Netflix_Business_case_by_Diptyajit_Das

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1 Netflix Data Exploration Business Case

1.1 Problem Statement

1.1.1 Netflix is one of the most popular media and video streaming platforms. They have over 8000 movies or tv shows available on their platform, as of mid-2021, they have over 200M Subscribers globally.The particular business case focuses on the Netflix show data and provides insightful information on 8807 shows. Analyzing the data and generating insights helps Netflix decide which type of shows/movies to produce and how to grow the business.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#!pip install wordcloud
from wordcloud import WordCloud
```

[2]:
```
df=pd.read_csv('netflix.csv',index_col=0)
df.shape
```

[2]:
```
(8807, 11)
```

1.2 8807 rows and 11 columns

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8807 entries, s1 to s8807
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   type          8807 non-null   object
 1   title         8807 non-null   object
 2   director      6173 non-null   object
 3   cast          7982 non-null   object
 4   country       7976 non-null   object
 5   date_added    8797 non-null   object
 6   release_year  8807 non-null   int64 
```

```
 7   rating        8803 non-null   object
 8   duration      8804 non-null   object
 9   listed_in     8807 non-null   object
 10  description   8807 non-null   object
dtypes: int64(1), object(10)
memory usage: 825.7+ KB
```

2 PREPROCESSING

2.1 Unnesting the columns

[4]:
```
df['director']=df['director'].str.strip()
df['director'] = df['director'].str.split(',')
df = df.explode('director')
df['director']=df['director'].str.strip()

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

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

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

df=df.drop_duplicates(subset=['title','country','director','cast','listed_in'])
df.head()
```

[4]:

show_id	type	title	director	cast	country	date_added	release_year	rating	duration
s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	NaN	United States	September 25, 2021	2020	PG-13	90 min
s2	TV Show	Blood & Water	NaN	Ama Qamata	South Africa	September 24, 2021	2021	TV-MA	2 Seasons
s2	TV Show	Blood & Water	NaN	Ama Qamata	South Africa	September 24, 2021	2021	TV-MA	2 Seasons
s2	TV Show	Blood & Water	NaN	Ama Qamata	South Africa	September 24, 2021	2021	TV-MA	2 Seasons
s2	TV Show	Blood & Water	NaN	Khosi Ngema	South Africa	September 24, 2021	2021	TV-MA	2 Seasons

```
s2        South Africa  September 24, 2021          2021  TV-MA  2 Seasons
s2        South Africa  September 24, 2021          2021  TV-MA  2 Seasons

                      listed_in  \
show_id
s1                Documentaries
s2       International TV Shows
s2                    TV Dramas
s2                  TV Mysteries
s2       International TV Shows

                                                 description
show_id
s1       As her father nears the end of his life, filmm…
s2       After crossing paths at a party, a Cape Town t…
s2       After crossing paths at a party, a Cape Town t…
s2       After crossing paths at a party, a Cape Town t…
s2       After crossing paths at a party, a Cape Town t…
```

[5]:
```
df.isna().sum()
```

[5]:
```
type               0
title              0
director       50643
cast            2149
country        11897
date_added       158
release_year       0
rating            67
duration           3
listed_in          0
description        0
dtype: int64
```

2.2 Adding week_added and month_added columns to use in Part 3

[6]:
```
df['date_added']=df['date_added'].str.strip()
df['date_added']=pd.to_datetime(df['date_added'],format="%B %d, %Y")
df['week_added']=df['date_added'].dt.isocalendar().week
df['month_added']=df['date_added'].dt.month
```

2.3 Adding datediff_day column to use in Part 6

2.3.1 Assuming release date as 'release_year-07-01' for simplicity

[7]:
```
df['datediff_day'] = (df['date_added'] - pd.to_datetime(df['release_year'].
 ↪astype(str) + '-07-01')).dt.days
```

2.4 Filling Missing Values

2.4.1 director:'Unknown Director'

2.4.2 cast :'Unknown Cast'

2.4.3 country :'International'

2.4.4 rating :'unrated'

2.4.5 For duration and date columns used reference column groupby mode method

[8]:
```
df.fillna({'director':'Unknown Director','cast':'Unknown Cast','country':
 ↪'International','rating':'unrated'},inplace=True)
mode_duration = df.groupby('type')['duration'].apply(lambda x: x.mode().iloc[0]␣
 ↪if not x.mode().empty else pd.NaT).reset_index()
mode_dict = dict(zip(mode_duration['type'], mode_duration['duration']))
df['duration'] = df['duration'].fillna(df['type'].map(mode_dict))
```

2.5 Date Columns

[9]:
```
mode_values = df.groupby('country').agg({
    'date_added': lambda x: x.dt.date.mode().iloc[0] if not x.dt.date.mode().
 ↪empty else pd.NaT,
    'week_added': lambda x: x.mode().iloc[0] if not x.mode().empty else pd.NaT,
    'month_added': lambda x: x.mode().iloc[0] if not x.mode().empty else pd.NaT,
    'datediff_day': lambda x: x.mode().iloc[0] if not x.mode().empty else pd.NaT
}).reset_index()

date_added_dict = dict(zip(mode_values['country'], mode_values['date_added']))
week_added_dict = dict(zip(mode_values['country'], mode_values['week_added']))
month_added_dict = dict(zip(mode_values['country'], mode_values['month_added']))
datediff_day_dict = dict(zip(mode_values['country'],␣
 ↪mode_values['datediff_day']))

df['date_added'] = df['date_added'].fillna(df['country'].map(date_added_dict))
df['week_added'] = df['week_added'].fillna(df['country'].map(week_added_dict))
df['month_added'] = df['month_added'].fillna(df['country'].
 ↪map(month_added_dict))
df['datediff_day'] = df['datediff_day'].fillna(df['country'].
 ↪map(datediff_day_dict))
df.isna().sum()
```

[9]:
```
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
week_added      0
month_added     0
datediff_day    0
dtype: int64
```

2.6 All null values carefully replaced

[10]:
```
df.head()
```

[10]:

show_id	type	title	director	cast	country	date_added	release_year	rating	duration	listed_in	description	week_added
s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	Unknown Cast	United States	2021-09-25	2020	PG-13	90 min	Documentaries	As her father nears the end of his life, filmm…	38
s2	TV Show	Blood & Water	Unknown Director	Ama Qamata	South Africa	2021-09-24	2021	TV-MA	2 Seasons	International TV Shows		
s2	TV Show	Blood & Water	Unknown Director	Ama Qamata	South Africa	2021-09-24	2021	TV-MA	2 Seasons	TV Dramas		
s2	TV Show	Blood & Water	Unknown Director	Ama Qamata	South Africa	2021-09-24	2021	TV-MA	2 Seasons	TV Mysteries		
s2	TV Show	Blood & Water	Unknown Director	Khosi Ngema	South Africa	2021-09-24	2021	TV-MA	2 Seasons	International TV Shows		

```
s2       After crossing paths at a party, a Cape Town t…          38
s2       After crossing paths at a party, a Cape Town t…          38
s2       After crossing paths at a party, a Cape Town t…          38
s2       After crossing paths at a party, a Cape Town t…          38

         month_added  datediff_day
show_id
s1               9.0         451.0
s2               9.0          85.0
s2               9.0          85.0
s2               9.0          85.0
s2               9.0          85.0
```

