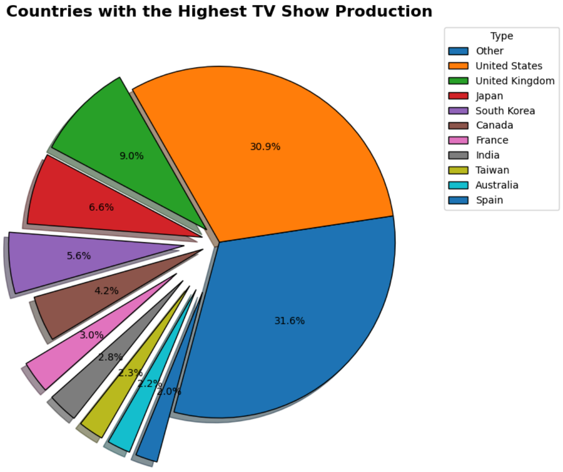
In [ ]:

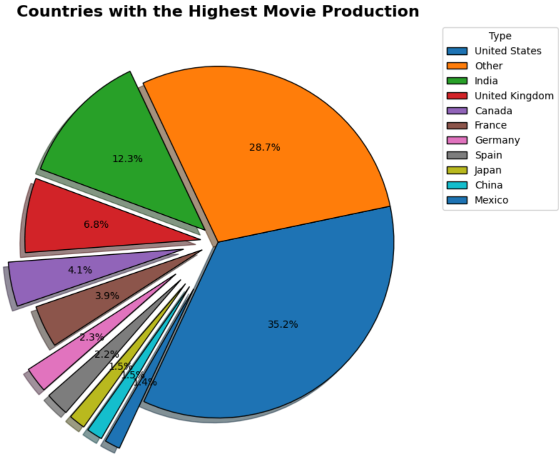
```
plt.figure(figsize=(20, 8), )

plt.subplot(1, 2, 1)
plt.pie( country_tv_show_data.value_counts() ,autopct='%1.1f%%' ,
startangle=255,
explode=(0, 0,0.1,0.1,0.2,0.1,0.3,0.3,0.3,0.3,0.3),
shadow=True,
wedgeprops={'edgecolor': 'black'})
plt.legend(country_tv_show_data.value_counts().index, title="Type", loc="upper l
plt.title('Countries with the Highest TV Show Production',fontsize=16, fontweigh

plt.subplot(1, 2, 2)
plt.pie( country_movie_data.value_counts() ,autopct='%1.1f%%' ,
startangle=245,
explode=(0, 0,0.1,0.1,0.2,0.1,0.3,0.3,0.3,0.3,0.3),
shadow=True,
wedgeprops={'edgecolor': 'black'}
)
```

```
plt.legend(country_movie_data.value_counts().index, title="Type", loc="upper lef
plt.title('Countries with the Highest Movie Production',fontsize=16, fontweight=
plt.show()
```





Observations Countries with the Highest TV Show Production:

- United States: The United States dominates TV show production, accounting for 27.8% of the total.
- Other Countries: A significant portion(34.8%) of TV shows is produced in other countries, indicating a diverse landscape.
- United Kingdom: The United Kingdom is the second largest producer of TV shows, contributing 12.9% of the total.
- Japan and South Korea: These countries have a notable presence in TV show production, each accounting for around 8% of the total.

Countries with the Highest Movie Production:

- United States: The United States also leads in movie production, accounting for 34.6% of the total.
- Other Countries: Other countries contribute 34.8% of movie production, showing a more balanced distribution compared to TV shows.
- India: India is a significant player in the movie industry, contributing 11.9% of the total.
- United Kingdom: The United Kingdom follows closely behind, accounting for 10.5% of movie production.

Comparison:

- United States: The United States has a slightly higher share in movie production compared to TV shows.
- Other Countries: Other countries have a more significant share in TV show production, indicating a more diverse landscape.
- India: India has a stronger presence in movie production compared to TV shows. - United Kingdom: The United Kingdom has a relatively equal presence in both movie and TV show production.

In [ ]:
```
groupedcountry= unnested_country.groupby(['country']).size().reset_index(name='c
```

```
groupedcountry.sort_values(by='content_count', ascending=False, inplace=True)
```

In [ ]:

```
import plotly.graph_objects as go
from plotly.offline import iplot
import plotly.graph_objects as go
import plotly.express as px
```

In [ ]:

```
fig = go.Figure(go.Choropleth(
locationmode='country names',
locations=groupedcountry['country'],
z=groupedcountry['content_count'],
colorscale='Viridis',
autocolorscale=False,
colorbar=dict(title='Content Count'),
hoverinfo='all',
hoverlabel=dict(
bgcolor='rgba(0,0,0,0.8)',
font=dict(color='white')
),
showlegend=False
))
fig.update_layout(
title={
'text': "Global Distribution of Netflix Content",
'y': 0.99,
'x': 0.5,
'xanchor': 'center',
'yanchor': 'top'
},
margin=dict(l=0, r=0, b=50, t=50)
)
fig.show()
```

Observations

Overall Distribution:

- Concentrated Presence: Netflix content appears to be heavily concentrated in North America, Europe, and parts of Asia.
- Limited Presence: Other regions, such as Africa and South America, have a more limited presence of Netflix content.

Regional Variations:

