AJJAPALLY NITHISH REDDY

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

```
from google.colab import files
```

```
uploaded=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
df=pd.read_csv('/content/netflix_titles.csv')
```

Problem Statement:

Examining Netflix content data to uncover trends in content type, genre preferences, country-wise production, and release patterns. The objective is to derive insights that can help understand content strategy, audience interests, and opportunities for expansion.

Basic Trends

-Content Type Distribution

-Genre Popularity

-Country-wise Content Production

-Release Year Trends

-Content Addition Over Time

-Duration Analysis

-Correlation Between Features

Observations on the shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), missing value detection, statistical summary

Basic Observations

```
df.head(5)
```

	show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description
0	s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	NaN	United States	September 25, 2021	2020	PG-13	90 min	Documentaries	As her father nears the end of his life, filmm...
1	s2	TV Show	Blood & Water	NaN	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...	South Africa	September 24, 2021	2021	TV-MA	2 Seasons	International TV Shows, TV Dramas, TV Mysteries	After crossing paths at a party, a Cape Town t...
2	s3	TV Show	Ganglands	Julien Leclercq	Sami Bouajila, Tracy Gotoas, Samuel	NaN	September 24, 2021	2021	TV-MA	1 Season	Crime TV Shows, International	To protect his family from a powerful


```
df.shape
```

```
(8807, 12)
```

```
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
```

```
df.describe()
```

	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

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

	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

```
df.show_id.nunique()
```

```
8807
```

Convert the dtypes

```
df['date_added']=df['date_added'].str.strip()
```

```
type(df['date_added'].iloc[0])
```

```
str
```

Here the datatype of the column date_added is string ,so we have to convert them into datatime datatype

```
df['date_added']=pd.to_datetime(df['date_added'],format='%B %d, %Y',errors='coerce')
```

Here the datatype of the column 'release_year' is int ,so we have to convert them into datatime datatype

```
df['release_year']=pd.to_datetime(df['release_year'],format='%Y',errors='coerce')
```

similarly convert the dtypes of categorical cloumns in to category

```
df['type']=df['type'].astype('category')
df['director']=df['director'].astype('category')
df['country']=df['country'].astype('category')
df['rating']=df['rating'].astype('category')
df['listed_in']=df['listed_in'].astype('category')
```

```
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   category
 2   title         8807 non-null   object
 3   director      6173 non-null   category
 4   cast          7982 non-null   object
 5   country       7976 non-null   category
 6   date_added    8797 non-null   datetime64[ns]
 7   release_year  8807 non-null   datetime64[ns]
 8   rating        8803 non-null   category
 9   duration      8804 non-null   object
 10  listed_in     8807 non-null   category
 11  description   8807 non-null   object
dtypes: category(5), datetime64[ns](2), object(5)
memory usage: 758.0+ KB
```

Before handling missing values, first unnest the columns that contain multiple values within a single entry. This step is important for effective visualization.

Unnesting the dataframe

-->For Cast Column

```
df['cast']=df['cast'].str.split(', ')
```

```
df=df.explode('cast',ignore_index=True)
```

--> For Country Column

```
df['country']=df['country'].str.split(', ')
```

```
df=df.explode('country',ignore_index=True)
```

--> For Director Column.

```
df['director']=df['director'].str.split(",")
```

```
df=df.explode('director',ignore_index=True)
```

```
df=df
```

--> For Listed_in Column

```
df['listed_in']=df['listed_in'].str.split(',')
```

```
df=df.explode('listed_in',ignore_index=True)
```

Handling the missing values

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

	0
show_id	0
type	0
title	0
director	50643
cast	2146
country	11897
date_added	158
release_year	0
rating	67
duration	3
listed_in	0
description	0

dtype: int64

-> HEre we can identify the missing values in the columns 'director', 'cast', 'country', 'date_added', 'rating', 'duration'.

--> for 'director' column.

> For the "Director" column, I am replacing the null values with the most frequent director for the respective country. If the entry has an empty value in place of the country, I am replacing the null with "Unknown" values.

```
director_counts = df.groupby('country')['director'].apply(lambda x:x.mode()[0] if not x.mode().empty else 'Unknown')
```

```
def fill_missing_values(row):

    if pd.isna(row['director']):
        if pd.notna(row['country']):
            return director_counts.get(row['country'])
        else:
          return 'Unknown'

    return row['director']
```

```
df['director'] = df.apply(fill_missing_values, axis=1)
```

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

	0
show_id	0
type	0
title	0
director	0
cast	2146
country	11897
date_added	158
release_year	0
rating	67
duration	3
listed_in	0
description	0

dtype: int64

--> for 'country' column

> For the "Country" column, I am replacing the null values with the first country associated with the respective director, or else keeping them as null if no director is available.

```
director_to_country = df.groupby('director')['country'].first().to_dict()
```

```
def fill_missing_country(row):
    if pd.isna(row['country']) and pd.notna(row['director']):
        country = director_to_country.get(row['director'])
        return country if country is not None else 'Unknown'
    else:
        return row['country']
```

```
df['country'] = df.apply(fill_missing_country, axis=1)
```

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

	0
show_id	0
type	0
title	0
director	0
cast	2146
country	0
date_added	158
release_year	0
rating	67
duration	3
listed_in	0
description	0

dtype: int64

--> for 'date_added' column.

> For the "Date Added" column, I have replaced the missing values using forward fill (

```
df['date_added'].isna().sum()
```

```
158
```

```
df['date_added']=df['date_added'].fillna(method='ffill')
```

Show hidden output

```
df['date_added']=df['date_added'].fillna(method='bfill')
```

Show hidden output

```
df['date_added'].isna().sum()
```

```
0
```

--> for 'cast' column

> For the "Cast" column, I have replaced the missing values with the director's most frequent cast, and if no frequent cast is available, I have replaced them with "unknown."

```
cast_counts=df.groupby('director')['cast'].apply(lambda x:x.mode()[0] if not x.mode().empty else 'Unknown')
```

```
def fill_missing_cast(row):
    if pd.isna(row['cast']):
        return cast_counts.get(row['director'])
    else:
         return row['cast']
```

```
df['cast']=df.apply(fill_missing_cast,axis=1)
```

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

Show hidden output

--> for 'rating' column

```
df['rating'].value_counts()
```

Show hidden output

> I noticed some irrelevant values in the "Rating" column, such as "77min," "84min," and "66min." First, I will replace these values with NaN to clean the data.

```
valid_ratings=['PG-13', 'TV-MA', 'PG', 'TV-14', 'TV-PG', 'TV-Y', 'TV-Y7', 'R',
       'TV-G', 'G', 'NC-17', 'NR','TV-Y7-FV', 'UR']
```

```
df['rating'] = df['rating'].apply(lambda x: x if x in valid_ratings else np.nan)
```

> For the "Rating" column, I will replace the missing values with the director's most frequent rating. If no frequent rating is available, I will replace them with "unknown."

```
rating_counts=df.groupby('director')['rating'].apply(lambda x:x.mode()[0] if not x.mode().empty else 'Unknown')
```

```
def fill_missing_rating(row):
    if pd.isna(row['rating']):
        return rating_counts.get(row['director'])
    else:
        return row['rating']
```

```
df['rating']=df.apply(fill_missing_rating,axis=1)
```

```
df['rating'].isna().sum()
```

```
0
```

--> for 'duration' coulumn

For the "Duration" column, I have two values: "min" for movies and "season1", "season2" for TV shows. To facilitate easier analysis, I will convert the durations into minutes and store them in another column. Then, I will drop the original "Duration" column.

> For TV shows, I am making a rough estimation where 1 season is assumed to have 10 episodes, and each episode is approximately 60 minutes long. Using this estimation, I will convert the duration of TV shows into minutes for better analysis.

```
def convert_duration(row):
    if isinstance(row, str):
        if 'min' in row:
            return int(row.split(' ')[0])
        elif 'season' in row.lower():
            return int(row.split(' ')[0]) * 10 * 60
    return None

df['duration_in_mins'] = df['duration'].apply(convert_duration)
```

```
df['duration_in_mins']=df['duration_in_mins'].astype('Int64')
```

> Now, I will fill the missing values in the duration column with the mean of the duration (in minutes) for movies and TV shows separately. This will ensure that the missing data is handled in a way that reflects the typical duration for each type.

```
movies=df[df['type']=='Movie']
```

```
movies_mean_duration=int(movies['duration_in_mins'].mean())
```

```
movies['duration_in_mins']=movies['duration_in_mins'].fillna(movies_mean_duration)
```

Show hidden output

```
tvshows=df[df['type']=='TV Show']
```

```
tvshows_mean_duration=int(tvshows['duration_in_mins'].mean())
```

```
tvshows['duration_in_mins']=tvshows['duration_in_mins'].fillna(tvshows_mean_duration)
```

Show hidden output

```
merged_df=pd.concat([movies,tvshows])
```

```
df=merged_df.sort_index()
```

```
df.drop('duration',axis=1,inplace=True)
```

```
df.rename({'duration_in_mins':'duration'},axis=1,inplace=True)
```

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

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

dtype: int64

Non-Graphical Analysis: Value counts and unique attributes .

```
df['title'].nunique()
```

```
8807
```

^We have a total of 8,807 unique entries in the dataset

```
df.nunique()
```

	0
show_id	8807
type	2
title	8807
director	5121
cast	36440
country	128
date_added	1714
release_year	74
rating	15
listed_in	73
description	8775
duration	220

dtype: int64

--> Top directors who featured on netflix

> "Here, I am using `unique_df` to store the unique values to avoid the duplication issues caused by unnesting."

```
unique_df=df[['show_id','director']].drop_duplicates()
```

```
unique_df[unique_df['director']!='Unknown']['director'].value_counts().head(20)
```

director	count
Martin Scorsese	952
Sarah Smith	268
Toshiya Shinohara	195
Bong Joon Ho	169
Robert Vince	134
David Dhawan	94
Thierry Donard	87
Clay Glen	69
Chen Rong-hui	64
Alfonso Cuarón	57
Fernando González Molina	55
Wilson Yip	53
Detlev Buck	51
Fernando Ayllón	39
Yılmaz Erdoğan	36
Bruno Garotti	31
Youssef Chahine	29
Lana Wachowski	26
Lars von Trier	24
Banjong Pisanthanakun	23

dtype: int64

--> Top actors who featured on netflix.

```
unique_df=df[['show_id','type','cast']].drop_duplicates()
```

```
unique_df[unique_df['cast']!='Unknown']['cast'].value_counts().head(20)
```

cast	count
Grey Griffin	160
Frederick Lee	102
David Attenborough	63
Anupam Kher	61
Julie Tejwani	36
Shah Rukh Khan	35
Takahiro Sakurai	35
Naseeruddin Shah	32
Rupa Bhimani	31
Om Puri	30
Akshay Kumar	30
Yuki Kaji	29
Amitabh Bachchan	28
Paresh Rawal	28
Boman Irani	27
Rajesh Kava	26
Vincent Tong	26
Andrea Libman	25
Kareena Kapoor	25
Samuel L. Jackson	24

dtype: int64

-->Top movie casts that appear on Netflix

```
movies=unique_df[unique_df['type']=='Movie']
```

```
movies[movies['cast']!='Unknown']['cast'].value_counts().head(20)
```

cast	count
Anupam Kher	44
Shah Rukh Khan	35
Naseeruddin Shah	32
Julie Tejwani	31
Om Puri	30
Akshay Kumar	30
Paresh Rawal	28
Amitabh Bachchan	28
Boman Irani	27
Rupa Bhimani	27
Kareena Kapoor	25
Grey Griffin	25
Samuel L. Jackson	22
Rajesh Kava	21
Ajay Devgn	21
Nawazuddin Siddiqui	20
Nicolas Cage	20
Adam Sandler	20
Salman Khan	20
Kay Kay Menon	20

dtype: int64

--> Top TV Show casts who appear on Netflix

```
tvshows=unique_df[unique_df['type']=='TV Show']
```

```
tvshows[tvshows['cast']!='Unknown']['cast'].value_counts().head(20)
```