[11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 202010 entries, s1 to s8807
Data columns (total 14 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   type          202010 non-null  object
 1   title         202010 non-null  object
 2   director      202010 non-null  object
 3   cast          202010 non-null  object
 4   country       202010 non-null  object
 5   date_added    202010 non-null  datetime64[ns]
 6   release_year  202010 non-null  int64
 7   rating        202010 non-null  object
 8   duration      202010 non-null  object
 9   listed_in     202010 non-null  object
 10  description   202010 non-null  object
 11  week_added    202010 non-null  UInt32
 12  month_added   202010 non-null  float64
 13  datediff_day  202010 non-null  float64
dtypes: UInt32(1), datetime64[ns](1), float64(2), int64(1), object(9)
memory usage: 22.5+ MB
```

2.7 There are 202010 rows and 14 columns.

2.8 Index:‘show_id’

2.9 String categorical columns:‘type’,‘title’,‘director’,‘cast’,‘country’,‘duration’,‘listed_in’,‘c converted to numerical)

2.10 Datetime column:‘date_added’

2.11 Numerical int and float columns:‘release_year’,‘week_added’,‘month_added’,‘datediff_

[12]:
```
df.describe()
```

[12]:

	date_added	release_year	week_added	month_added	datediff_day
count	202010	202010.000000	202010.0	202010.000000	202010.000000
mean	2019-06-19 19:50:28.305529088	2013.448334	26.685877	6.634186	2015.155784
min	2008-01-01 00:00:00	1925.000000	1.0	1.000000	-1188.000000
25%	2018-06-26 00:00:00	2012.000000	14.0	4.000000	123.000000
50%	2019-09-06 00:00:00	2016.000000	27.0	7.000000	609.000000
75%	2020-09-10 00:00:00	2019.000000	39.0	10.000000	2588.000000
max	2021-09-25 00:00:00	2021.000000	53.0	12.000000	34150.000000
std	NaN	9.013446	15.059867	3.443575	3310.996342

2.12 Basic Metrics Analysis:

Dataset Overview: - The dataset contains information on 8,807 shows available on Netflix. - Key attributes include ‘show_id,’ ‘type’ (Movie or TV Show), ‘title,’ ‘director,’ ‘cast,’ ‘country,’ ‘date_added,’ ‘release_year,’ ‘duration,’ ‘listed_in,’ and ‘rating.’

Temporal Scope: - The dataset spans multiple years, providing a temporal perspective on the content available on Netflix.

Geographical Reach: - Shows are distributed across various countries, allowing for a region-wise analysis.

Content Types: - The dataset categorizes shows into two main types: Movies and TV Shows.