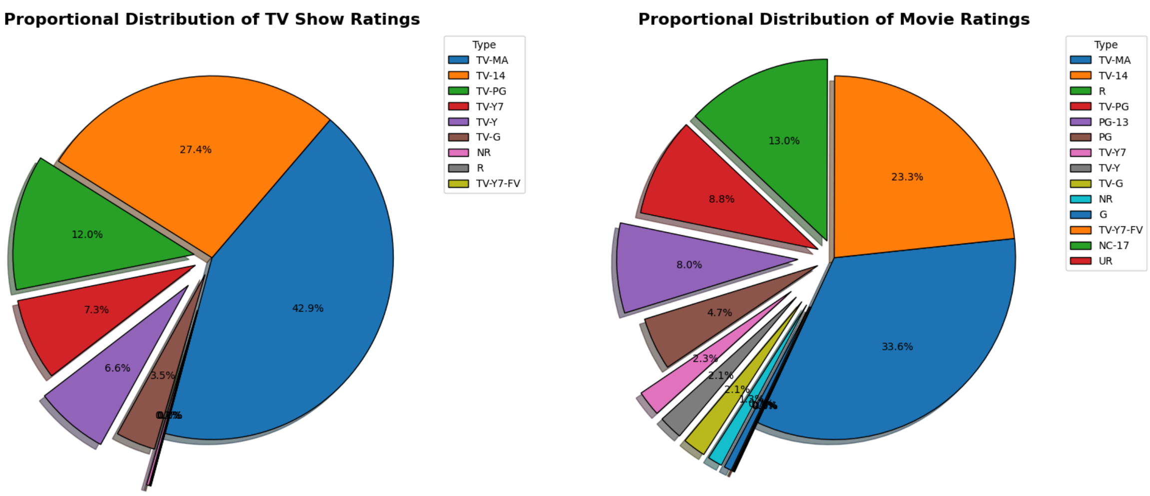
- North America: The United States and Canada have a strong presence of Netflix content, with many countries displaying high levels of availability.
- Europe: Western European countries, such as the United Kingdom, France, and Germany, also have a significant presence of Netflix content.
- Asia: Countries in East Asia, including Japan, South Korea, and Taiwan, have a notable presence of Netflix content.
- Other Regions: Africa, South America, and Oceania have limited or no coverage, suggesting that Netflix's expansion into these regions may be ongoing or less extensive.

Potential Implications:

- Market Penetration: The concentration of Netflix content in certain regions indicates that Netflix has established a strong presence in these markets.
- Content Localization: The varying levels of content availability across regions may suggest differences in content localization efforts or market preferences.
- Expansion Opportunities: Regions with limited Netflix content could represent potential growthareas for the platform.

In [ ]:
```
tv_show_rated_data = df[(df['type']=='TV Show')]['rating'].value_counts()
movie_rated_data = df[(df['type']=='Movie')]['rating'].value_counts()
```

In [ ]:
```
plt.figure(figsize=(20, 8), )
plt.subplot(1, 2, 1)
plt.pie( tv_show_rated_data ,autopct='%1.1f%%' ,
startangle=255,
shadow=True,
explode=(0, 0,0.1,0.1,0.2,0.1,0.3,0.3,0.3),
wedgeprops={'edgecolor': 'black'})
plt.legend(tv_show_rated_data.index, title="Type", loc="upper left", bbox_to_anc
plt.title('Proportional Distribution of TV Show Ratings',fontsize=16, fontweight
plt.subplot(1, 2, 2)
plt.pie( movie_rated_data ,autopct='%1.1f%%' ,
startangle=245,
explode=(0, 0,0.1,0.1,0.2,0.1,0.3,0.3,0.3,0.3,0.3,0.3,0.3,0.3),
shadow=True,
wedgeprops={'edgecolor': 'black'}
)
plt.legend(movie_rated_data.index, title="Type", loc="upper left", bbox_to_anchc
plt.title('Proportional Distribution of Movie Ratings',fontsize=16, fontweight='
plt.show()
```



Observation Observations from the Pie Charts Proportional Distribution of TV Show Ratings:

- TV-14: The most common rating for TV shows is TV-14, indicating that a significant portion of TV content is suitable for viewers aged 14 and above.
- TV-MA: The second most common rating is TV-MA, suggesting that a considerable amount of TV content is intended for mature audiences.

Diversity of Ratings: The pie chart shows a diverse range of ratings, indicating that TV content caters to various age groups and sensitivities. Lower Ratings: Ratings such as TV-

Y7, TV-Y, and TV-G are less prevalent, suggesting that a smaller portion of TV content is targeted towards younger audiences.

Proportional Distribution of Movie Ratings:

- R: The R rating dominates the movie ratings, indicating that a significant portion of movies are intended for mature audiences. - PG-13: The second most common rating is PG-13, suggesting that a considerable amount of movies are suitable for viewers aged 13 and above with parental guidance.

Variety of Ratings: Similar to TV shows, movies exhibit a diverse range of ratings, catering to different age groups. Fewer Lower Ratings: Compared to TV shows, there are fewer movies with ratings like PG, TV-Y7, and TV-Y, suggesting a higher emphasis on mature content in the movie industry.

Comparison:

TV-14 vs. R: TV-14 is the most common rating for TV shows, while R is the most common for movies, suggesting a difference in content maturity levels between the two mediums.

- Lower Ratings: TV shows have a higher proportion of lower ratings (TV-Y7, TV-Y, TV-G) compared to movies, indicating a greater focus on family-friendly content in television.

- Mature Content: Movies have a higher proportion of mature ratings (R, NC-17, UR) compared to TV shows, suggesting a greater emphasis on adult themes and content in films.

Overall: The pie charts provide insights into the rating distribution for TV shows and movies. While both mediums exhibit a diverse range of ratings, TV shows tend to have a higher proportion of lower ratings, suggesting a greater focus on family-friendly content. Movies, on the other hand, have a higher proportion of mature ratings, indicating a greater emphasis on adult themes and content.

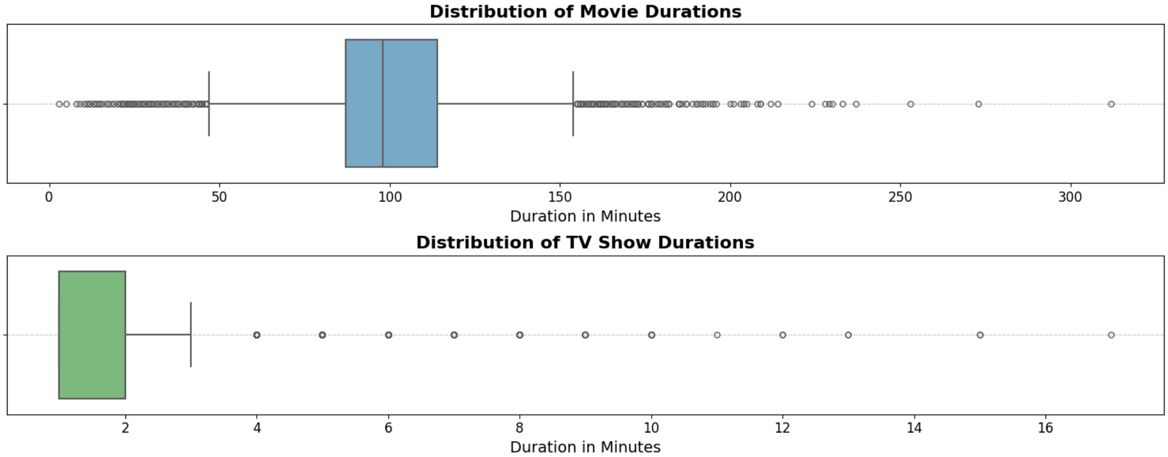
Understanding Distribution and Identifying Outliers