cast	count
Grey Griffin	135
Frederick Lee	85
David Attenborough	50
Takahiro Sakurai	28
Yuki Kaji	19
Daisuke Ono	17
Junichi Suwabe	17
Ai Kayano	17
Anupam Kher	17
Yuichi Nakamura	16
Yoshimasa Hosoya	15
Jun Fukuyama	15
Takehito Koyasu	13
Hiroshi Kamiya	13
Wille Lindberg	13
Vincent Tong	13
Kana Hanazawa	13
Yoshitsugu Matsuoka	13
Mamoru Miyano	13
Natsuki Hanae	12

dtype: int64

--> Top genres on Netflix

```
unique_df=df[['show_id','listed_in']].drop_duplicates()
```

```
unique_df['listed_in'].value_counts().head(10)
```

listed_in	count
International Movies	2624
Dramas	1600
Comedies	1210
Action & Adventure	859
Documentaries	829
Dramas	827
International TV Shows	774
Independent Movies	736
TV Dramas	696
Romantic Movies	613

dtype: int64

--> Top countries producing the content

```
unique_df=df[['show_id','country']].drop_duplicates()
```

```
unique_df['country'].value_counts().head(20)
```

country	count
United States	3725
India	1104
United Kingdom	808
Canada	447
Belarus	410
France	394
Japan	326
Unknown	272
Spain	234
South Korea	233
Germany	227
Mexico	173
China	162
Australia	160
Egypt	125
Turkey	114
Nigeria	113
Hong Kong	105
Brazil	101
Italy	100

dtype: int64

--> The top ratings we have on Netflix

```
unique_df=df[['show_id','rating']].drop_duplicates()
```

```
unique_df['rating'].value_counts().head(20)
```

rating	count
TV-MA	3209
TV-14	2161
TV-PG	863
R	799
PG-13	490
TV-Y7	334
TV-Y	307
PG	287
TV-G	220
NR	80
G	41
TV-Y7-FV	6
Unknown	4
NC-17	3
UR	3

dtype: int64

--> Number of movies/tvshows released per year

```
unique_df=df[['show_id','release_year']].drop_duplicates()
```

```
unique_df['release_year']=unique_df['release_year'].dt.year
```

```
unique_df["release_year"].value_counts().head(20)
```

release_year	count
2018	1147
2017	1032
2019	1030
2020	953
2016	902
2021	592
2015	560
2014	352
2013	288
2012	237
2010	194
2011	185
2009	152
2008	136
2006	96
2007	88
2005	80
2004	64
2003	61
2002	51

dtype: int64

--> content added per year

```
unique_df=df[['show_id','date_added']].drop_duplicates()
```

```
unique_df['date_added'].dt.year.value_counts().head(20)
```

date_added	count
2019	2017
2020	1879
2018	1652
2021	1498
2017	1193
2016	430
2015	82
2014	24
2011	13
2013	11
2012	3
2009	2
2008	2
2010	1

dtype: int64

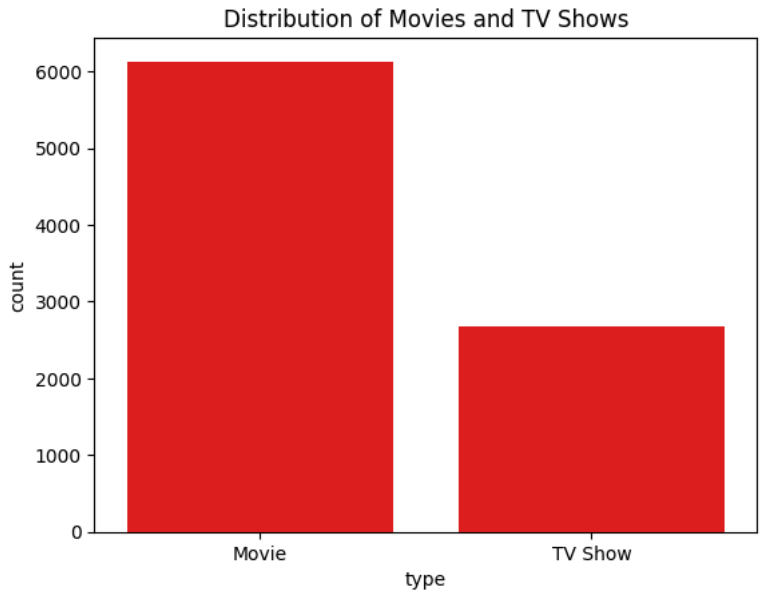
Visual Analysis - Univariate, Bivariate after pre-processing of the data

--> UNIVARIATE ANALYSIS

> Movies vs. TV Shows Count

```
unique_df=df[['show_id','type']].drop_duplicates()
```

```
sns.countplot(data=unique_df,x='type',color='red')
plt.title('Distribution of Movies and TV Shows')
plt.show()
```



^ **Insights**:The dataset reveals that Netflix has a significantly higher number of movies compared to TV shows, indicating a stronger emphasis on movies within its content library

--> propotion of movies and tvshowls

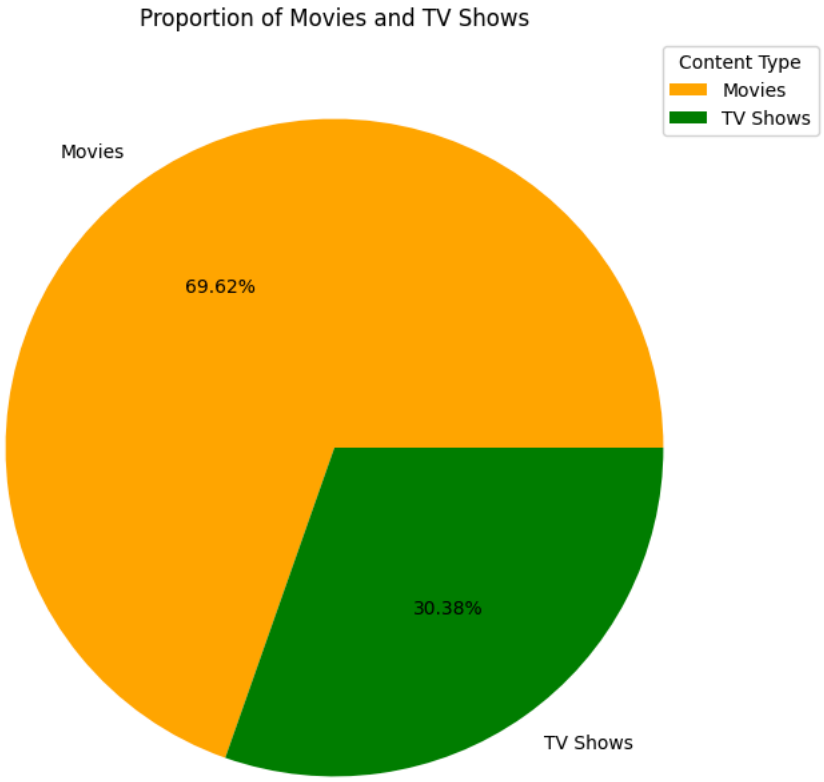
```
moviesp=unique_df[unique_df['type']=='Movie']['type'].count()
```

```
tvshowsp=unique_df[unique_df['type']=='TV Show']['type'].count()
```

```
labels=[moviesp,tvshowsp]
```

```
plt.figure(figsize=(10,8))
plt.pie(labels,labels=['Movies','TV Shows'],autopct='%1.2f%%',colors=['orange','green'])
plt.title('Proportion of Movies and TV Shows')
plt.legend(labels=['Movies','TV Shows'],title='Content Type',loc='upper right',bbox_to_anchor=(1.1,1))
plt.show()

plt.show()
```



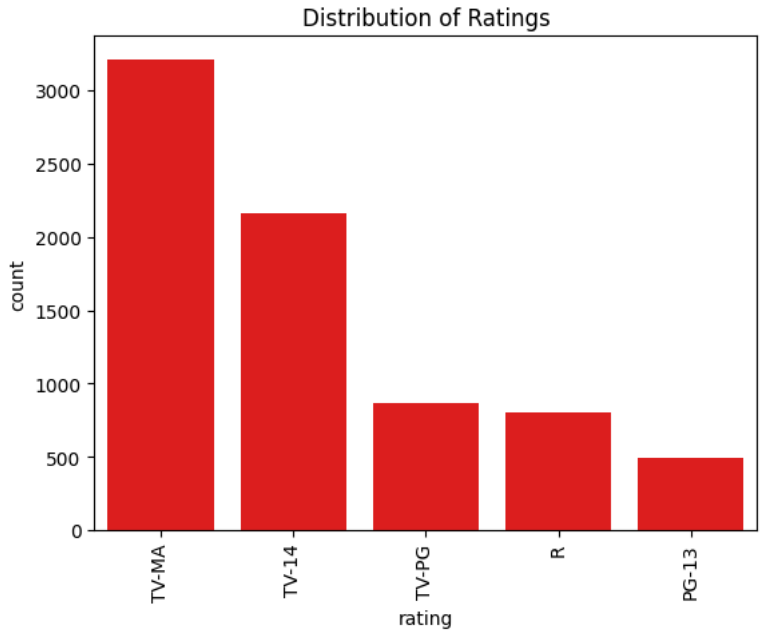
--> Distribution of Ratings

```
unique_rating=df[['show_id','rating']].drop_duplicates()
```

```
top5_ratings =unique_rating['rating'].value_counts().head(5)
```

```
df_top5=unique_rating[unique_rating['rating'].isin(top5_ratings.index)]
```

```
sns.countplot(data=df_top5,x=df_top5['rating'],color='red',order=top5_ratings.index)
plt.title('Distribution of Ratings')
plt.xticks(rotation=90)
plt.show()
```



^ **Insights**:The Top 5 ratings are TV-MA,TV-14,TV-PG,R,PG-13

-->Distribution of countries

```
unique_country=df[['show_id','country']].drop_duplicates()
```

```
top10=unique_country['country'].value_counts().head(10)
```

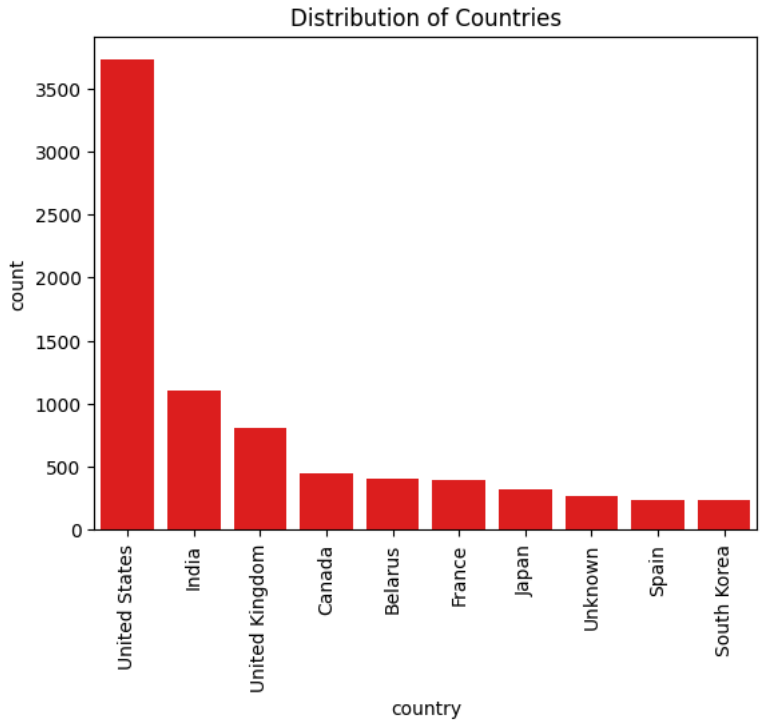
```
df_top10=unique_country[unique_country['country'].isin(top10.index)]
```

```
df_top10['country'].value_counts()
```

country	count
United States	3725
India	1104
United Kingdom	808
Canada	447
Belarus	410
France	394
Japan	326
Unknown	272
Spain	234
South Korea	233

dtype: int64

```
sns.countplot(data=df_top10,x='country',color='red',order=top10.index)
plt.title('Distribution of Countries')
plt.xticks(rotation=90)
plt.show()
```



^ **Insights**:The top countries producing movies and TV shows on Netflix are the USA, with a count of 3,725, followed by India with 1,104, and the UK with 808. The USA dominates with a vast number compared to others.