Data Quality: - Initial analysis reveals missing values, especially in attributes like ‘director,’ ‘cast,’ ‘country,’ and ‘rating.’ - Strategies such as filling missing values with defaults (‘Unknown Director,’ ‘Unknown Cast,’ ‘International,’ ‘unrated’) have been employed. - For date columns and duration reference column groupby mode method applied to replace missing values.

Duration Information: - Duration information is available for both Movies (in minutes) and TV Shows (in seasons).

Timing of inclusion: - The dataset includes information on when shows were added to Netflix ('date_added'). - Additional columns ('week_added,' 'month_added') have been created for temporal analysis.

Datediff Calculation: - A 'datediff_day' column has been introduced, representing the difference between 'date_added' and a presumed release date ('release_year-07-01').

Preliminary Analysis: - Preliminary univariate analysis(and bivariate for some attributes) has been conducted on key attributes such as 'type,' 'director,' 'cast,' 'country,' 'rating,' 'listed_in,' and 'duration.'

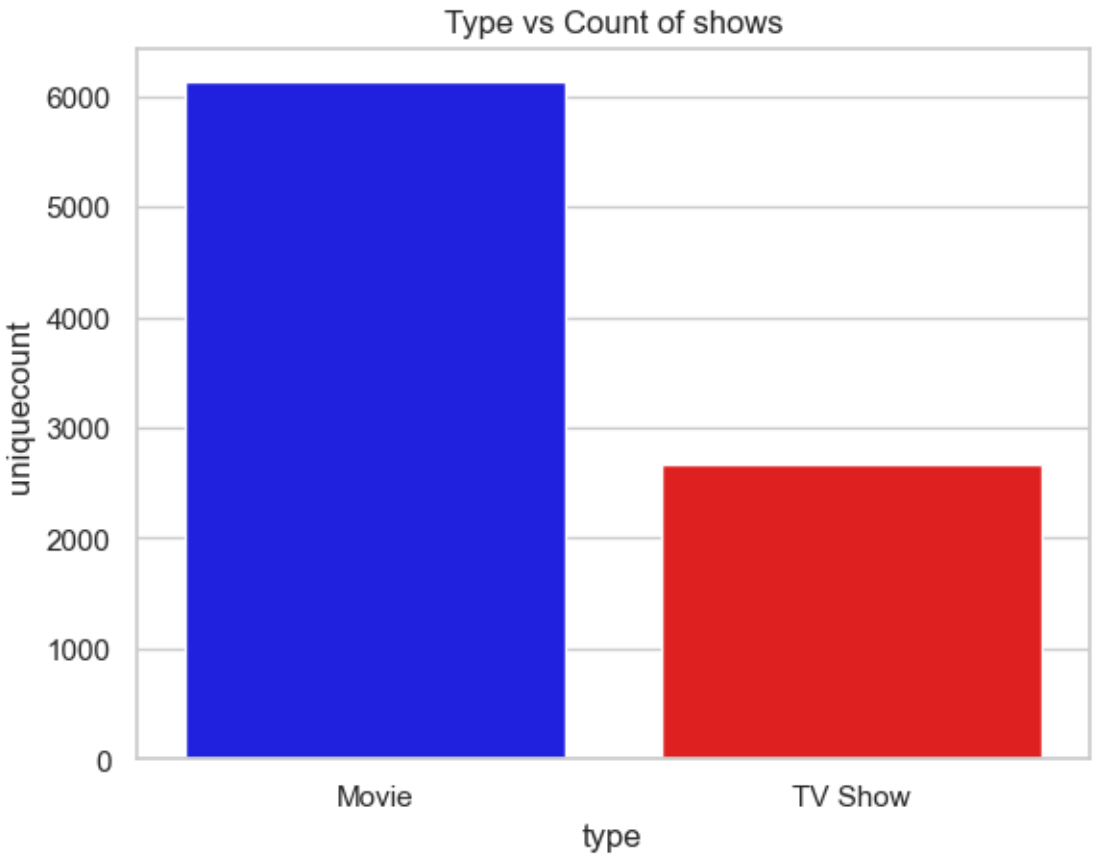
2.13 1. Preliminary Analysis

[13]:
```
#a.type
type_group=df.groupby('type')['title'].nunique().reset_index()
type_group.columns=['type','uniquecount']
type_group.head()
```

[13]:

	type	uniquecount
0	Movie	6131
1	TV Show	2676

[14]:
```
sns.set(style="whitegrid")
palette = {'Movie': 'blue', 'TV Show': 'red'}
ax=sns.barplot(data=type_group, x='type', y='uniquecount', hue='type',␣
 ↪palette=palette)
plt.title('Type vs Count of shows')
plt.show()
```



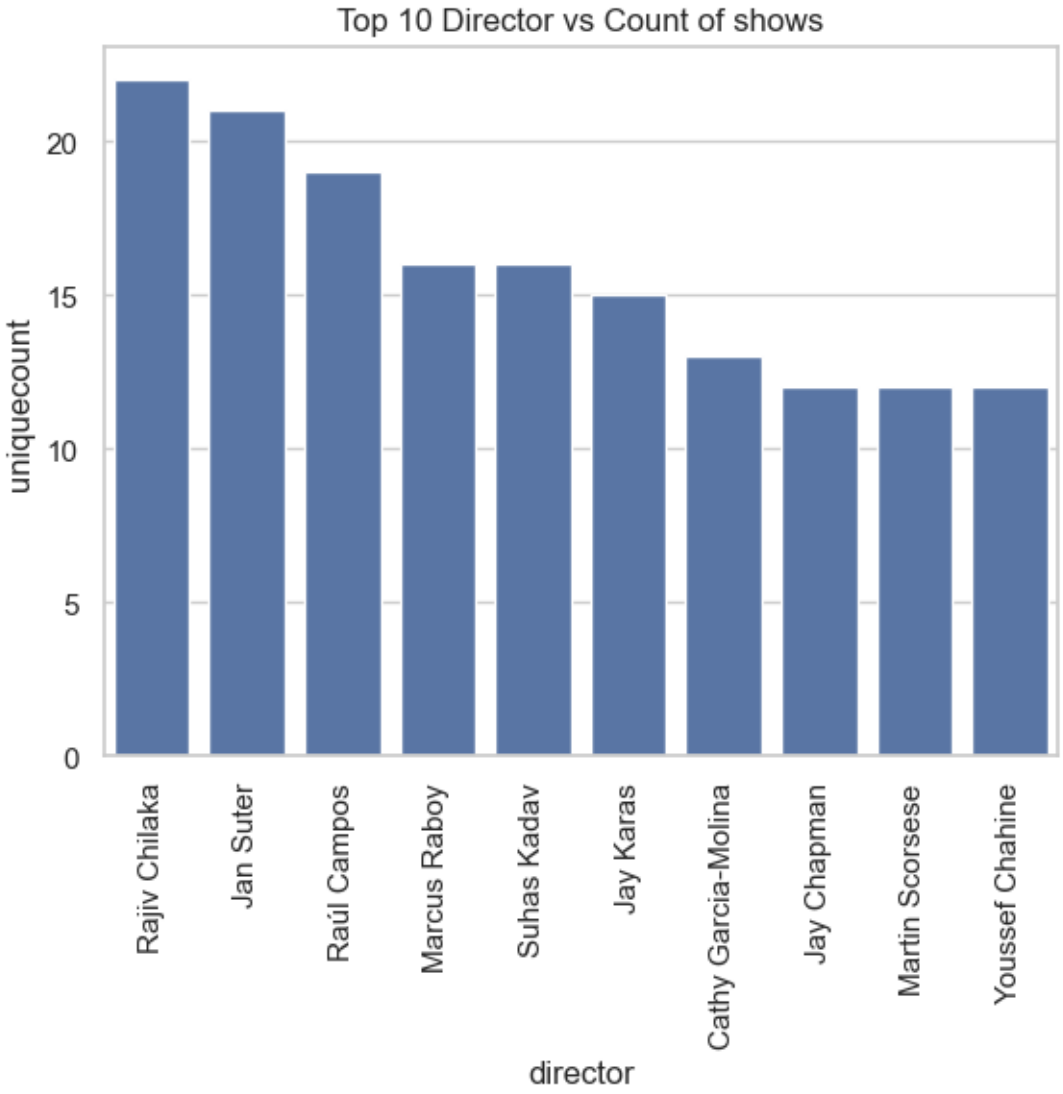
2.14 Insights: 6131 movies and 2676 TV Shows are added.More movies have been added.

[15]:
```
#b.director
director_group=df.groupby('director')['title'].nunique().reset_index().
 ↪sort_values('title',ascending=False)
director_group.columns=['director','uniquecount']
director_group=director_group.iloc[:11]
director_group=director_group[director_group['director']!='Unknown Director'].
 ↪reset_index()
director_group.drop(columns='index',inplace=True)
director_group.head()
```

[15]:

	director	uniquecount
0	Rajiv Chilaka	22
1	Jan Suter	21
2	Raúl Campos	19
3	Marcus Raboy	16
4	Suhas Kadav	16

[16]:
```
sns.set(style="whitegrid")
sns.barplot(data=director_group,x='director',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 Director vs Count of shows')
plt.show()
```



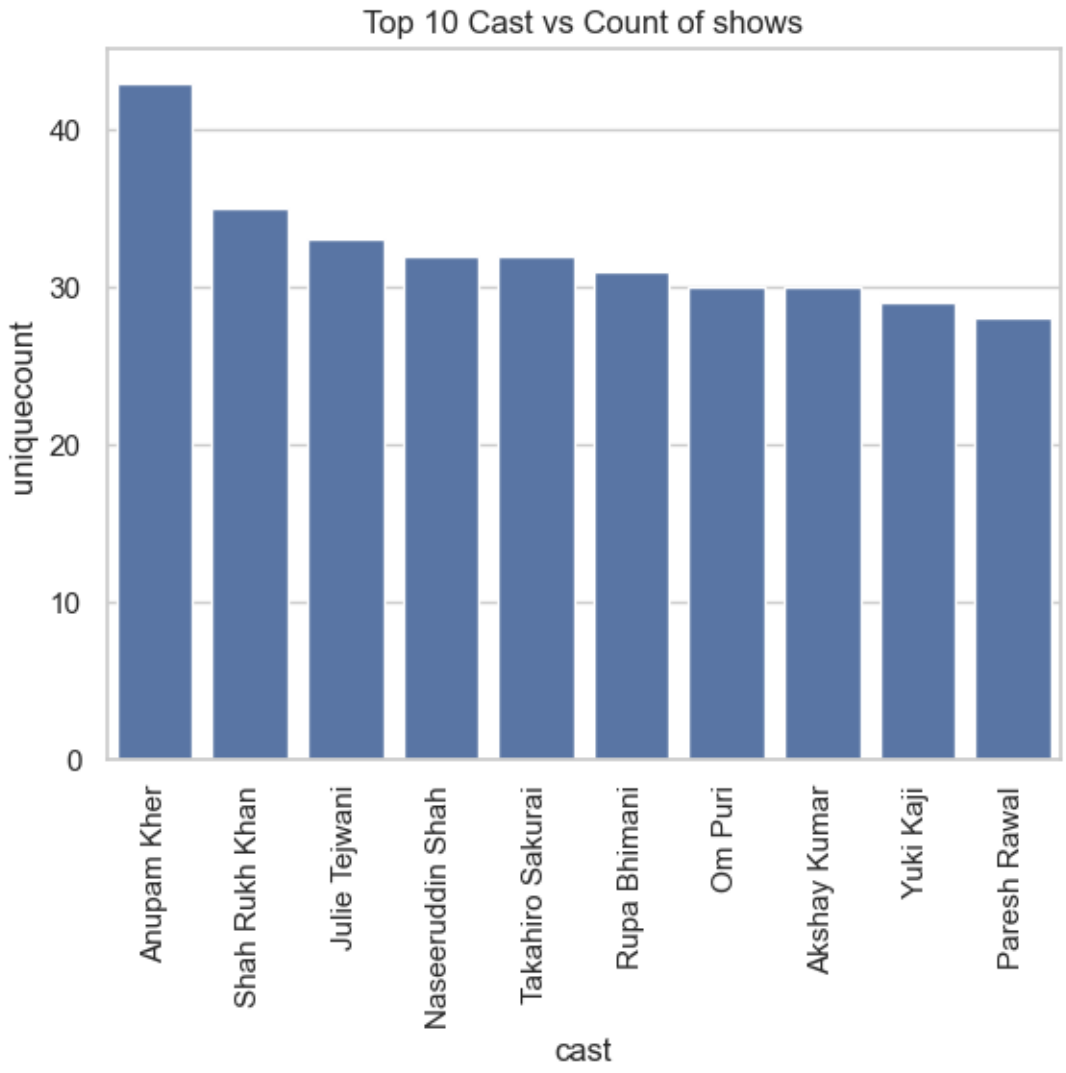
[17]:
```
#c.cast
cast_group=df.groupby('cast')['title'].nunique().reset_index().
 ↪sort_values('title',ascending=False)
cast_group.columns=['cast','uniquecount']
cast_group=cast_group.iloc[:11]
cast_group=cast_group[cast_group['cast']!='Unknown Cast'].reset_index()
cast_group.drop(columns='index',inplace=True)
```