Box plot-Visiual Analysis Before Outlier treament

In [ ]:
```
fig, ax = plt.subplots(2, 1, figsize=(15, 6))
sns.boxplot(data=movie, x='duration', ax=ax[0], palette='Blues', fliersize=5, li
ax[0].set_xlabel('Duration in Minutes', fontsize=14)
ax[0].set_title('Distribution of Movie Durations', fontsize=16, fontweight='bold
ax[0].tick_params(axis='x', labelsize=12)
ax[0].tick_params(axis='y', labelsize=12)
ax[0].grid(axis='y', linestyle='--', alpha=0.7)

sns.boxplot(data=tv_shows, x='duration', ax=ax[1], palette='Greens', fliersize=5
ax[1].set_xlabel('Duration in Minutes', fontsize=14)
```

```
ax[1].set_title('Distribution of TV Show Durations', fontsize=16, fontweight='bc
ax[1].tick_params(axis='x', labelsize=12)
ax[1].tick_params(axis='y', labelsize=12)
ax[1].grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Observations:

Movie Durations:

- Median Duration: The median duration for movies is around 100 minutes.
- IQR: The interquartile range (IQR) is relatively large, indicating a significant spread in movie durations.
- Outliers: There are several outliers, particularly on the right side of the box plot, suggesting some movies have significantly longer durations.
- Distribution: The distribution is skewed to the right, with a longer tail on the right side. This means there are more movies with longer durations compared to shorter ones.

TV Show Durations:

- Median Duration: The median duration for TV shows is around 4 minutes.
- IQR: The IQR is relatively small, indicating a narrower range of TV show durations.
- Outliers: There are fewer outliers compared to movies, suggesting a more concentrated distribution.
- Distribution: The distribution appears to be roughly symmetrical, with a slight skew to the right.

Comparison:

- Duration Range: Movies generally have much longer durations compared to TV shows.
- Variability: Movie durations exhibit more variability than TV show durations, as evidenced by the larger IQR and the presence of more outliers.

Identifying Maximum and Minimum Durations of Movies and TV Shows for Outlier Analysis

In [ ]:
```
movie_duration =movie['duration'].max(), movie['duration'].min()
tv_shows_duration = tv_shows['duration'].max(), tv_shows['duration'].min()
```

In [ ]:
```
print(f"Maximum Duration of Movies: {movie_duration[0]}")
print(f"Minimum Duration of Movies: {movie_duration[1]}")
print("-"*30)
print(f"Maximum Duration of TV Shows: {tv_shows_duration[0]}")
print(f"Minimum Duration of TV Shows: {tv_shows_duration[1]}")
```

```
Maximum Duration of Movies: 312
Minimum Duration of Movies: 3
------------------------------
Maximum Duration of TV Shows: 17
Minimum Duration of TV Shows: 1
```

Conducting Outlier Analysis for Movies and TV Shows

Movies Outlier Analysis

In [ ]:
```
Q1 = movie['duration'].quantile(0.25)
Q3 = movie['duration'].quantile(0.75)
IQR = Q3 - Q1
movie_lower_bound = Q1 - 1.5 * IQR
movie_upper_bound = Q3 + 1.5 * IQR
print(f"Upper Bound: {movie_upper_bound}, Lower Bound: {movie_lower_bound}")
is_outlier_upper = movie_upper_bound < movie_duration[0]
is_outlier_lower = movie_lower_bound > movie_duration[1]
print(f"Is the value exceeding the upper bound limit? {is_outlier_upper}")
print(f"Is the value falling below the lower bound limit? {is_outlier_lower}.")
```

```
Upper Bound: 154.5, Lower Bound: 46.5
Is the value exceeding the upper bound limit? True
Is the value falling below the lower bound limit? True.
```

Observations for Movies Outlier

Upper Bound: The calculated upper bound for movie durations is 154.5 minutes. This means that any movie with a duration exceeding this limit is considered an outlier, indicating it falls outside the typical range of durations.

Lower Bound: The calculated lower bound for movie durations is 46.5 minutes. Any movie with a duration below this limit is also classified as an outlier, suggesting it is unusually short compared to the majority of movies.

Outlier Assessment: The analysis indicates that there are values exceeding the upper bound limit, which confirms that certain movies have significantly longer durations than what is typical in the dataset. Additionally, there are values falling below the lower bound limit, suggesting that some movies are notably shorter than the standard durations observed in the dataset.

Tv Shows Outlier Analysis

In [ ]:
```
Q1 = tv_shows['duration'].quantile(0.25)
Q3 = tv_shows['duration'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
tv_show_lower_bound = Q1 - 1.5 * IQR
tv_show_upper_bound = Q3 + 1.5 * IQR
print(f"Upper Bound: {tv_show_upper_bound}, Lower Bound: {tv_show_lower_bound}")
is_outlier_upper = tv_show_upper_bound < movie_duration[0]
is_outlier_lower = tv_show_lower_bound > movie_duration[1]
print(f"Is the value exceeding the upper bound limit? {is_outlier_upper}")
print(f"Is the value falling below the lower bound limit? {is_outlier_lower}.")
```