--> Distribution of movies and tvshows duration

```
unique_duration=df[['show_id','type','duration']].drop_duplicates()
```

```
movies_d=unique_duration[unique_duration['type']=='Movie']
```

```
tvshows_d=unique_duration[unique_duration['type']=='TV Show']
```

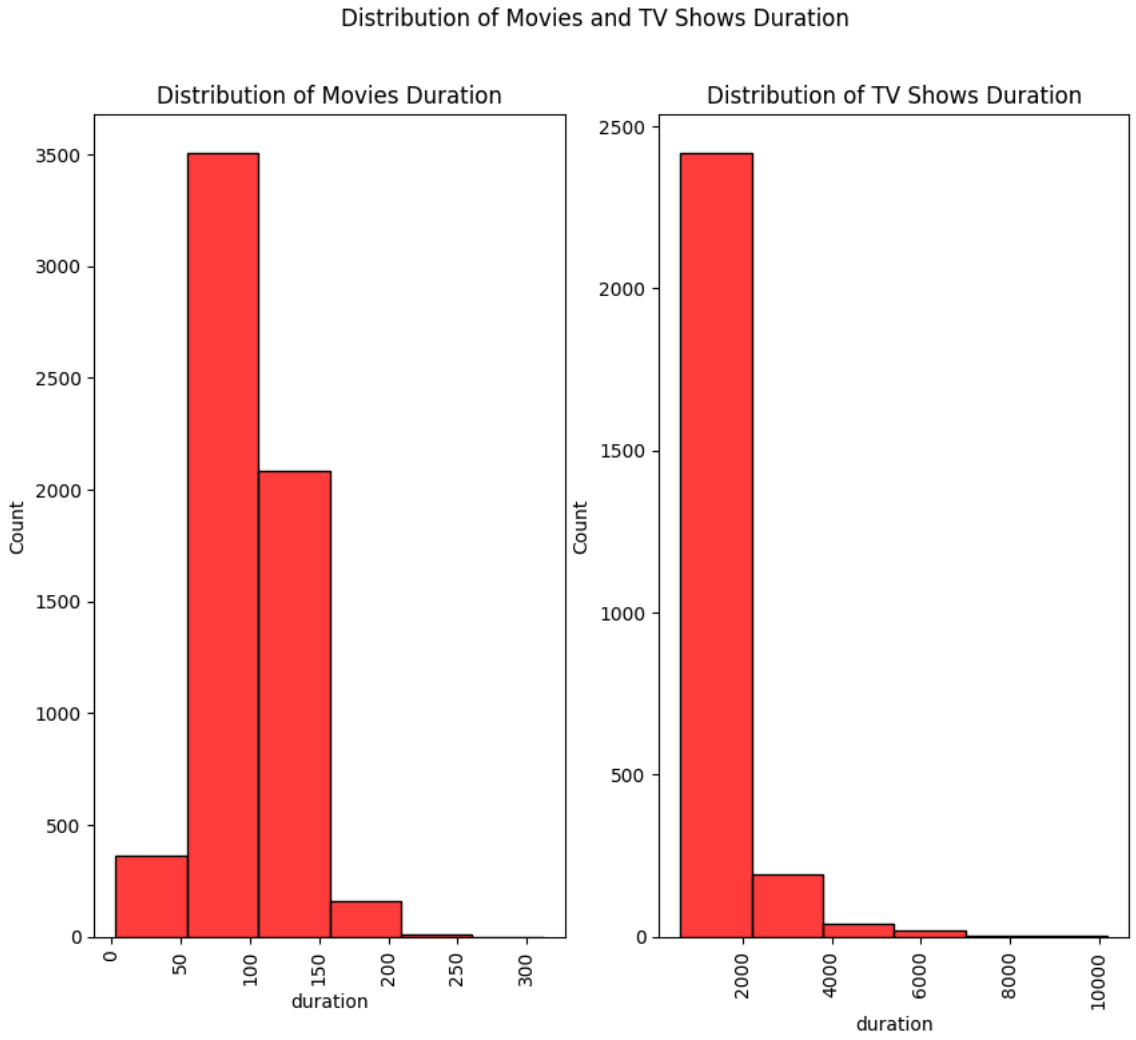
```
plt.figure(figsize=(10, 8))
plt.suptitle('Distribution of Movies and TV Shows Duration')

plt.subplot(1, 2, 1)
sns.histplot(data=movies_d, x='duration',bins=6, color='red')
plt.title('Distribution of Movies Duration')
plt.xticks(rotation=90)



plt.subplot(1, 2, 2)
sns.histplot(data=tvshows_d, x='duration',bins=6, color='red')
plt.title('Distribution of TV Shows Duration')
plt.xticks(rotation=90)

plt.show()
```



^ **Insights**: Here, most movie runtimes lie between 80-160 minutes (1.33-2.67 hours), while TV show runtimes are mostly below 2,200 minutes (36.67 hours).

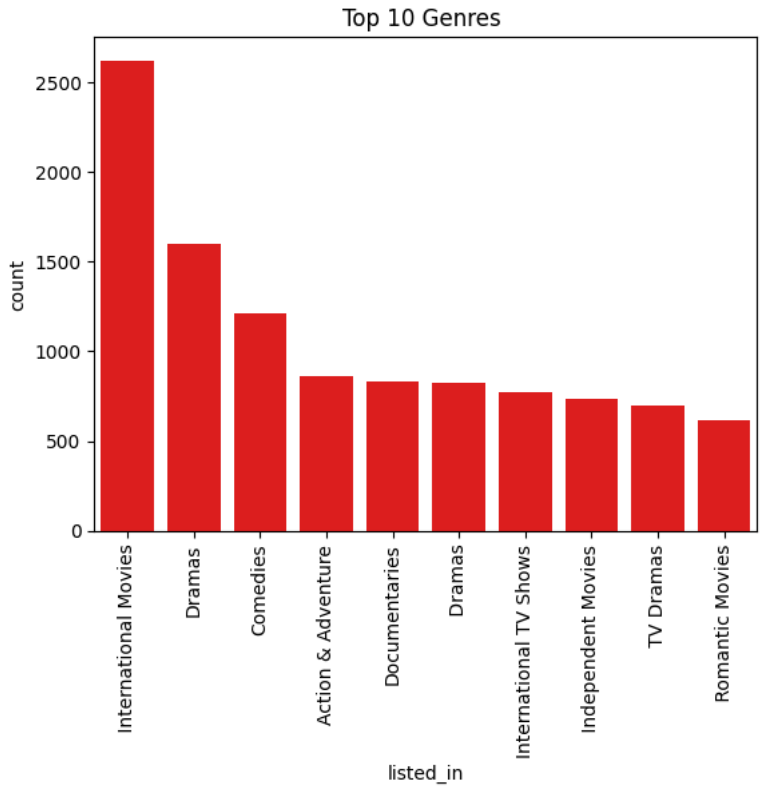
--> most popular genres in netflix

```
unique_df=df[['show_id','type','listed_in']].drop_duplicates()
```

```
top10_genres=unique_df['listed_in'].value_counts().head(10)
```

```
top10_df_tv=unique_df[unique_df['listed_in'].isin(top10_genres.index)]
```

```
sns.countplot(data=top10_df_tv,x='listed_in',color='red',order=top10_genres.index)
plt.title('Top 10 Genres ')
plt.xticks(rotation=90)
plt.show()
```



^**Insights**: The top genres are International Movies, Dramas, Comedies, Action & Adventure, and Documentaries.

--> Distribution of Genre

```
movies=unique_df[unique_df['type']=='Movie']
```

```
tvshows=unique_df[unique_df['type']=='TV Show']
```

```
unique_m=movies[['show_id','listed_in']].drop_duplicates()
```

```
top10=unique_m['listed_in'].value_counts().head(10)
```

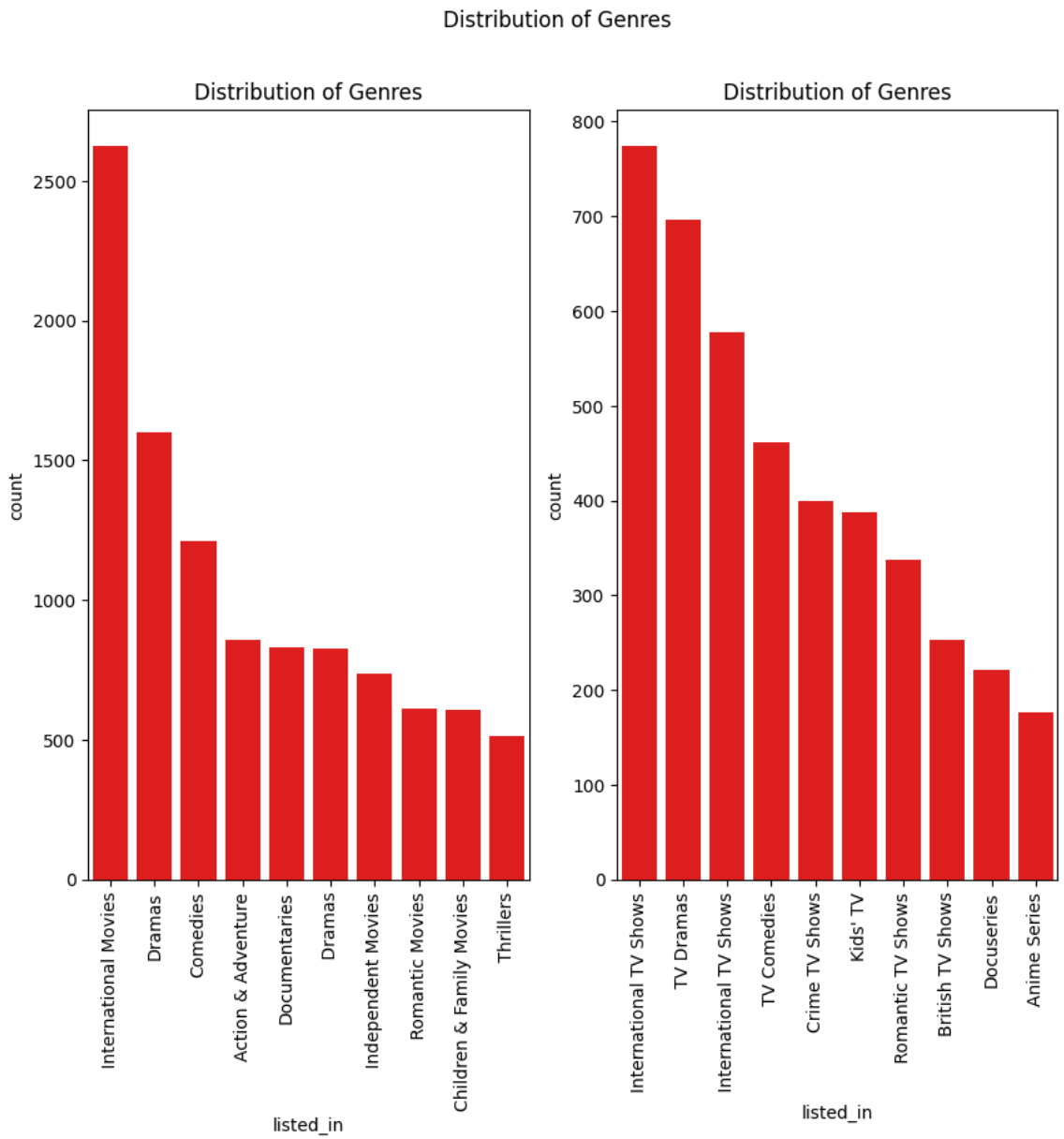
```
top_10_df=unique_m[unique_m['listed_in'].isin(top10.index)]
```

```
unique_tv=tvshows[['show_id','listed_in']].drop_duplicates()
```

```
top10tv=unique_tv['listed_in'].value_counts().head(10)
```

```
top10_df_tv=unique_tv[unique_tv['listed_in'].isin(top10tv.index)]
```

```
plt.figure(figsize=(10,8))
plt.suptitle('Distribution of Genres')
plt.subplot(1,2,1)
sns.countplot(data=top_10_df,x='listed_in',color='red',order=top10.index)
plt.title('Distribution of Genres')
plt.xticks(rotation=90)
plt.subplot(1,2,2)
sns.countplot(data=top10_df_tv,x='listed_in',color='red',order=top10tv.index)
plt.title('Distribution of Genres')
plt.xticks(rotation=90)
plt.show()
```