```
cast_group.head()
```

[17]:

	cast	uniquecount
0	Anupam Kher	43
1	Shah Rukh Khan	35
2	Julie Tejwani	33
3	Naseeruddin Shah	32
4	Takahiro Sakurai	32

[18]:
```
sns.set(style="whitegrid")
sns.barplot(data=cast_group,x='cast',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 Cast vs Count of shows')
plt.show()
```

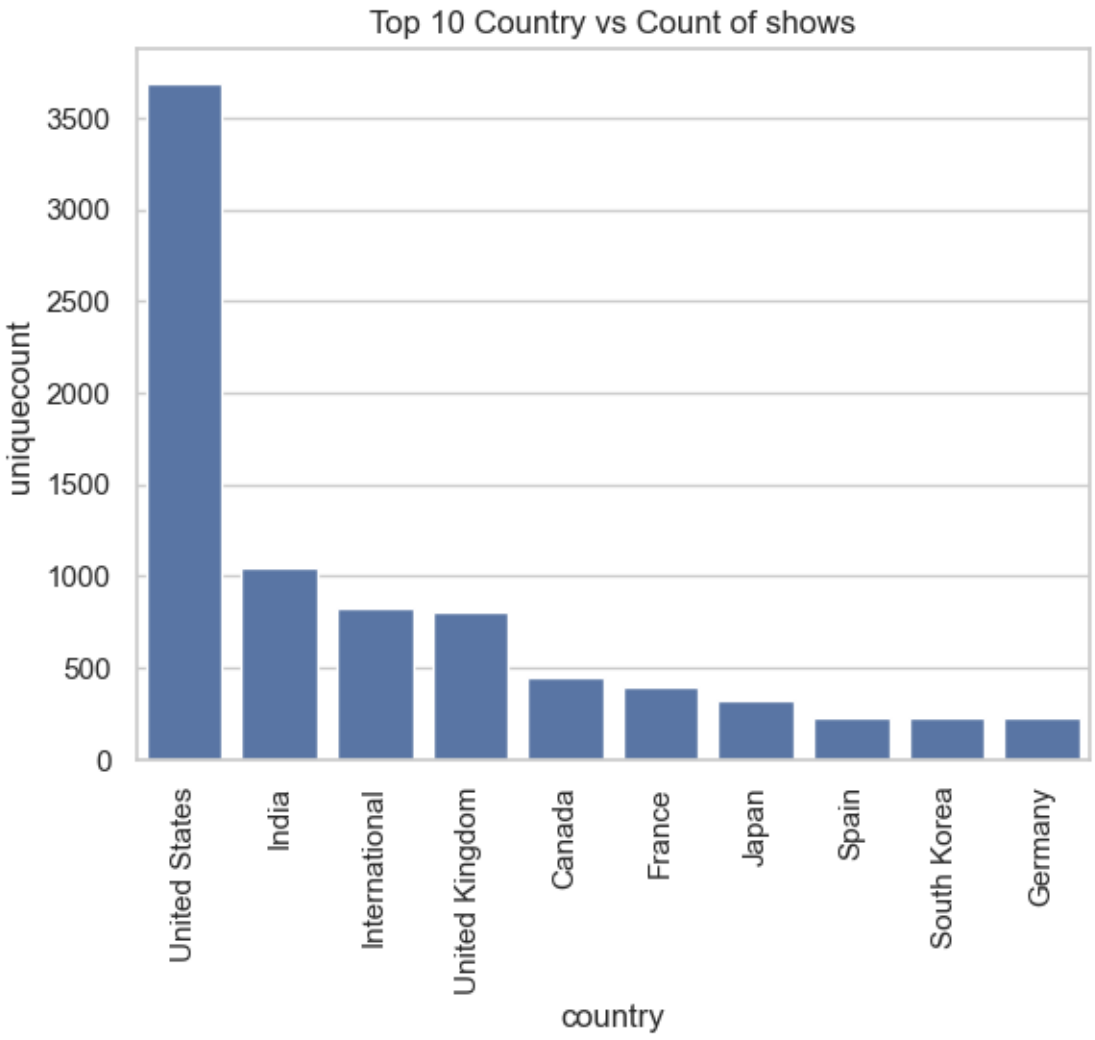


[19]:
```
#d.country
country_group=df.groupby('country')['title'].nunique().reset_index().
 ↪sort_values('title',ascending=False)
country_group.columns=['country','uniquecount']
country_group=country_group.iloc[:10].reset_index()
country_group.drop(columns='index',inplace=True)
country_group.head()
```

[19]:

	country	uniquecount
0	United States	3690
1	India	1046
2	International	831
3	United Kingdom	806
4	Canada	445

[20]:
```
sns.set(style="whitegrid")
sns.barplot(data=country_group,x='country',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 Country vs Count of shows')
plt.show()
```



2.15 Insights: USA,India and UK are the most common countries.

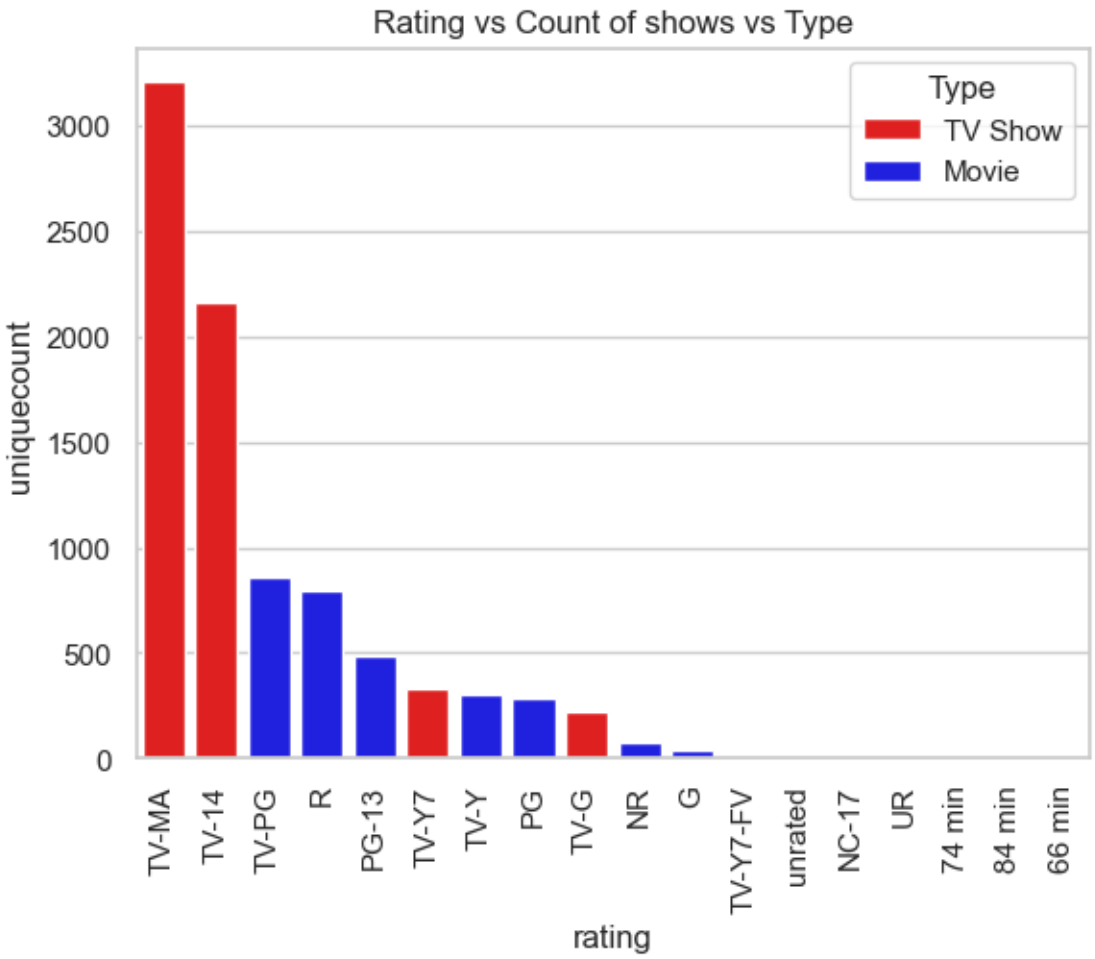
[21]:
```
#e.rating
rating_group=df.groupby('rating')['title'].nunique().reset_index().
 ↪sort_values('title',ascending=False)
rating_group.columns=['rating','uniquecount']
rating_group=pd.merge(rating_group, df[['rating', 'type']], on='rating',␣
 ↪how='left')
rating_group=rating_group.drop_duplicates(subset='rating').reset_index().
 ↪drop(columns=['index'])
rating_group.head()
```

[21]:

	rating	uniquecount	type
0	TV-MA	3207	TV Show