```
Upper Bound: 3.5, Lower Bound: -0.5
Is the value exceeding the upper bound limit? True
Is the value falling below the lower bound limit? False.
```

Observations for Tv Shows Outlier

Upper Bound: The calculated upper bound for the dataset is 3.5. This indicates that any values exceeding this threshold are considered outliers, reflecting observations that are significantly higher than the typical range.

Lower Bound: The calculated lower bound for the dataset is -0.5. Values below this threshold are also classified as outliers, indicating that they fall below what is generally expected.

Outlier Assessment: The analysis confirms that there are values exceeding the upper bound limit (3.5), suggesting that certain observations are significantly higher than most other values in the dataset. This may point to exceptional cases or anomalies that require further investigation.

However, there are no values falling below the lower bound limit (-0.5). This indicates that all observations in the dataset are within the acceptable range and do not exhibit unusually low values.

Cleaning data for Movie and Tv Shows Datasets

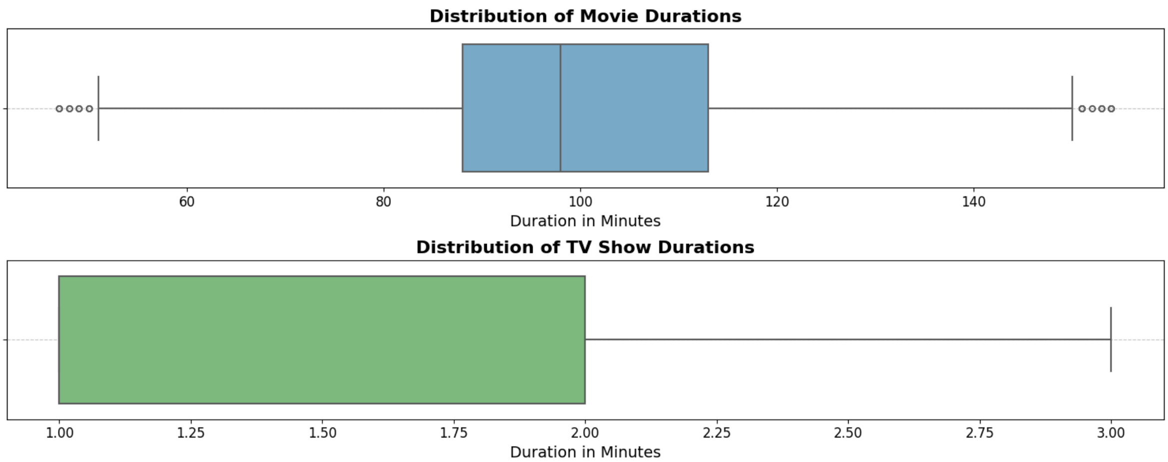
In [ ]:
```
# Clean movies data based on duration bounds
clean_Movies_data = movie[
    (movie['duration'] >= movie_lower_bound) &
    (movie['duration'] <= movie_upper_bound)
]

# Clean TV shows data based on duration bounds
clean_Tv_shows_data = tv_shows[
    (tv_shows['duration'] >= tv_show_lower_bound) &
    (tv_shows['duration'] <= tv_show_upper_bound)
]
```

Box plot-Visiual Analysis After Outlier treament

```
In [ ]: fig, ax = plt.subplots(2, 1, figsize=(15, 6))
sns.boxplot(data=clean_Movies_data, x='duration', ax=ax[0], palette='Blues', fli
ax[0].set_xlabel('Duration in Minutes', fontsize=14)
ax[0].set_title('Distribution of Movie Durations', fontsize=16, fontweight='bold
ax[0].tick_params(axis='x', labelsize=12)
ax[0].tick_params(axis='y', labelsize=12)
ax[0].grid(axis='y', linestyle='--', alpha=0.7)

sns.boxplot(data=clean_Tv_shows_data, x='duration', ax=ax[1], palette='Greens',
ax[1].set_xlabel('Duration in Minutes', fontsize=14)
ax[1].set_title('Distribution of TV Show Durations', fontsize=16, fontweight='bo
ax[1].tick_params(axis='x', labelsize=12)
ax[1].tick_params(axis='y', labelsize=12)
ax[1].grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Observations:

Movie Durations: Reduced Outliers: The number of outliers on the right side of the box plot has significantly decreased, suggesting that the outlier treatment was effective in removing extreme values.

Distribution: The distribution remains skewed to the right, but the overall spread has been reduced.

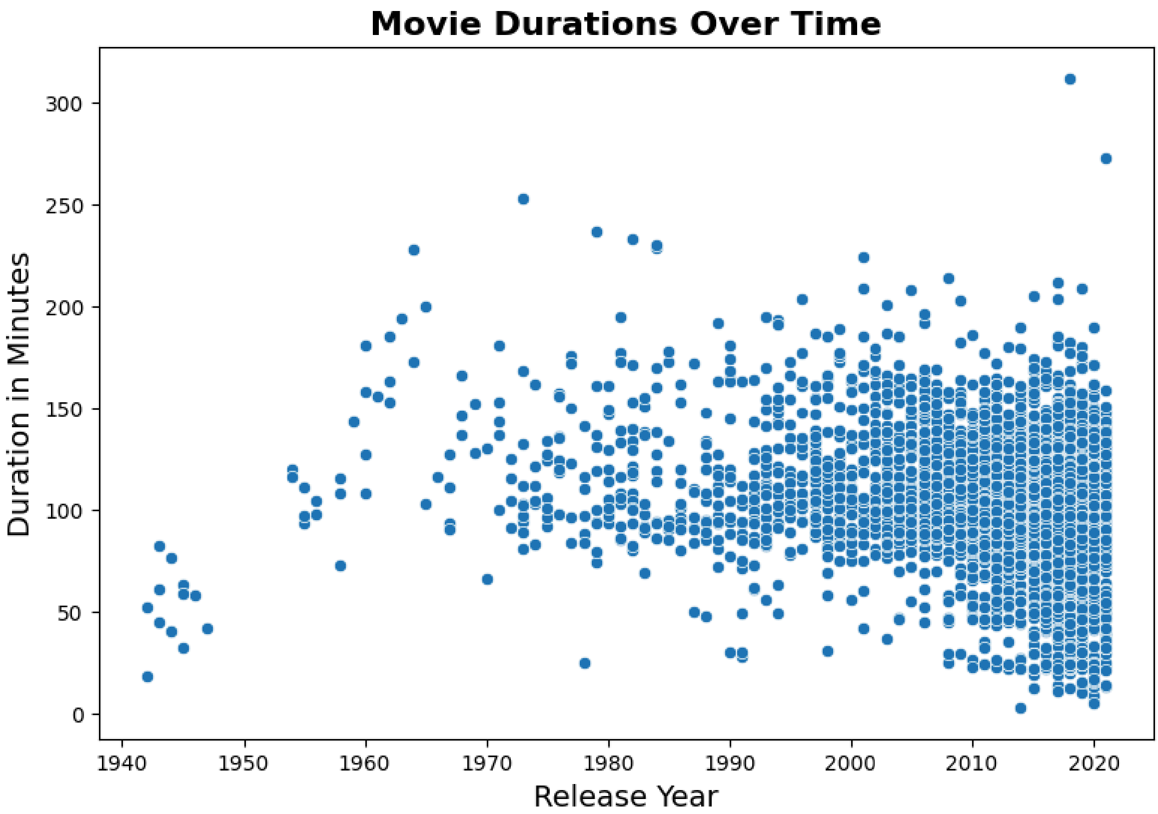
Median and IQR: The median duration and interquartile range (IQR) may have shifted slightly due to the removal of outliers.