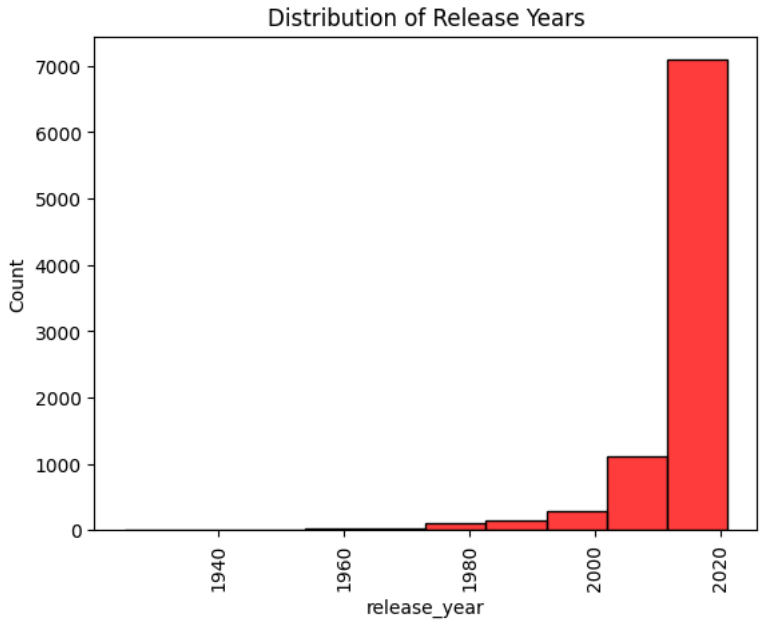


^**Insights** :The top movie genres are International Movies, Dramas, Comedies, Action & Adventure, and Documentaries. The top TV genres are International TV Shows, TV Dramas, TV Comedies, and Crime TV Shows.

--> content released over the years

```
unique_year=df[['show_id','release_year']].drop_duplicates()
```

```
sns.histplot(x=unique_year['release_year'],bins=10,color='red')
plt.title('Distribution of Release Years')
plt.xticks(rotation=90)
plt.show()
```

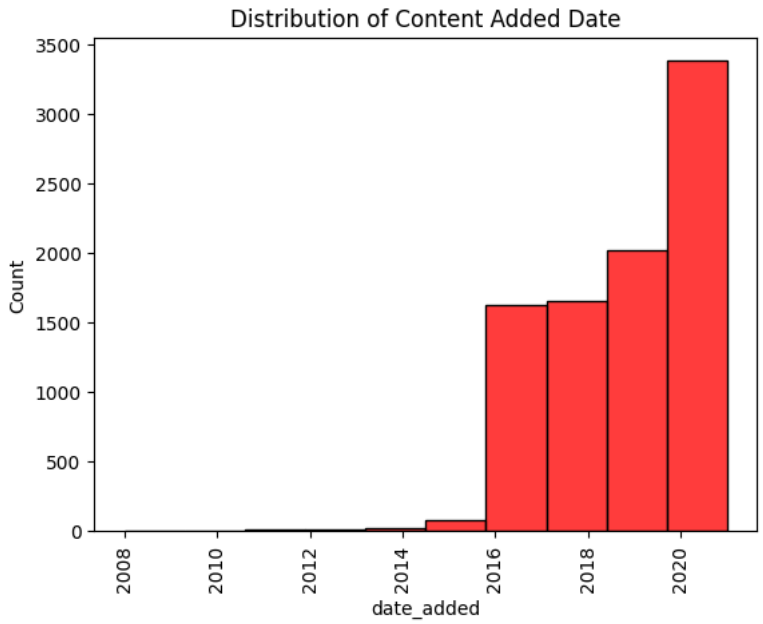


^ **Insights**:We can observe that most of the films that Netflix acquired were released primarily in the past 8-10 years, with the majority being released after 2015.

-->Content added over the years

```
unique_year2=df[['show_id','date_added']].drop_duplicates()
```

```
sns.histplot(x=unique_year2['date_added'].dt.year,bins=10,color='red')
plt.title('Distribution of Content Added Date')
plt.xticks(rotation=90)
plt.show()
```

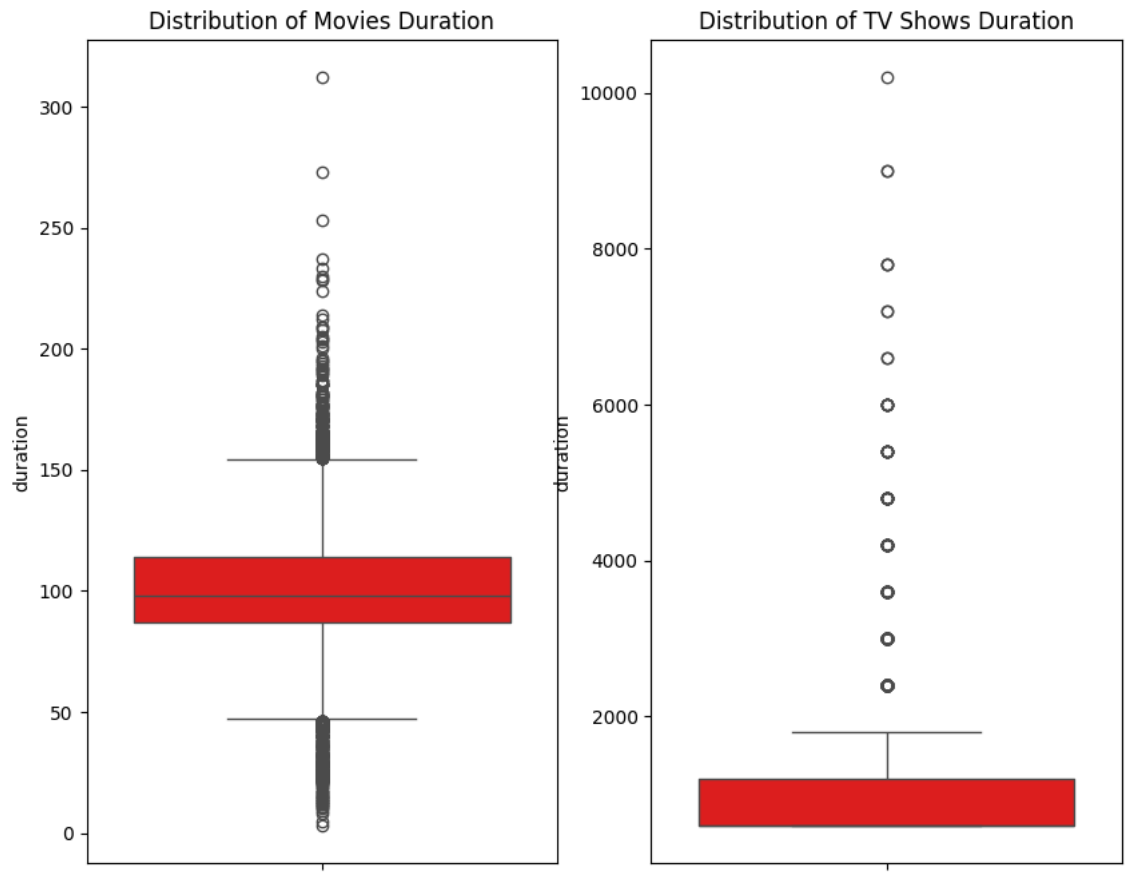


^ **Insights**: Most of the content was added after 2014, with a significant increase year by year. There was a rapid rise in the number of content additions after 2019, especially during and after the COVID-19 pandemic.

--> visual summuary of duration is distributed by boxplot

```
plt.figure(figsize=(10, 8))
plt.subplot(1, 2, 1)
sns.boxplot(data=movies_d,y='duration',color='red')
plt.title('Distribution of Movies Duration')
plt.xticks(rotation=90)
```

```
plt.subplot(1, 2, 2)
sns.boxplot(data=tvshows_d,y='duration',color='red')
plt.title('Distribution of TV Shows Duration')
plt.xticks(rotation=90)
plt.show()
```



^**Insights**: Movies: There are some movies with either very short runtimes (under 30 minutes) or very long runtimes (over 200 minutes). These could be special types of movies, like short films or extended versions.

TV Shows: Some TV shows have very few episodes, while others have a lot. The ones with fewer episodes could be limited series, and the ones with more episodes could be long-running shows.

Bivariate analysis

--> Distribution of movies vs. TV shows across different countries.

```
unique_df=df[['show_id','type','country']].drop_duplicates()
```

```
top_10=unique_df['country'].value_counts().head(10)
```

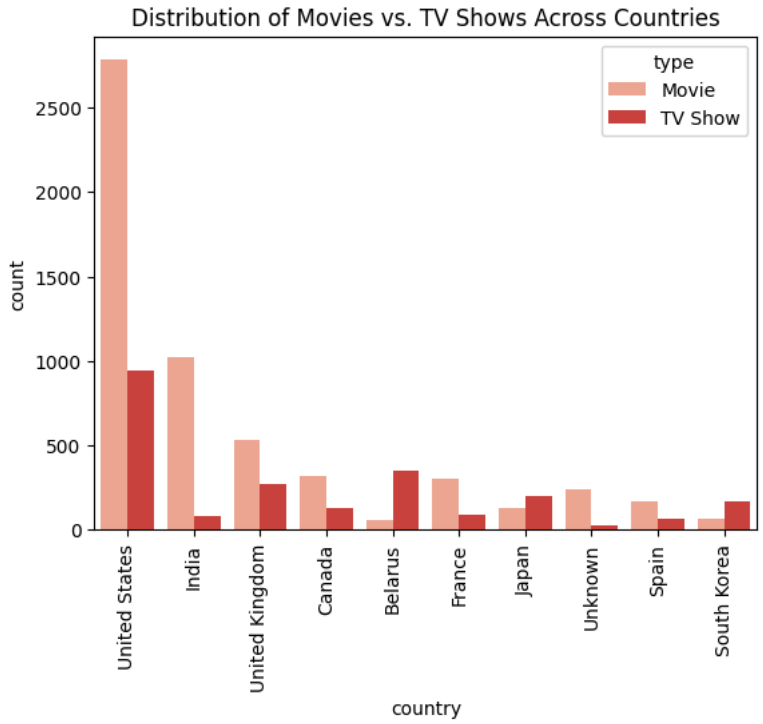
```
top_10_df=unique_df[unique_df['country'].isin(top_10.index)]
```

```
top_10_df['country'].value_counts()
```

country	count
United States	3725
India	1104
United Kingdom	808
Canada	447
Belarus	410
France	394
Japan	326
Unknown	272
Spain	234
South Korea	233

dtype: int64

```
sns.countplot(data=top_10_df,x='country',hue='type',palette='Reds',order=top_10_df['country'].value_counts().index)
plt.title('Distribution of Movies vs. TV Shows Across Countries')
plt.xticks(rotation=90)
plt.show()
```



^**Insights**: USA, India, UK: Movies dominate the content in these countries. These regions produce a larger number of movies compared to TV shows, reflecting their well-established movie industries.

Belarus and Japan: TV shows dominate in these countries. This could be due to local preferences or changing market trends that favor TV shows over movies.