```
1  TV-14          2160  TV Show
2  TV-PG           863    Movie
3      R           799    Movie
4  PG-13           490    Movie
```

[22]:
```
sns.set(style="whitegrid")
sns.
 ↪barplot(data=rating_group,x='rating',y='uniquecount',hue='type',palette={'Movie':
 ↪ 'blue', 'TV Show': 'red'})
plt.xticks(rotation=90)
plt.title('Rating vs Count of shows vs Type')
plt.legend(title='Type')
plt.show()
```



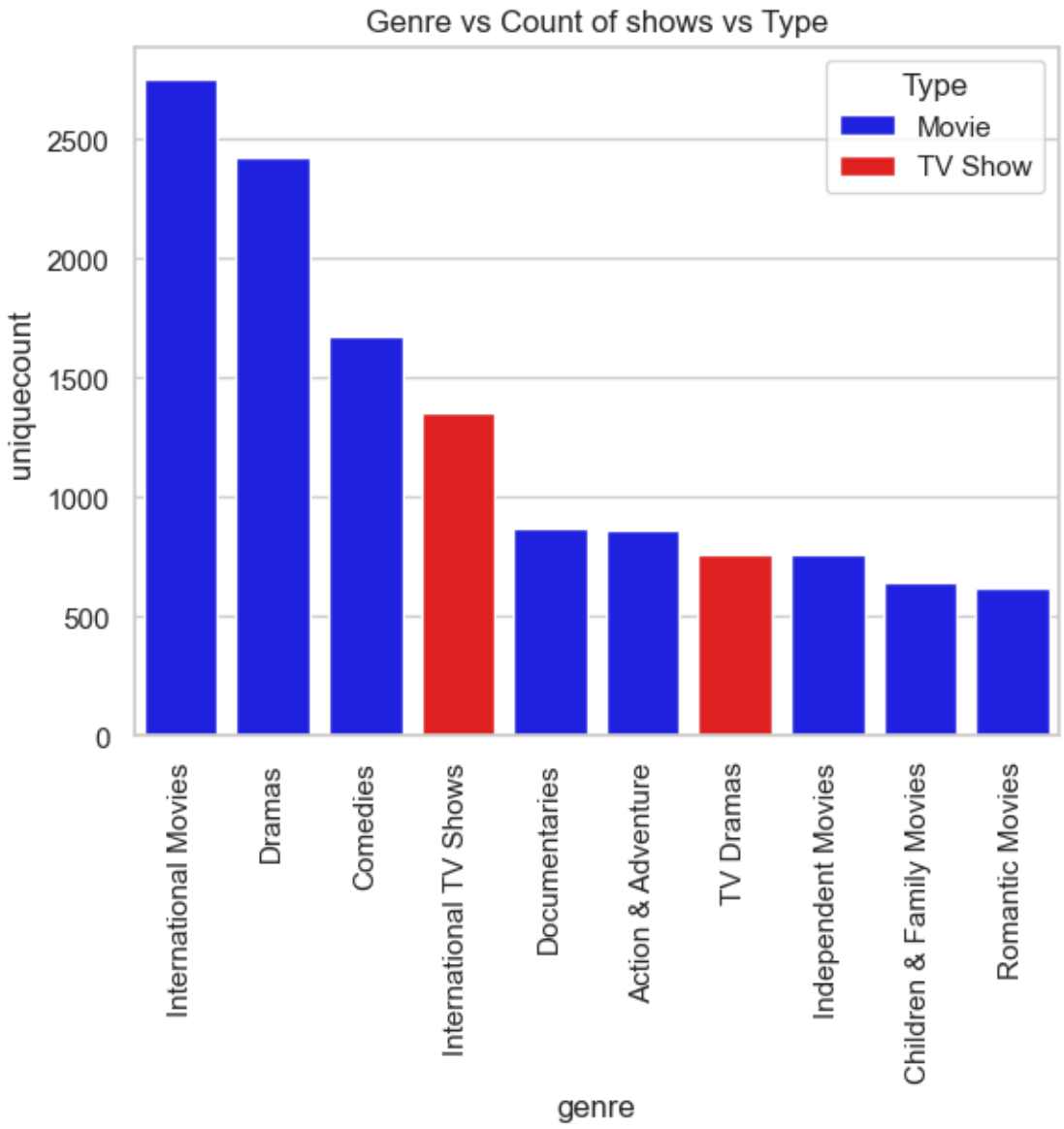
[23]:
```
#f.listed_in
listed_in_group=df.groupby('listed_in')['title'].nunique().reset_index().
 ↪sort_values('title',ascending=False)
```