TV Show Durations: No Significant Changes: The box plot for TV show durations appears to be unchanged, indicating that there were likely no outliers or that the outlier treatment had minimal impact on this dataset.

Analyzing the Variation of Durations Over Time for Movies and TV Shows

```
In [ ]: plt.figure(figsize = (20,6))
plt.subplot(1,2,1)
sns.scatterplot(y=movie['duration'],x= movie['release_year'], alpha=1)
plt.title('Movie Durations Over Time', fontsize=16, fontweight='bold')
```

```
plt.xlabel('Release Year', fontsize=14)
plt.ylabel('Duration in Minutes', fontsize=14)
plt.show()
```



Observation

Observations from the Scatter Plot Overall Trend: There seems to be a slight increase in movie durations over time, particularly in the later decades. However, there is also a significant amount of variation within each year.

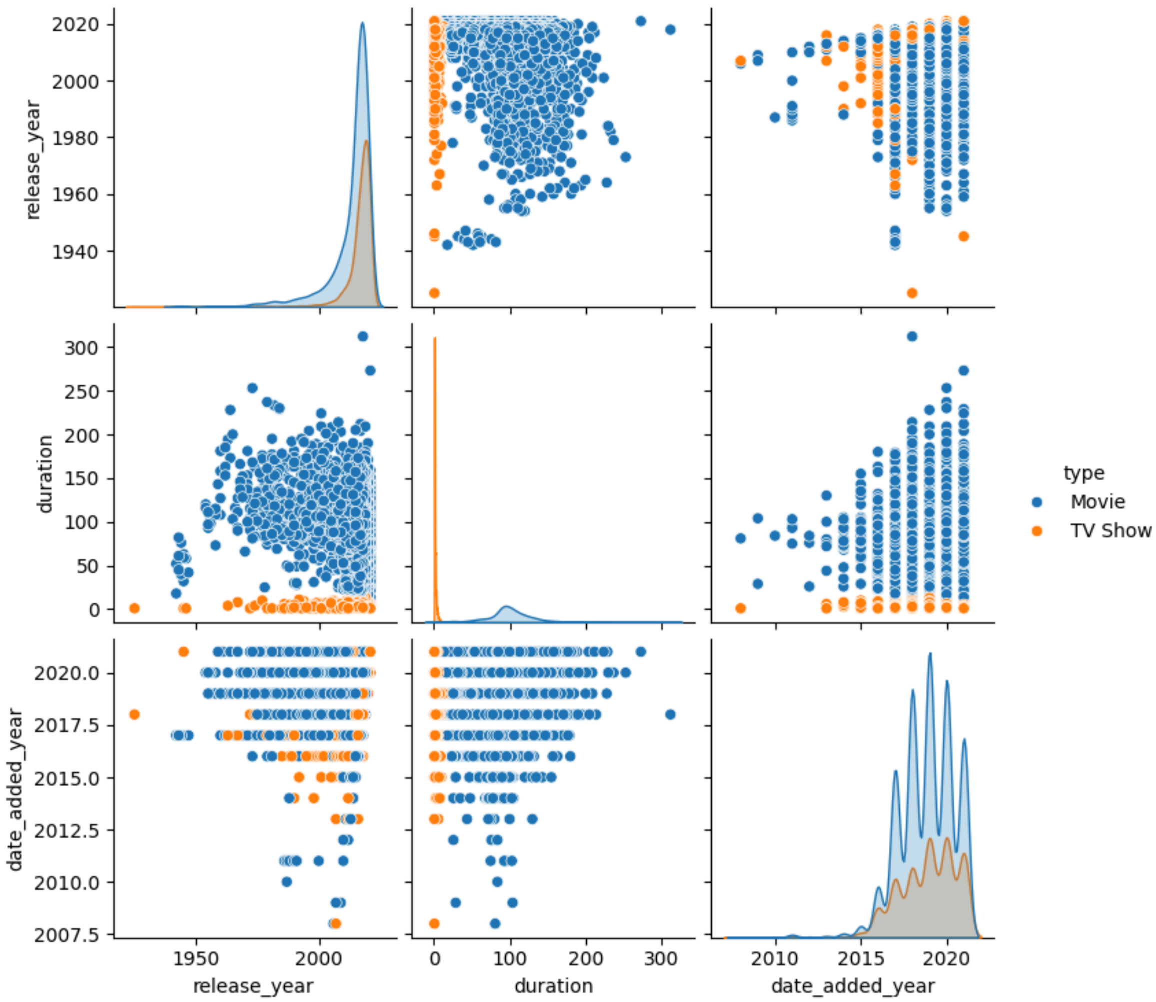
Specific Observations: Early Years: Movies released in the 1940s and 1950s tended to be shorter in duration. Mid-20th Century: Movie durations started to increase in the mid-20th century, with a noticeable cluster of movies around the 100-minute mark.

Recent Years: In recent decades, there is a wider range of movie durations, with some movies exceeding 200 minutes. However, the majority of movies still fall within the 90-150 minute range.

Analyzing Relationships Between Variables: A Pair Plot Approach

In [ ]:
```
plt.figure(figsize = (20,6))
df['duration']=df['duration'].str.split(' ').str[0].astype(int)
sns.pairplot(data=df,hue='type')
plt.show()
```

```
<Figure size 2000x600 with 0 Axes>
```



Observation

Relationships Between Variables:

Duration vs. Release Year: There seems to be a slight positive correlation between duration and release year, suggesting that movies released in recent years tend to be slightly longer than those released in earlier years.