-->How Top 5 ratings differ across different countries.

```
movies=df[df['type']=='Movie']
```

```
tvshows=df[df['type']=='TV Show']
```

```
unique_movies=movies[['show_id','duration','rating']].drop_duplicates()
```

```
unique_tvshows=tvshows[['show_id','duration','rating']].drop_duplicates()
```

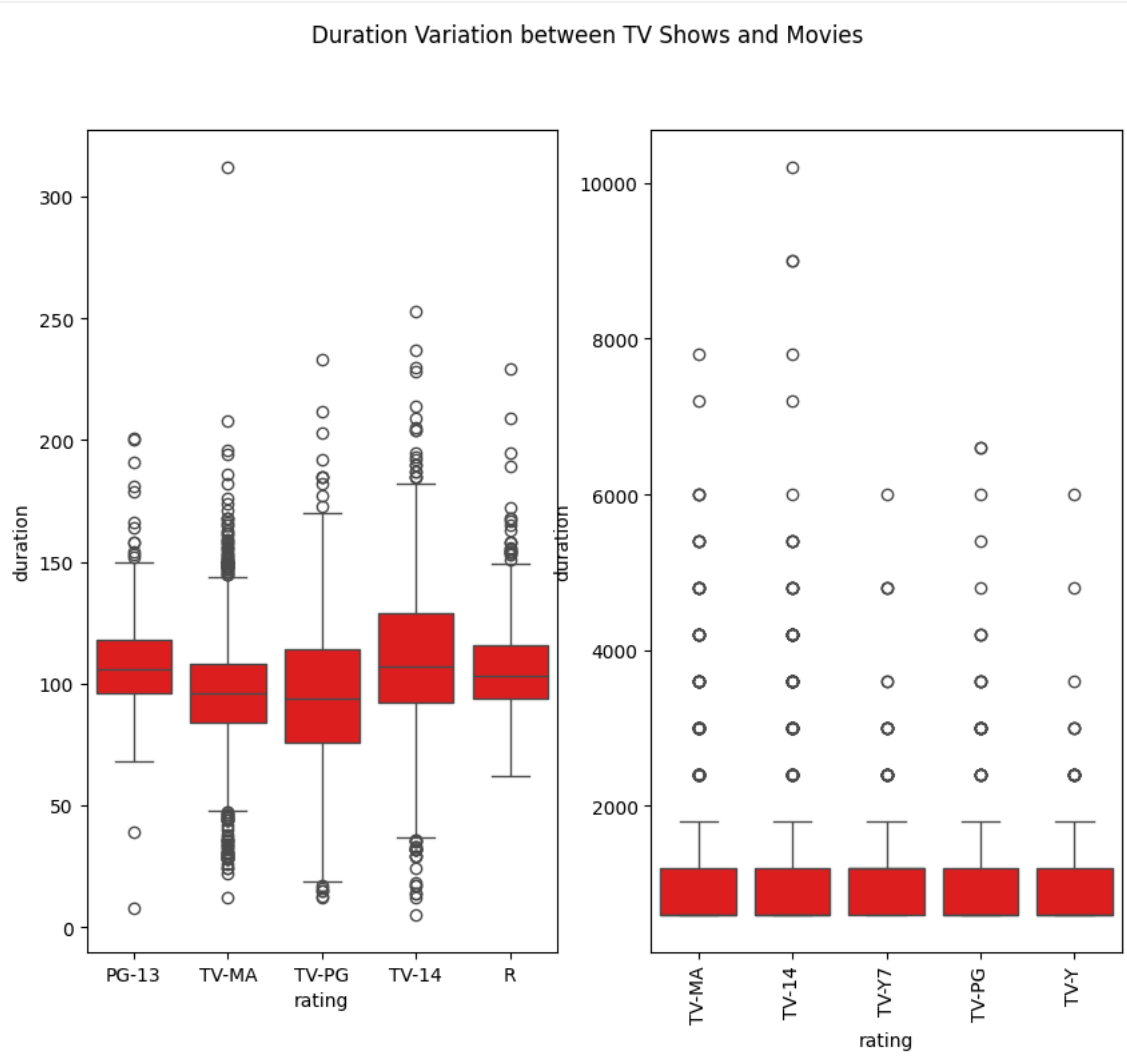
```
top5_mrating=unique_movies['rating'].value_counts().head(5)
```

```
top5_df_m=unique_movies[unique_movies['rating'].isin(top5_mrating.index)]
```

```
top5_tvrating=unique_tvshows['rating'].value_counts().head(5)
```

```
top5_df_tv=unique_tvshows[unique_tvshows['rating'].isin(top5_tvrating.index)]
```

```
fig, (ax1,ax2)=plt.subplots(1,2, figsize=(10,8))
sns.boxplot(data=top5_df_m,x='rating',y='duration',color='red',ax=ax1)
sns.boxplot(data=top5_df_tv,x='rating',y='duration',color='red',ax=ax2)
fig.suptitle('Duration Variation between TV Shows and Movies')
plt.xticks(rotation=90)
plt.show()
```



^**Insights**: From the box plot of movie genres, we see that some movie genres have counts that are much higher or lower than most others. For TV shows, the top 5 genres mostly have counts that are higher than the usual range, meaning these genres are more common or popular compared to the others.

--> Top 10 genre popularity across the top 5 countries.

```
unique_df=df[['show_id','listed_in','country']].drop_duplicates()
```

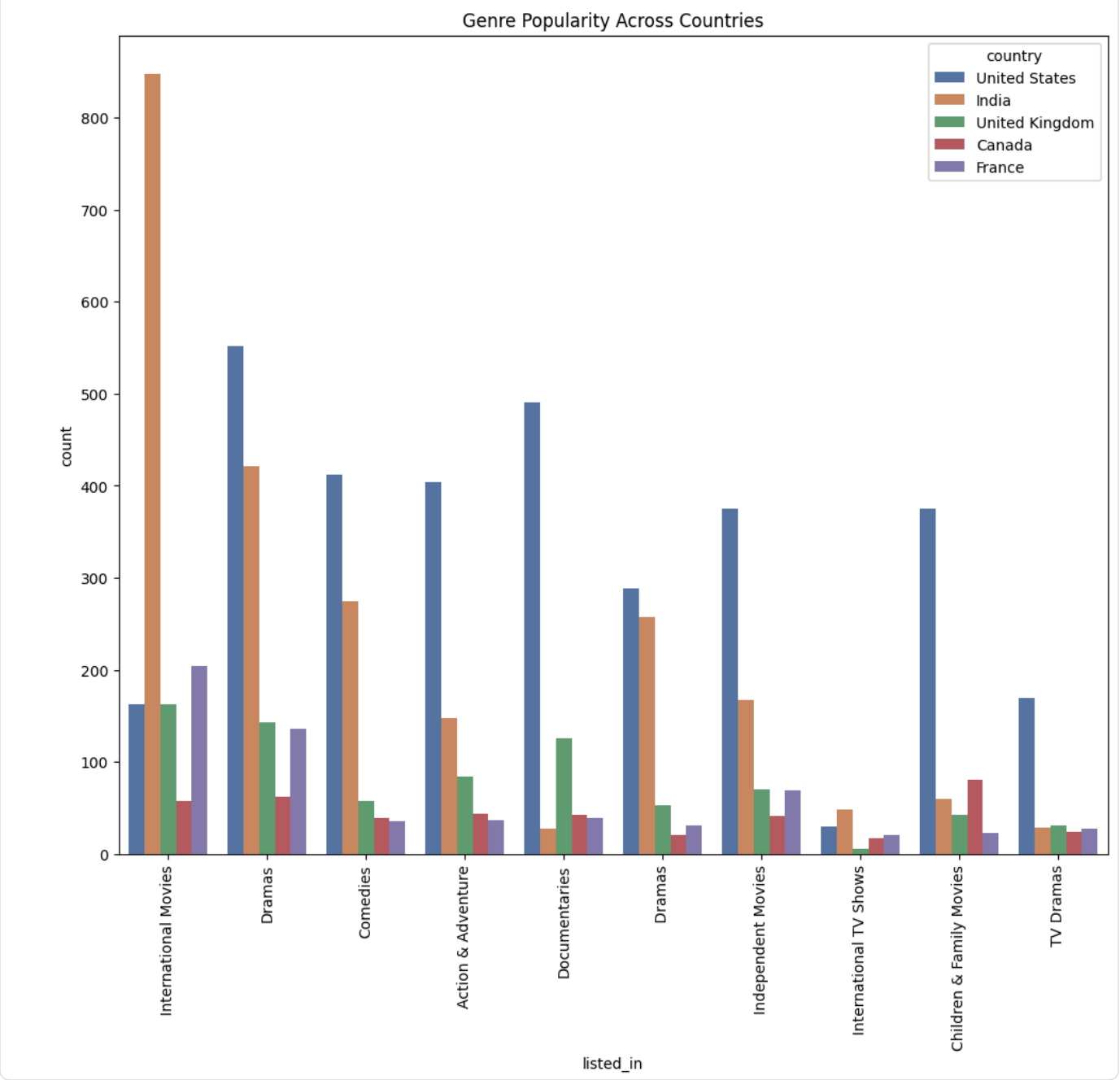
```
top10_c=unique_df['country'].value_counts().head(5)
```

```
top10_g=unique_df['listed_in'].value_counts().head(10)
```

```
top10_df=unique_df[(unique_df['country'].isin(top10_c.index))&(unique_df['country']!='Unknown') & (unique_df['listed_in'].isin(
```

```
plt.figure(figsize=(12,10))
sns.countplot(data=top10_df,x='listed_in',hue='country',palette='deep',order=
plt.title('Genre Popularity Across Countries')
plt.xticks(rotation=90)
```

```
plt.show()
```



^**Insights**:The count plot shows that India has the highest count for International Movies, while the US dominates in most of the other genres. India usually comes in second, and the UK ranks third across various genres.

-->correlation between Duration , release_year and date added columns

```
unique_df=df[['show_id','type','duration','release_year']].drop_duplicates()
```

```
unique_df['release_year']=unique_df['release_year'].dt.year
```

```
moviesc=unique_df[unique_df['type']=='Movie']
```