```
listed_in_group.columns=['listed_in','uniquecount']
listed_in_group=pd.merge(listed_in_group, df[['listed_in', 'type']],␣
 ↪on='listed_in', how='left')
listed_in_group=listed_in_group.drop_duplicates(subset=['listed_in','type']).
 ↪reset_index().drop(columns=['index'])
listed_in_group=listed_in_group.iloc[:10]
listed_in_group.head()
```

[23]:

	listed_in	uniquecount	type
0	International Movies	2752	Movie
1	Dramas	2427	Movie
2	Comedies	1674	Movie
3	International TV Shows	1351	TV Show
4	Documentaries	869	Movie

[24]:
```
sns.set(style="whitegrid")
sns.
 ↪barplot(data=listed_in_group,x='listed_in',y='uniquecount',hue='type',palette={'Movie':
 ↪ 'blue', 'TV Show': 'red'})
plt.xticks(rotation=90)
plt.title('Genre vs Count of shows vs Type')
plt.xlabel('genre')
plt.legend(title='Type')
plt.show()
```



2.16 Insights: International Movies,Dramas,and Comedies are the most common Movie genres whreas for TV Shows it is International TV Shows and TV Dramas.In Part 5 the result for Movies is confirmed again.

[25]:
```
#g. duration
movie=df[df['type']=='Movie']
tv_show=df[df['type']=='TV Show']