Duration vs. Date Added Year: There appears to be a weak negative correlation between duration and date added year, indicating that movies and TV shows added more recently might have slightly shorter durations.

Release Year vs. Date Added Year: There's a strong positive correlation between release year and date added year, as expected, since movies and TV shows are typically added after they are released.

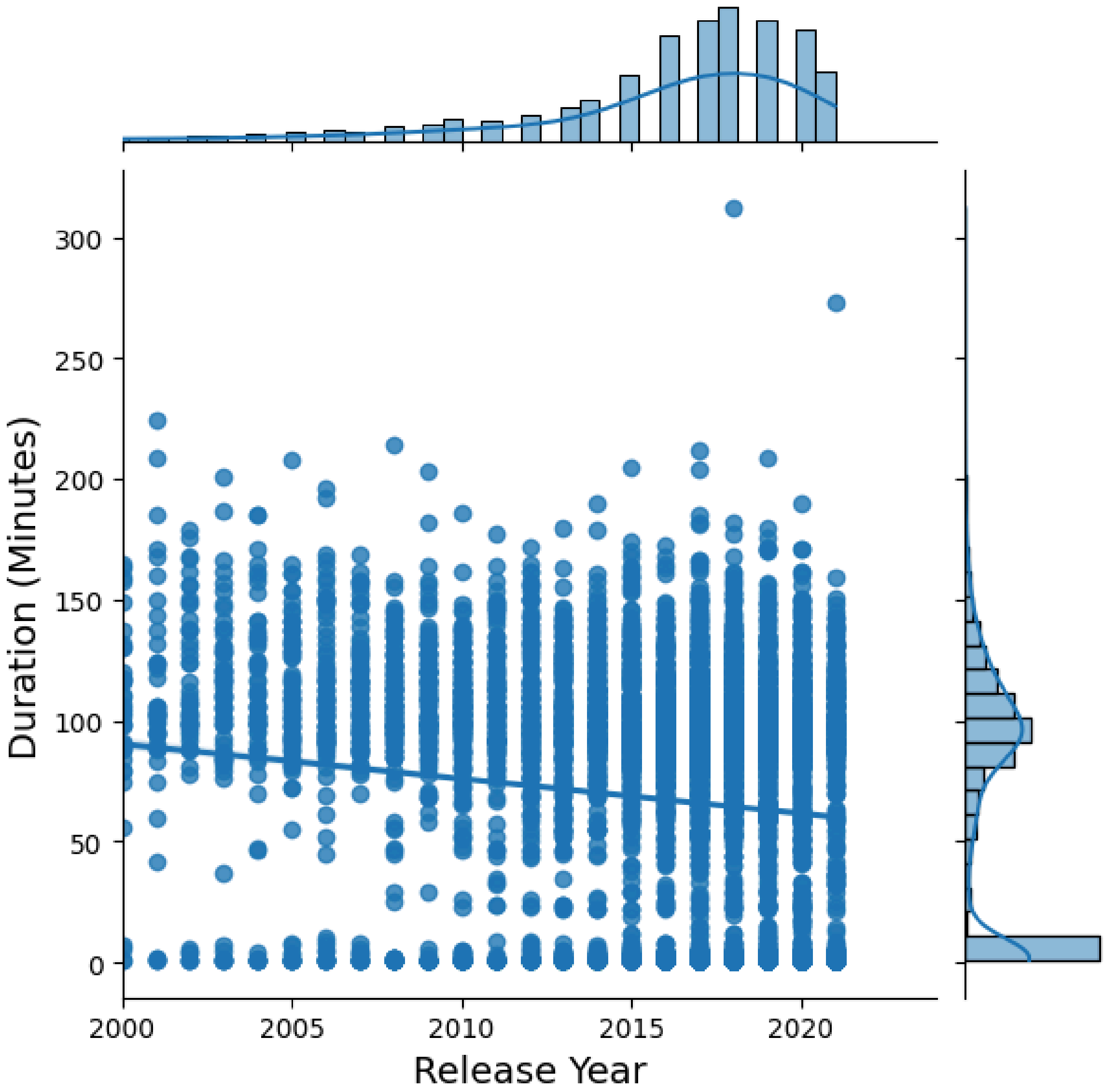
Analyzing the Relationship Between Movie Release Year and Duration Using Joint Plot Approach

In [ ]:

```
plt.figure(figsize=(12, 6))
sns.jointplot(x='release_year', y='duration', kind='reg', data=df, xlim=(2000, 2
plt.xlabel('Release Year', fontsize=14)
```

```
plt.ylabel('Duration (Minutes)', fontsize=14)
plt.show()
```

<Figure size 1200x600 with 0 Axes>



Observation

Relationship Between Release Year and Duration:

Weak Negative Correlation: There appears to be a weak negative correlation between release year and duration. This suggests that, on average, movies released in more recent years tend to be slightly shorter than those released in earlier years. However, the correlation is not very strong, indicating that there are other factors influencing movie durations.

In [ ]:
```
top_20_country = unnested_country.country.value_counts().head(20).index
top_20_country = unnested_country.loc[unnested_country['country'].isin(top_20_cc
x = top_20_country.merge(df , on = 'show_id').groupby(['country_x' , 'rating_y']
country_rating = x.pivot(index = ['country_x'] , columns = 'rating_y' , values =
```