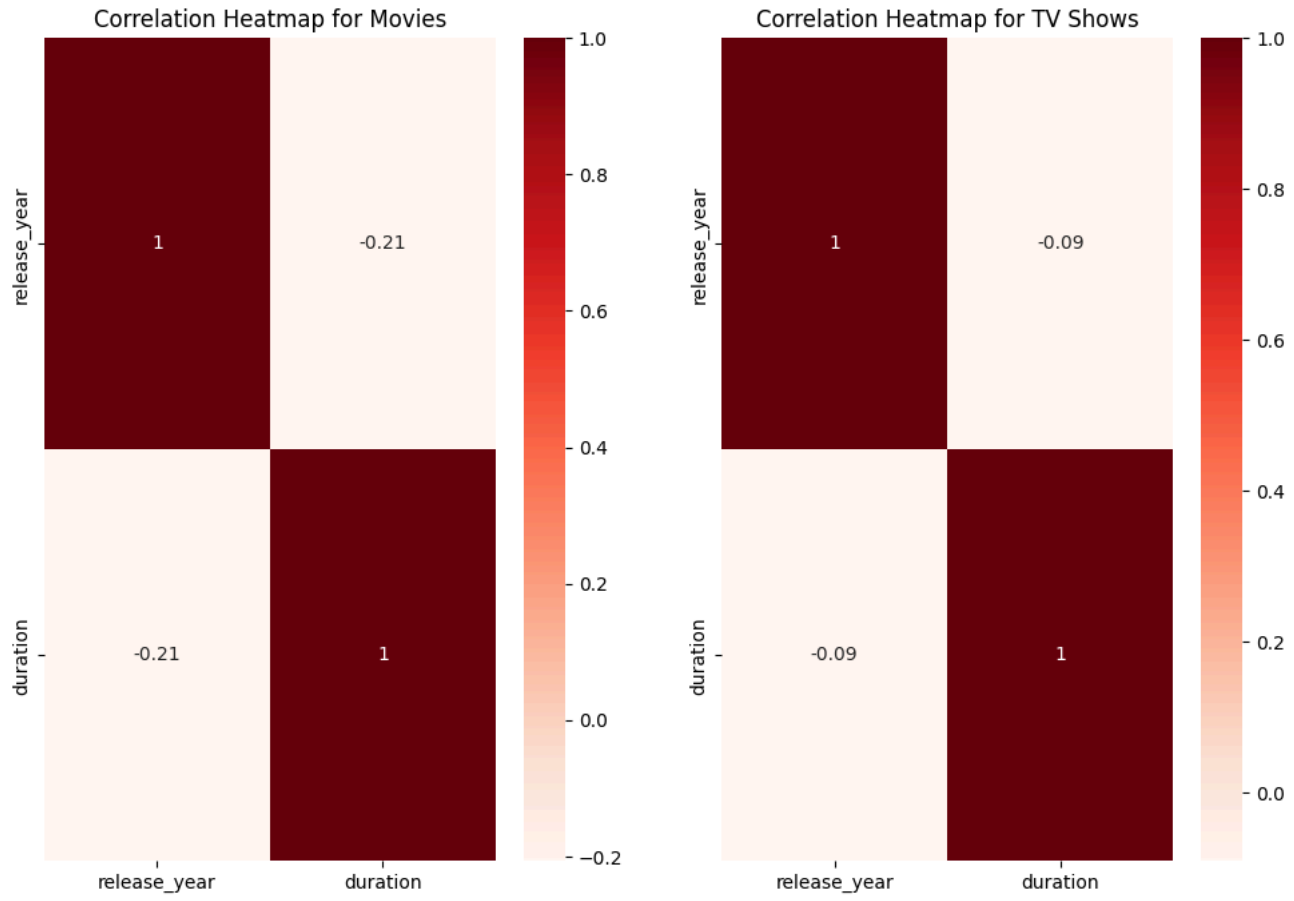
```
tvshows=unique_df[unique_df['type']=='TV Show']
```

```
df_m=moviesc[['release_year','duration']]
```

```
df_tv=tvshows[['release_year','duration']]
```

```
plt.figure(figsize=(12,8))
plt.subplot(1,2,1)
sns.heatmap(df_m.corr(),annot=True,cmap='Reds')
```

```
plt.title('Correlation Heatmap for Movies')
plt.subplot(1,2,2)
sns.heatmap(df_tv.corr(),annot=True,cmap='Reds')
plt.title('Correlation Heatmap for TV Shows')
plt.show()
```



^**Insights**: Movies:This weak negative correlation might imply that newer movies on Netflix tend to be slightly shorter in duration. However, the weak value suggests that this relationship is not strong.

TV Shows : This weak negative correlation suggests that there isn't much of a relationship between when TV shows were released and how long they are.

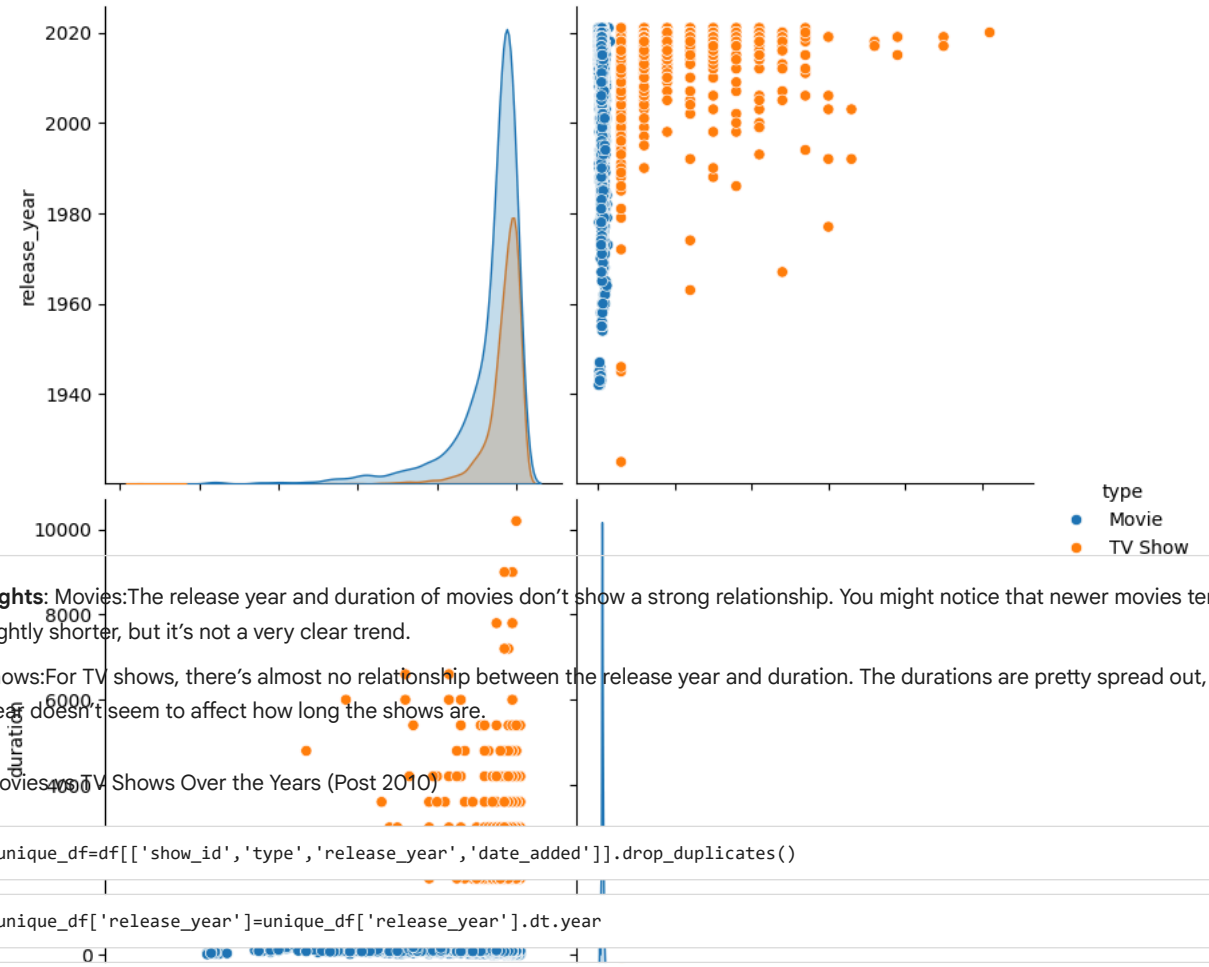
--> Pair Plot between duration and release year

```
type(df_m['release_year'][0])
```

```
numpy.int32
```

```
plt.figure(figsize=(12,8))
plt.suptitle('Pair Plot between Duration and Release Year')
sns.pairplot(unique_df,vars=['release_year','duration'],hue='type',height=4)
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



^ **Insights**: Movies:The release year and duration of movies don't show a strong relationship. You might notice that newer movies tend to be slightly shorter, but it's not a very clear trend.

TV Shows:For TV shows, there's almost no relationship between the release year and duration. The durations are pretty spread out, and the year doesn't seem to affect how long the shows are.

--> Movies vs TV Shows Over the Years (Post 2010)

```
unique_df=df[['show_id','type','release_year','date_added']].drop_duplicates()
```

```
unique_df['release_year']=unique_df['release_year'].dt.year
```

```
unique_df['date_added']=unique_df['date_added'].dt.year
```

```
unique_df['release_year']=unique_df['release_year'].astype('int64')
```

```
unique_df['date_added']=unique_df['date_added'].astype('int64')
```

```
recent_years = unique_df[unique_df['release_year'] >= 2010]
tv_vs_movies_recent = recent_years.groupby(['release_year', 'type']).size().unstack()
```

```
<ipython-input-238-d1665460daf1>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a
  tv_vs_movies_recent = recent_years.groupby(['release_year', 'type']).size().unstack()
```

```
recent_years_content=unique_df[unique_df['date_added']>=2010]
tv_vs_movies_recent_content=recent_years_content.groupby(['date_added','type']).size().unstack()
```

```
<ipython-input-239-81c83a571d9e>:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a
  tv_vs_movies_recent_content=recent_years_content.groupby(['date_added','type']).size().unstack()
```

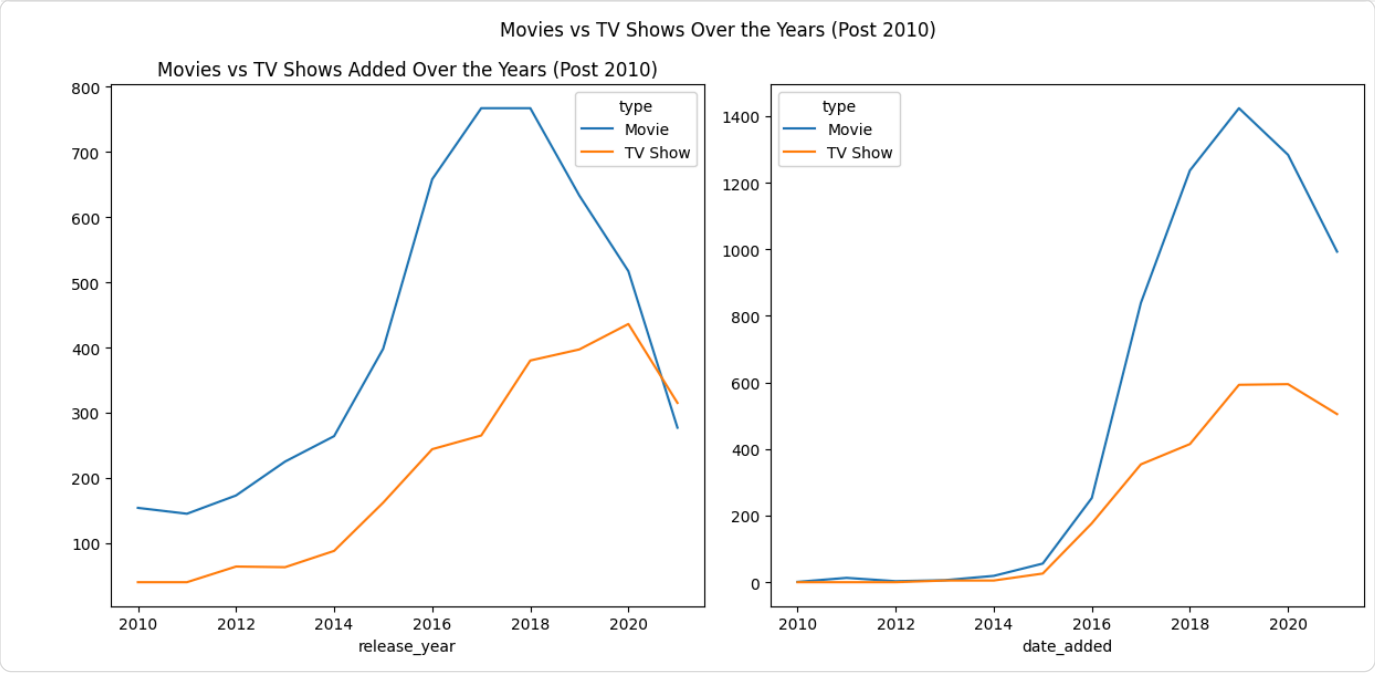
```
fig,ax=plt.subplots(1, 2, figsize=(12, 6))


plt.suptitle('Movies vs TV Shows Over the Years (Post 2010)')

tv_vs_movies_recent.plot(kind='line',ax=ax[0])
ax[0].set_title('Movies vs TV Shows Released Over the Years (Post 2010)')


tv_vs_movies_recent_content.plot(kind='line',ax=ax[1])
ax[0].set_title('Movies vs TV Shows Added Over the Years (Post 2010)')

plt.tight_layout()
plt.show()
```



^**Insights** Duration vs. Release Year: Movies: Movies dominate in terms of duration, and we can see a trend where they are mostly consistent, with some fluctuations. TV Shows: TV shows are increasing over time, especially post-2019, likely due to the growth of streaming platforms and the demand for more content.

Duration vs. Date Added: Movies: Movies have a steady presence in the content library over time. TV Shows: TV shows have been increasing rapidly after 2019, particularly after the global surge in streaming, which might be linked to the pandemic when more TV shows were produced and added to platforms like Netflix.

-->Number of Movies vs TV Shows Released per Year'