movieduration=movie.groupby('duration')['title'].nunique().reset_index().
  ↪sort_values('title',ascending=False)
movieduration.columns=['duration','uniquecount']
```

```
movieduration.reset_index(inplace=True)
movieduration.drop(columns=['index'],inplace=True)
movieduration.head()
```

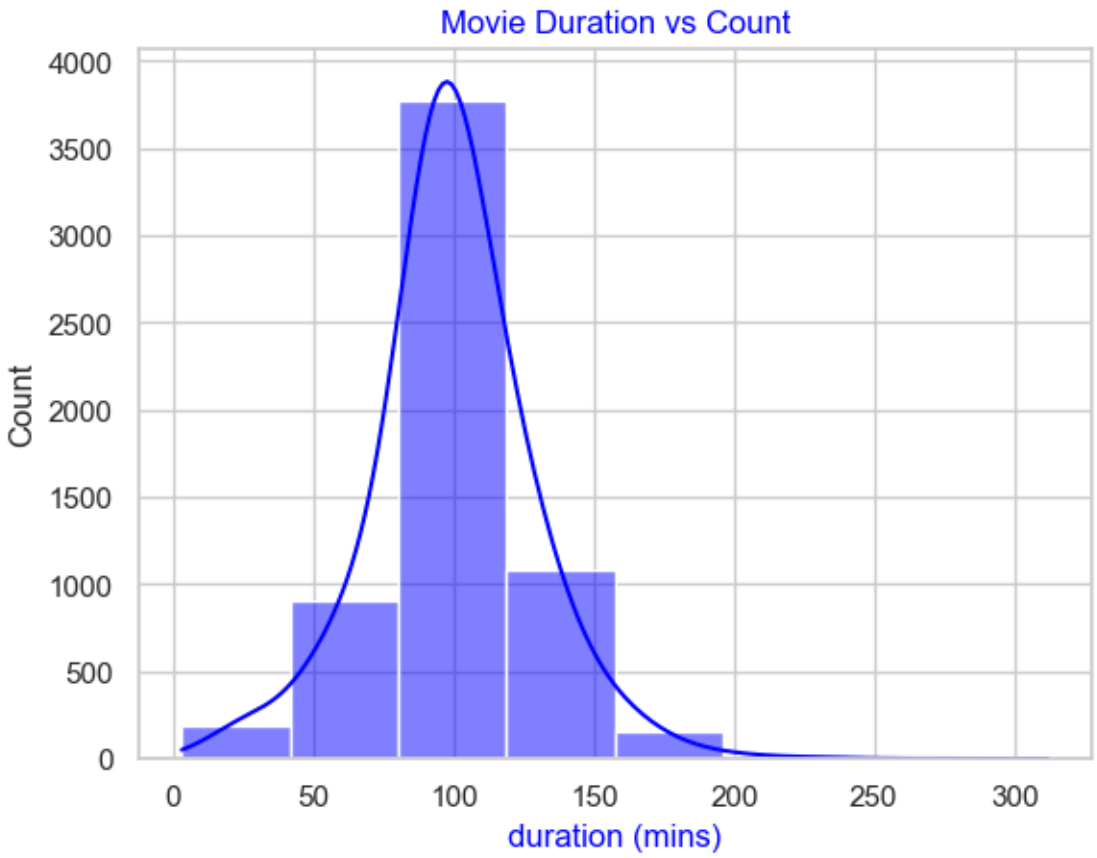
[25]:

	duration	uniquecount
0	90 min	152
1	94 min	149
2	93 min	146
3	97 min	146
4	91 min	144

2.17 Extracting Duration of Movies

[26]:
```
movieduration['duration'] = movieduration['duration'].str.extract('(\d+)',␣
↪expand=False)
movieduration['duration'] = pd.to_numeric(movieduration['duration'])
```

[27]:
```
sns.set(style="whitegrid")
sns.
↪histplot(data=movieduration,x='duration',weights='uniquecount',bins=8,kde=True,color='blue'
plt.title('Movie Duration vs Count',color='blue')
plt.xlabel('duration (mins)',color='blue')
plt.show()
```



[28]:
```
tv_showduration=tv_show.groupby('duration')['title'].nunique().reset_index().
  ↪sort_values('title',ascending=False)
tv_showduration.columns=['duration','uniquecount']
tv_showduration.reset_index(inplace=True)
tv_showduration.drop(columns=['index'],inplace=True)
tv_showduration.head()
```

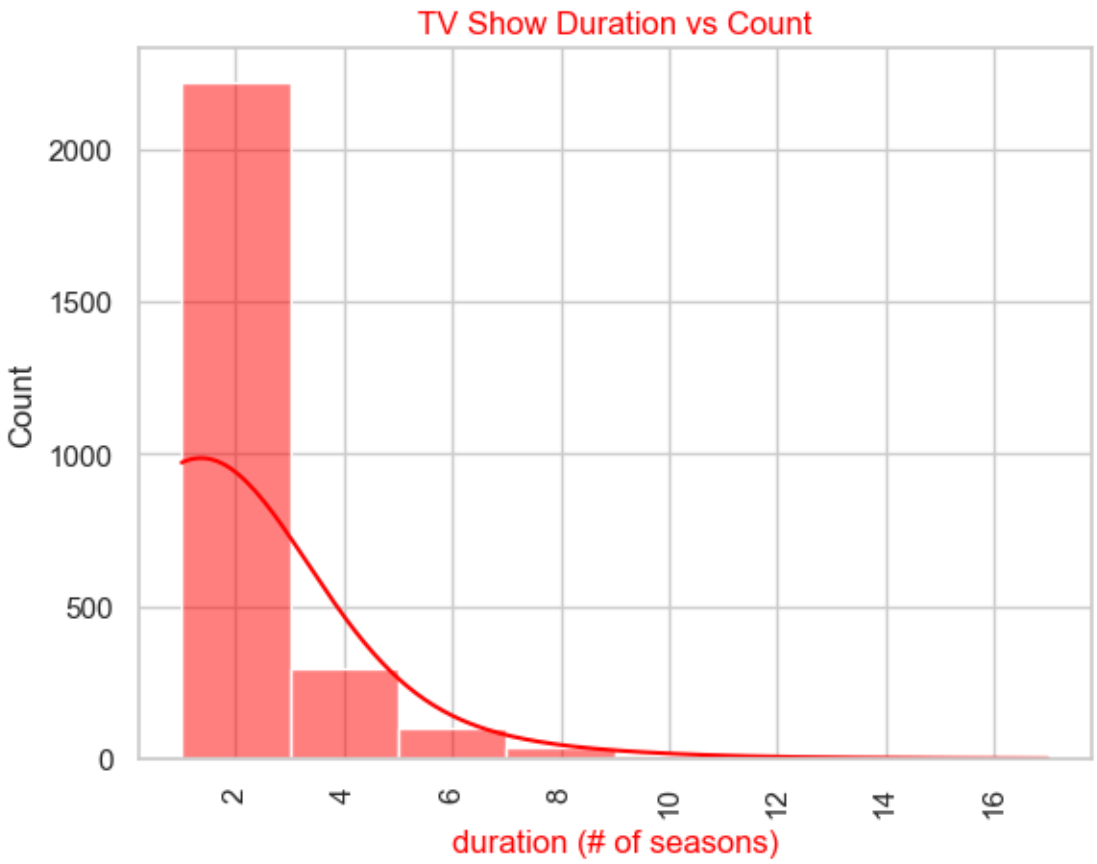
[28]:

	duration	uniquecount
0	1 Season	1793
1	2 Seasons	425
2	3 Seasons	199
3	4 Seasons	95
4	5 Seasons	65

2.18 Extracting Duration of TV Shows

[29]:
```
tv_showduration['duration'] = tv_showduration['duration'].str.extract('(\d+)',␣
  ↪expand=False)
tv_showduration['duration'] = pd.to_numeric(tv_showduration['duration'])
```

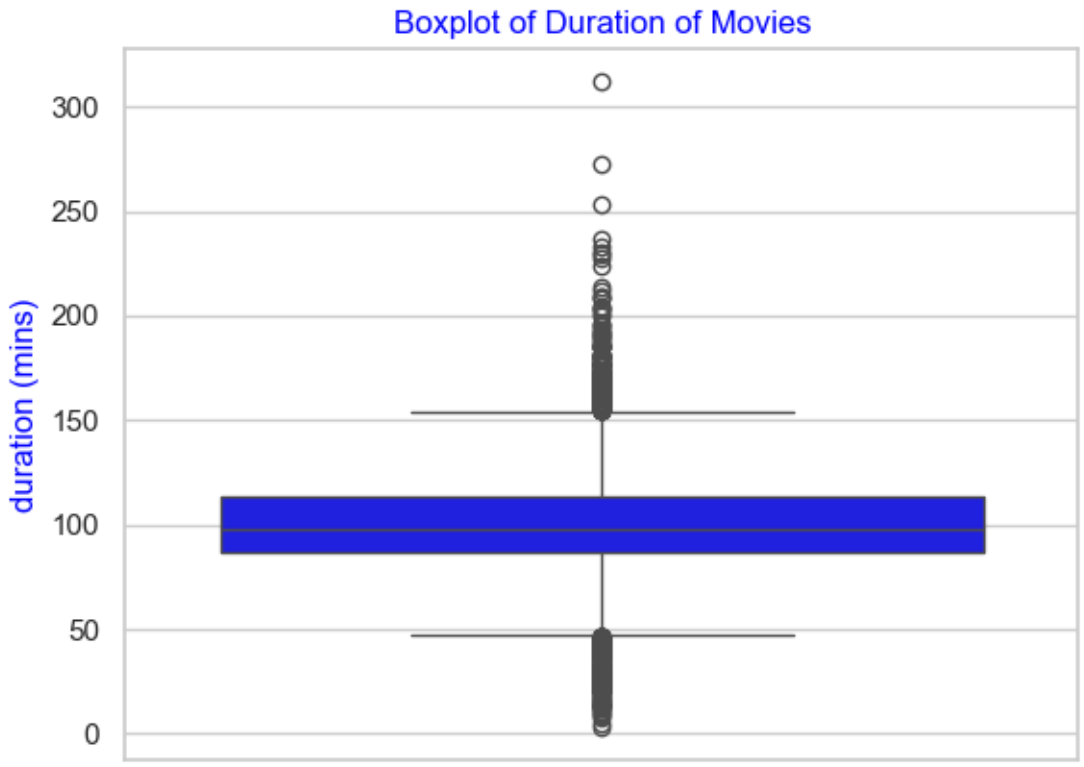
[30]:
```
sns.set(style="whitegrid")
sns.