In [ ]:
```
country_rating
```

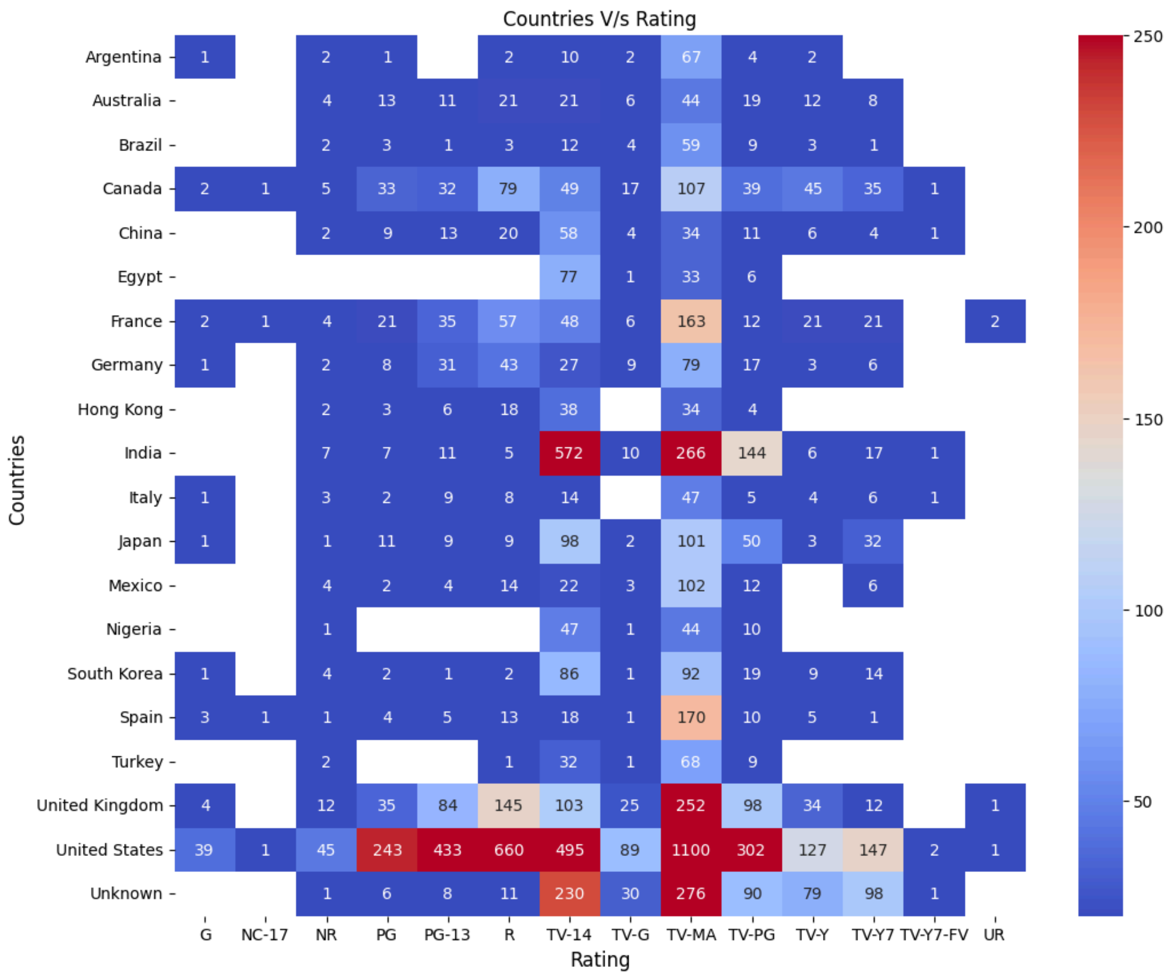
Out[ ]:

rating_y	G	NC-17	NR	PG	PG-13	R	TV-14	TV-G	TV-MA	TV-PG	TV-Y	TV Y
country_x												
Argentina	1.0	NaN	2.0	1.0	NaN	2.0	10.0	2.0	67.0	4.0	2.0	Na
Australia	NaN	NaN	4.0	13.0	11.0	21.0	21.0	6.0	44.0	19.0	12.0	8.
Brazil	NaN	NaN	2.0	3.0	1.0	3.0	12.0	4.0	59.0	9.0	3.0	1.
Canada	2.0	1.0	5.0	33.0	32.0	79.0	49.0	17.0	107.0	39.0	45.0	35.
China	NaN	NaN	2.0	9.0	13.0	20.0	58.0	4.0	34.0	11.0	6.0	4.
Egypt	NaN	NaN	NaN	NaN	NaN	NaN	77.0	1.0	33.0	6.0	NaN	Na
France	2.0	1.0	4.0	21.0	35.0	57.0	48.0	6.0	163.0	12.0	21.0	21.
Germany	1.0	NaN	2.0	8.0	31.0	43.0	27.0	9.0	79.0	17.0	3.0	6.
Hong Kong	NaN	NaN	2.0	3.0	6.0	18.0	38.0	NaN	34.0	4.0	NaN	Na
India	NaN	NaN	7.0	7.0	11.0	5.0	572.0	10.0	266.0	144.0	6.0	17.
Italy	1.0	NaN	3.0	2.0	9.0	8.0	14.0	NaN	47.0	5.0	4.0	6.
Japan	1.0	NaN	1.0	11.0	9.0	9.0	98.0	2.0	101.0	50.0	3.0	32.
Mexico	NaN	NaN	4.0	2.0	4.0	14.0	22.0	3.0	102.0	12.0	NaN	6.
Nigeria	NaN	NaN	1.0	NaN	NaN	NaN	47.0	1.0	44.0	10.0	NaN	Na
South Korea	1.0	NaN	4.0	2.0	1.0	2.0	86.0	1.0	92.0	19.0	9.0	14.
Spain	3.0	1.0	1.0	4.0	5.0	13.0	18.0	1.0	170.0	10.0	5.0	1.
Turkey	NaN	NaN	2.0	NaN	NaN	1.0	32.0	1.0	68.0	9.0	NaN	Na
United Kingdom	4.0	NaN	12.0	35.0	84.0	145.0	103.0	25.0	252.0	98.0	34.0	12.
United States	39.0	1.0	45.0	243.0	433.0	660.0	495.0	89.0	1100.0	302.0	127.0	147.
Unknown	NaN	NaN	1.0	6.0	8.0	11.0	230.0	30.0	276.0	90.0	79.0	98.

In [ ]:

```
plt.figure(figsize = (12,10))
sns.heatmap(data = country_rating , annot = True ,cmap= "coolwarm", fmt=".0f" ,
plt.xlabel('Rating' , fontsize = 12)
plt.ylabel('Countries ' , fontsize = 12)
plt.title('Countries V/s Rating' , fontsize = 12)
```

Out[ ]: `Text(0.5, 1.0, 'Countries V/s Rating')`



Observations

Overall Distribution:

- United States: The United States has the highest number of movies and TV shows across almost all ratings, indicating its dominance in the content market.
- Diverse Content: The other countries have a more diverse range of content, with varying numbers of movies and TV shows across different ratings. Regional
- Trends: Some regions, such as Europe and Asia, have a higher concentration of content in certain rating categories, suggesting regional preferences or production trends.