```
unique_df=df[['show_id','type','release_year','date_added']].drop_duplicates()
```

```
unique_df['release_year']=unique_df['release_year'].dt.year
```

```
unique_df['date_added']=unique_df['date_added'].dt.year
```

```
recent_dataset=unique_df[(unique_df['release_year']>=2010) & (unique_df['date_added']>=2010)]
```

```
yearly_release = recent_dataset.groupby(['release_year', 'type']).size().unstack()
```

```
<ipython-input-245-2b381142863d>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a
  yearly_release = recent_dataset.groupby(['release_year', 'type']).size().unstack()
```

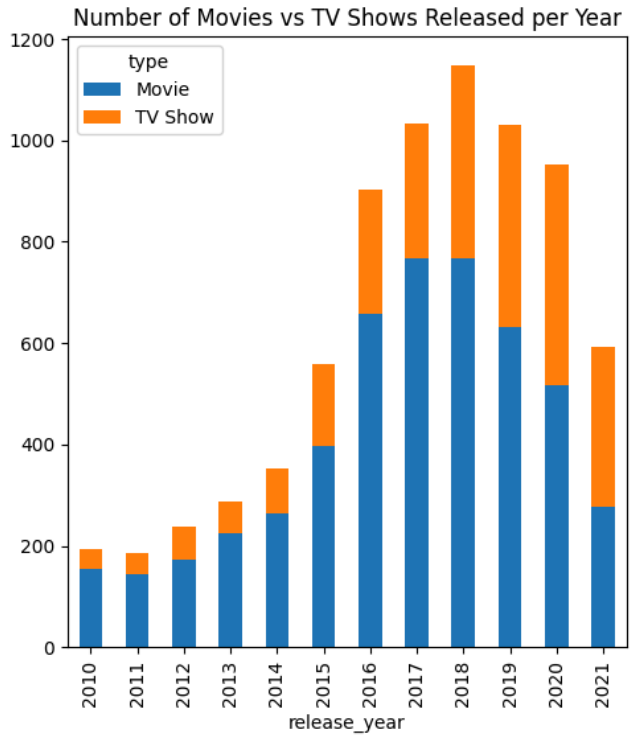
```
yearly_added = recent_dataset.groupby(['date_added', 'type']).size().unstack()
```

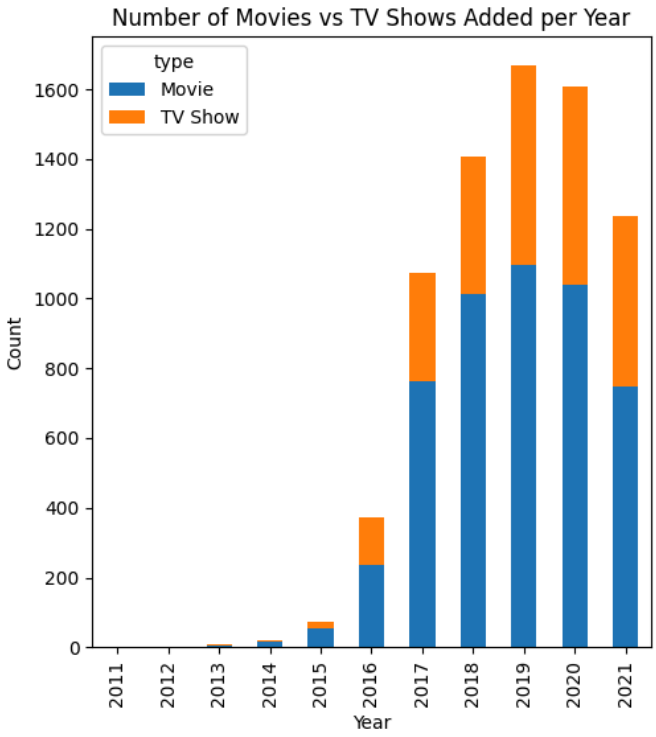
```
<ipython-input-246-8228ace7f187>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a
  yearly_added = recent_dataset.groupby(['date_added', 'type']).size().unstack()
```

```
fig,ax= plt.subplots(1,2,figsize=(12, 6))

yearly_release.plot(kind='bar', ax=ax[0],stacked=True)
ax[0].set_title('Number of Movies vs TV Shows Released per Year')
plt.xlabel('Year')
plt.ylabel('Count')
plt.xticks(rotation=90)


yearly_added.plot(kind='bar',ax=ax[1], stacked=True)
ax[1].set_title('Number of Movies vs TV Shows Added per Year')
plt.xlabel('Year')
plt.show()
```





^**Insights**:Release Year and Duration: Movies were more common: Until 2019, Netflix had more movies than TV shows. Equal in 2021: In 2021, the number of movies and TV shows with similar durations became almost the same.

Date Added and Duration: Movies were added more: Before 2019, movies were added in larger numbers. TV Shows Increased After 2019: After 2019, TV shows started to be added more, with a big jump in 2021. Equal in 2021: In 2021, Netflix added almost the same number of movies and TV shows

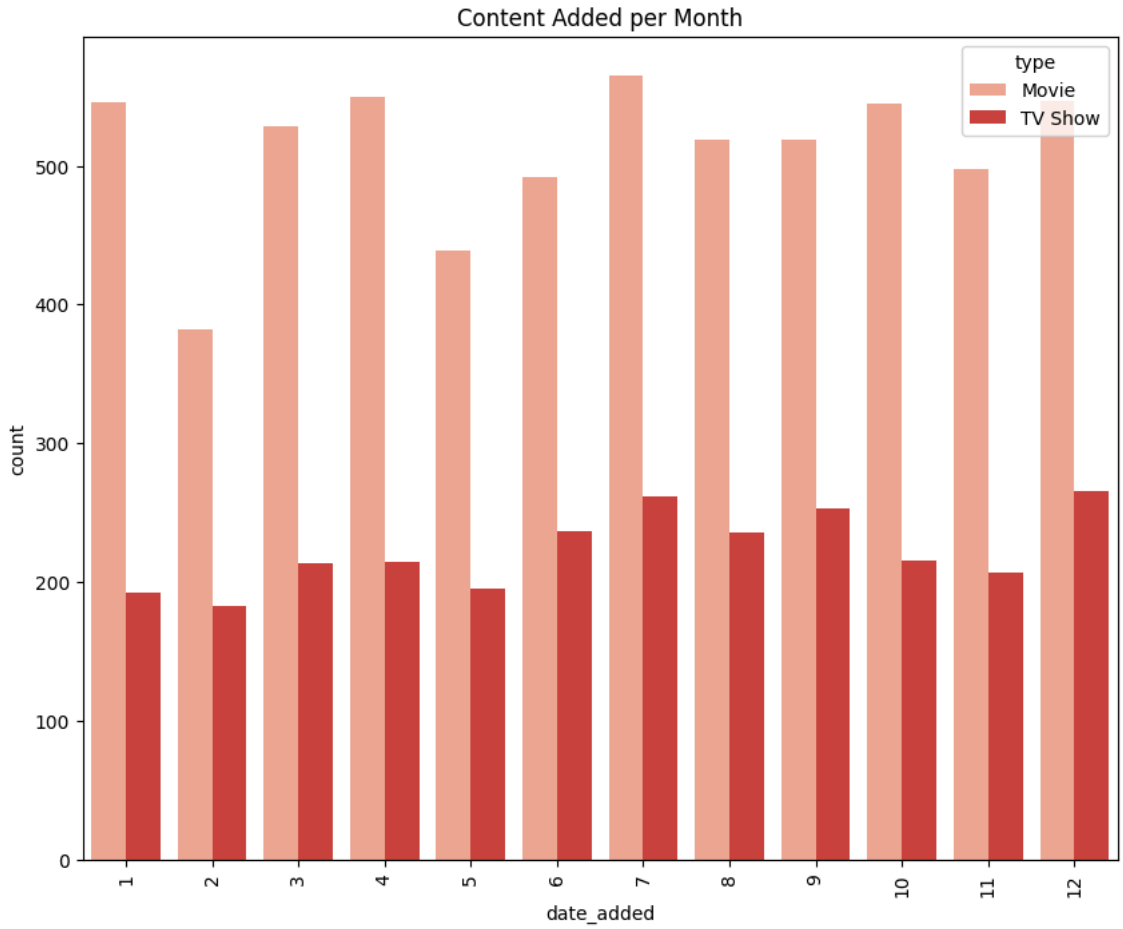
-->Content Added per Month

```
unique_df=df[['show_id','type','date_added']].drop_duplicates()
```

```
unique_df['date_added'] = unique_df['date_added'].dt.month
```

```
plt.figure(figsize=(10,8))
sns.countplot(data=unique_df,x='date_added',hue='type',palette='Reds')
plt.title('Content Added per Month')

plt.xticks(rotation=90)
plt.show()
```



^**Insights**: shows that Netflix adds more content in certain months, with noticeable spikes after 2019, especially post-COVID. This indicates Netflix is adding more content to keep up with growing demand and keep viewers engaged.

-->Top Directors in Movies and TV Shows

```
unique_df=df[['show_id','type','director','cast']].drop_duplicates()
```

```
unique_df_m=unique_df[unique_df['type']=='Movie']
```

```
unique_df_tv=unique_df[unique_df['type']=='TV Show']
```

```
top10_m=unique_df_m['director'].value_counts().head(10)
```

```
top10_tv=unique_df_tv['director'].value_counts().head(10)
```

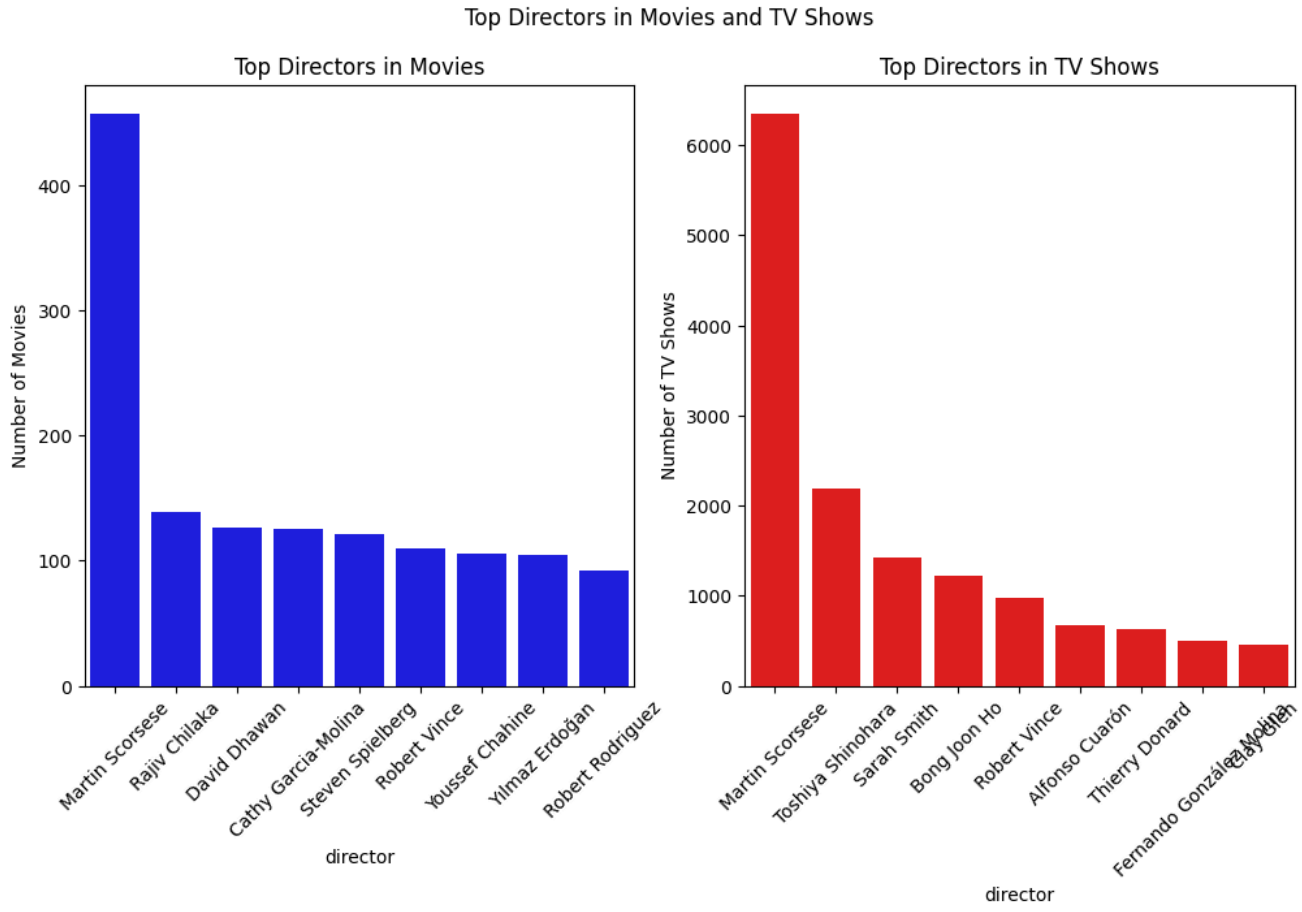
```
top10_df_m=unique_df_m[(unique_df_m['director'].isin(top10_m.index)) & (unique_df_m['director']!='Unknown')]
```

```
top10_df_tv=unique_df_tv[(unique_df_tv['director'].isin(top10_tv.index))  & (unique_df_tv['director']!='Unknown')]
```

```
fig, ax = plt.subplots(1, 2, figsize=(12, 6))
plt.suptitle('Top Directors in Movies and TV Shows')
sns.countplot(data=top10_df_m,x='director',ax=ax[0], color='blue',order=top10_df_m['director'].value_counts().index)
ax[0].set_title('Top Directors in Movies')
ax[0].set_ylabel('Number of Movies')
ax[0].set_xticklabels(top10_df_m['director'].value_counts().index,rotation=45)


sns.countplot(data=top10_df_tv,x='director',ax=ax[1], color='red',order=top10_df_tv['director'].value_counts().index)
ax[1].set_title('Top Directors in TV Shows')
ax[1].set_ylabel('Number of TV Shows')
ax[1].set_xticklabels(top10_df_tv['director'].value_counts().index,rotation=45)
plt.show()
```

```
<ipython-input-262-730a1139c456>:6: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after s
  ax[0].set_xticklabels(top10_df_m['director'].value_counts().index,rotation=45)
<ipython-input-262-730a1139c456>:12: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after
  ax[1].set_xticklabels(top10_df_tv['director'].value_counts().index,rotation=45)
```



^**Insights**:For movies, Martin Scorsese is the most prominent director, with a significant lead in the number of movies, followed by Rajiv Chilaka, David Dhawan, Cathy Garcia-Molina, and Steven Spielberg. This suggests that Martin Scorsese has made a significant contribution to the movie industry on Netflix.

For TV shows, Toshiya Shinohara leads the list, followed by Sarah Smith, Bong Joon Ho, Robert Vince, and Martin Scorsese. Unlike movies, TV shows have a more diverse set of top directors, with Shinohara standing out in the genre.

Overall, Martin Scorsese dominates in movies, but in TV shows, there is more variety, with other directors like Shinohara gaining a strong presence.

-->Top Actors in Movies and TV Shows

```
movie_actors=unique_df_m['cast'].value_counts().head(10)
tvshow_actors=unique_df_tv['cast'].value_counts().head(10)
```

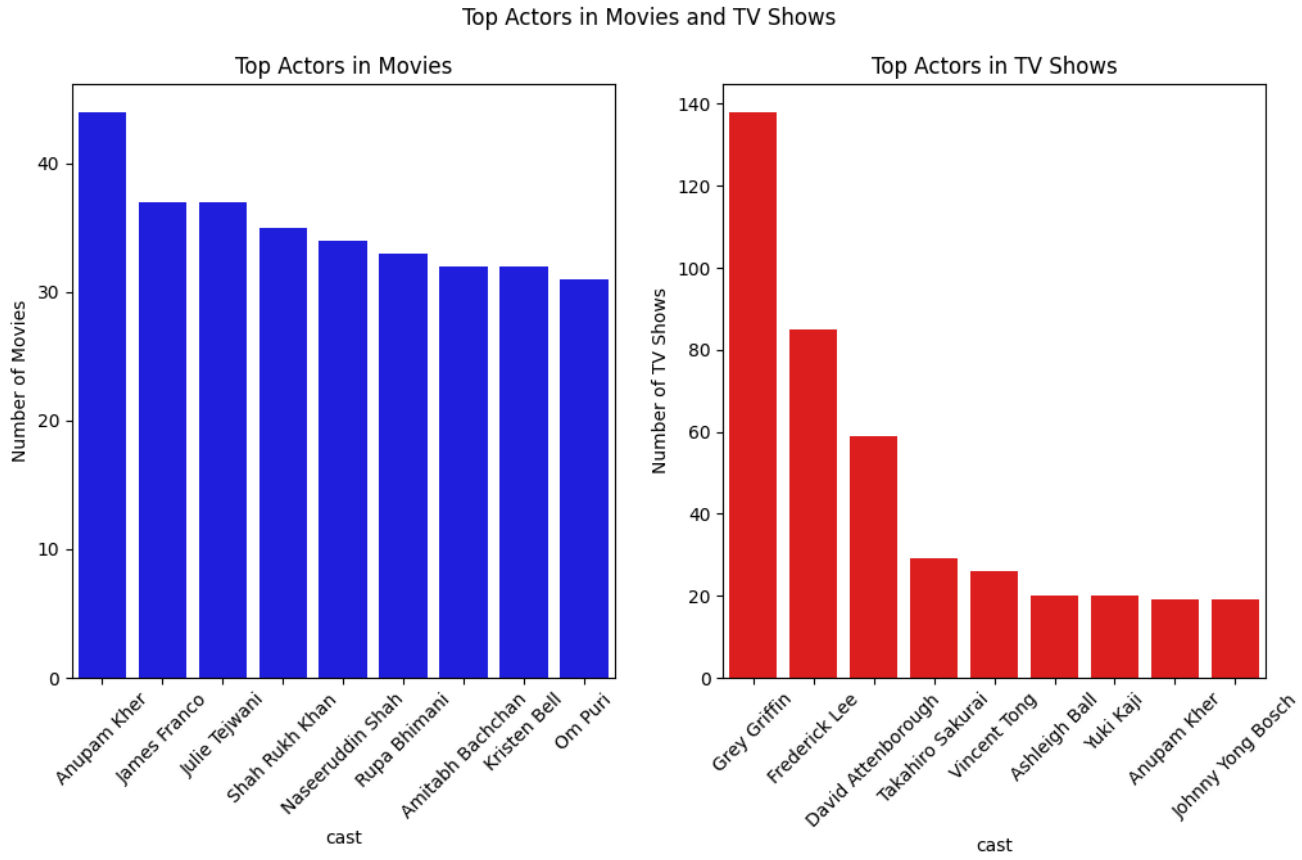
```
top10_df_m=unique_df_m[(unique_df_m['cast'].isin(movie_actors.index)) & (unique_df_m['cast']!='Unknown')]
top10_df_tv=unique_df_tv[(unique_df_tv['cast'].isin(tvshow_actors.index)) & (unique_df_tv['cast']!='Unknown')]
```

```
fig,ax=plt.subplots(1,2,figsize=(12,6))
plt.suptitle('Top Actors in Movies and TV Shows')

plt.xticks(rotation=90)
sns.countplot(data=top10_df_m,x='cast',ax=ax[0],color='blue',order=top10_df_m['cast'].value_counts().index)
ax[0].set_title('Top Actors in Movies')
ax[0].set_ylabel('Number of Movies')
ax[0].set_xticklabels(top10_df_m['cast'].value_counts().index,rotation=45)

sns.countplot(data=top10_df_tv,x='cast',ax=ax[1],color='red',order=top10_df_tv['cast'].value_counts().index)
ax[1].set_title('Top Actors in TV Shows')
ax[1].set_ylabel('Number of TV Shows')
ax[1].set_xticklabels(top10_df_tv['cast'].value_counts().index,rotation=45)
plt.show()
```

```
<ipython-input-265-4a6232930a9d>:8: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after s
  ax[0].set_xticklabels(top10_df_m['cast'].value_counts().index,rotation=45)
<ipython-input-265-4a6232930a9d>:13: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after
  ax[1].set_xticklabels(top10_df_tv['cast'].value_counts().index,rotation=45)
```



^**Insights:**In movies, Anupam Kher appears the most, followed by James Franco, Julie Tejwani, Shah Rukh Khan, and Naseeruddin Shah. This shows a mix of Bollywood and Hollywood actors, with Indian actors having a strong presence in Netflix movies.

For TV shows, Grey Griffin dominates with a significant lead, followed by Frederick Lee, David Attenborough, Takahiro Sakurai, and Vincent Tong. The presence of voice actors like Grey Griffin and Takahiro Sakurai suggests a strong representation in TV shows.

Overall, movies feature more traditional film actors, while TV shows highlight voice actors and documentary narrators.

Recomendations:

Balance Movies & TV Shows: Movies dominate, but TV shows are growing fast, especially after 2019. Investing more in TV shows can attract more viewers.

Expand in Key Regions: The USA, India, and the UK lead in content, but countries like Japan and Belarus prefer TV shows. More localized content can help reach a wider audience.

Focus on Popular Genres: International Movies, Dramas, and Comedies are top movie genres, while TV Dramas and International TV Shows lead for series. Prioritizing these can boost engagement.

Work with Top Creators: Directors like Martin Scorsese and actors like Anupam Kher have contributed heavily. Collaborating with well-known creators can enhance content appeal.

Add Content Strategically: Most content was added after 2014, with a big jump post-2019. Planning releases based on trends can maximize viewership.

Optimize Content Length: Most movies are 80-160 minutes long, while TV shows vary a lot. Understanding what works best can improve viewer experience.

Strengthen Local Productions: The USA dominates, but India and the UK are also key players. More content from different regions can attract diverse audiences.

Better Recommendations: With so much content, improving recommendations will help us

Time Content Releases Well: Identifying peak months for adding content can help plan

Check Content Length Outliers: Some movies and TV shows are much longer or shorter than usual. Studying these can help understand what works best.

Business Insights

Growing Demand for TV Shows: TV shows have seen significant growth, especially after 2019. Expanding TV content can help retain and attract more viewers.

Regional Content Trends: The USA leads in content production, followed by India and the UK. Increasing investment in regional content, particularly in India, can drive more engagement.

Popular Genres: International Movies, Dramas, and Comedies dominate in movies, while TV Dramas and International TV Shows lead in TV content. Prioritizing these genres can enhance audience retention.

Content Growth Over Time: A major increase in content addition has been observed after 2014, with a sharp rise post-2019. Maintaining a consistent content release strategy is essential for sustained growth.

Influence of Top Creators: Directors like Martin Scorsese and actors like Anupam Kher are highly featured in movies, while Grey Griffin and Frederick Lee are prominent in TV shows. Partnering with popular creators can improve content appeal.

Seasonal Content Trends: Certain months see higher content additions. Aligning new releases with audience engagement patterns can optimize viewership.

Content Duration Preferences: Most movies are between 80-160 minutes, while TV shows typically stay under 2200 minutes (≈37 hours). Offering a mix of short and long-form content can cater to different viewer habits.

Expansion Opportunities: TV shows are more popular than movies in regions like Japan and Belarus. Investing in region-specific content can help Netflix strengthen its global presence.

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