Specific Observations:

- TV-14: The TV-14 rating is the most common across most countries, suggesting that a significant portion of content is suitable for viewers aged 14 and above.
- R: The R rating is prevalent in the United States, indicating a higher emphasis on mature content in American productions.
- NC-17: The NC-17 rating is less common overall, suggesting that explicit content is less prevalent in the content library.

- Regional Variations: Countries like India and Egypt have a higher concentration of movies and TV shows with lower ratings (G, PG, PG-13), while countries like the United States and United Kingdom have a higher proportion of mature-rated content.

- Potential Implications: Content Preferences: The distribution of ratings can provide insights into the content preferences of viewers in different regions.

- Regulatory Influences: Variations in rating distributions across countries may be influenced by different regulatory frameworks and cultural sensitivities.

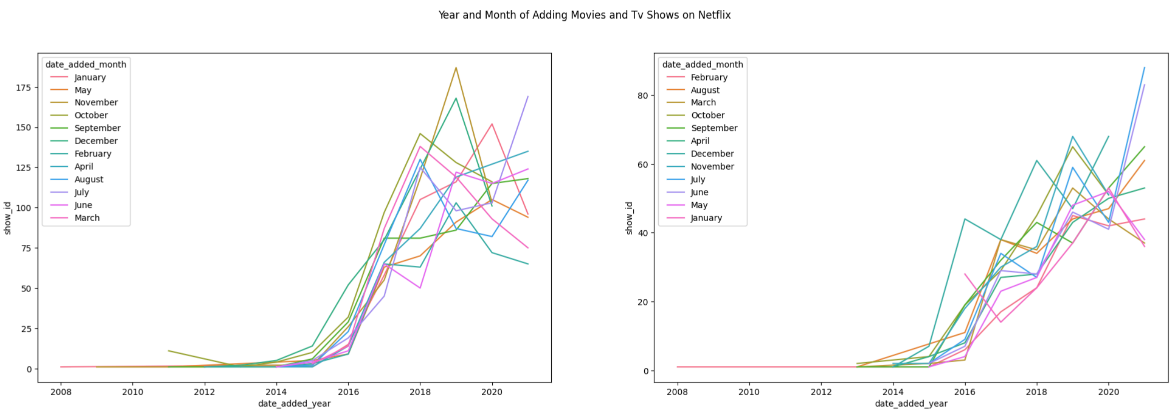
- Content Diversity: The presence of a diverse range of ratings suggests a diverse content library catering to different audiences.

Release Patterns of TV Shows and Movies on Netflix

In [ ]:
```
movies_month_year = movie.groupby(['date_added_year' , 'date_added_month'])['shc
tv_shows_month_year = tv_shows.groupby(['date_added_year' , 'date_added_month'])
```

In [ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(24, 7))
sns.lineplot(data=movies_month_year, x = 'date_added_year', y = 'show_id', hue='
sns.lineplot(data=tv_shows_month_year, x = 'date_added_year', y = 'show_id', hue
plt.suptitle('Year and Month of Adding Movies and Tv Shows on Netflix')
```

Out[ ]:
```
Text(0.5, 0.98, 'Year and Month of Adding Movies and Tv Shows on Netflix')
```



Observations

Overall Trends:

Both subplots show an increasing trend in the number of movies and TV shows added to Netflix over the years. The rate of growth seems to have accelerated in recent years, particularly after 2016.

Month-to-Month Variations:

- Subplot 1: There are noticeable seasonal fluctuations in the number of movies and TV shows added. December and January tend to have higher additions, possibly due to holiday seasons and year-end releases. Summer months (June, July, and August) generally have lower additions.

- Subplot 2: The seasonal variations in TV show additions are less pronounced compared to movies. There is a more consistent pattern of growth throughout the year, with some minor fluctuations

Business Insights

Content Distribution

- Geographical Concentration: Netflix's content is heavily concentrated in North America, Europe, and parts of Asia, with a limited presence in regions like Africa and South America.
- U.S. Dominance: The U.S. leads with the highest content offerings, particularly in mature ratings (R, NC-17).
- Content Growth: Content growth has accelerated significantly, especially after 2016, with more additions in high-demand months like December and January.

Content Localization & Genre Preferences

- Regional Preferences: Regional preferences are evident, with different regions favoring specific ratings and genres.
- Dominant Genres: Key genres include International Movies, Dramas, and Action & Adventure.

Content Release Patterns

- Movies vs. TV Shows: While both movies and TV shows have seen consistent growth, the increase in TV shows has been sharper since 2019.
- Movie Releases: Movies still outnumber TV shows in terms of total releases.

Financial and Competitive Landscape

- Competitive Pressures: Netflix faces increasing competition from other platforms with varied content offerings, potentially leading to subscriber churn

Business Recommendations

1. Expand Content Localization and Presence

- Action Item: Increase content localization efforts in regions with limited content like Africa and South America.
- Goal: Investing in local productions and tailoring content to regional preferences can drive subscriber growth.

2. Diversify Genre Offerings

- Action Item: While dominant genres like Dramas and Action perform well, Netflix should expand niche genres like Anime and LGBT content.
- Goal: This will help cater to diverse audience segments and attract new viewers.

3. Capitalize on Seasonal Content Demand

- Action Item: Boost content releases in high-demand months like December and January.
- Goal: Leveraging seasonal peaks for exclusive releases can enhance viewership and engagement.

4. Combat Churn with Personalized Recommendations

- Action Item: Strengthen personalized content recommendations based on user preferences and viewing history.
- Goal: This will help combat churn and retain subscribers by offering tailored experiences.

5. Enhance Mature Content Offerings in Key Markets

- Action Item: Given the success of mature-rated content in the U.S., invest in producing high-quality content for this segment in key markets.
- Goal: This will help maintain Netflix's appeal in regions that favor mature content.

6. Optimize Global Expansion Strategy

- Action Item: Focus on penetrating untapped markets with localized content and partnerships with local creators. Goal: This strategy will solidify Netflix's position as a global leader in streaming services.

In [280…

```
!jupyter nbconvert --to html
```