 ↪histplot(data=tv_showduration,x='duration',weights='uniquecount',bins=8,kde=True,color='red
plt.title('TV Show Duration vs Count',color='red')
plt.xlabel('duration (# of seasons)',color='red')
plt.xticks(rotation=90)
plt.show()
```



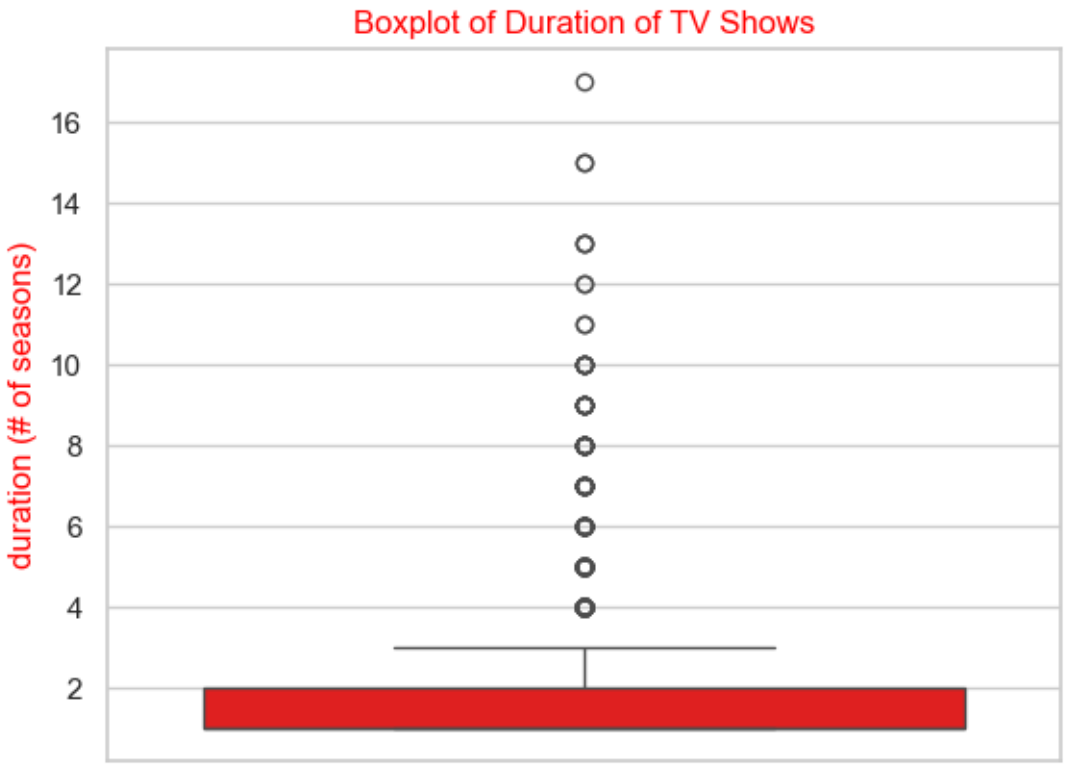
2.19 Insights: Distribution of Movie Duration is unimodal and slightly right skewed with peak at 90 minutes and mean slightly higher than the median which is around 100 minutes.For TV Shows also it is unimodal right skewed with peak at 1 season,median around 2-3 seasons and mean slightly higher than that.

[31]:
```
moviecopy=movie.copy(deep=False)
moviecopy['duration'] = moviecopy['duration'].str.extract('(\d+)', expand=False)
moviecopy['duration'] = pd.to_numeric(moviecopy['duration'])
movieboxduration=moviecopy.drop_duplicates(subset=['title','duration'])
sns.set(style="whitegrid")
```

```
sns.boxplot(data=movieboxduration,y='duration',color='blue')
plt.title('Boxplot of Duration of Movies',color='blue')
plt.ylabel('duration (mins)',color='blue')
plt.show()
```



[32]:
```
tv_show_copy=tv_show.copy(deep=False)
tv_show_copy['duration'] = tv_show_copy['duration'].str.extract('(\d+)',␣
↪expand=False)
tv_show_copy['duration'] = pd.to_numeric(tv_show_copy['duration'])
tv_show_boxduration=tv_show_copy.drop_duplicates(subset=['title','duration'])
sns.set(style="whitegrid")
sns.boxplot(data=tv_show_boxduration,y='duration',color='red')
plt.title('Boxplot of Duration of TV Shows',color='red')
plt.ylabel('duration (# of seasons)',color='red')
plt.show()
```



2.20 There are outliers for Movie duration in both ends whereas for TV Shows there are outliers only in the higher end.

2.21 2.a Number of Movies by country (Top 10)

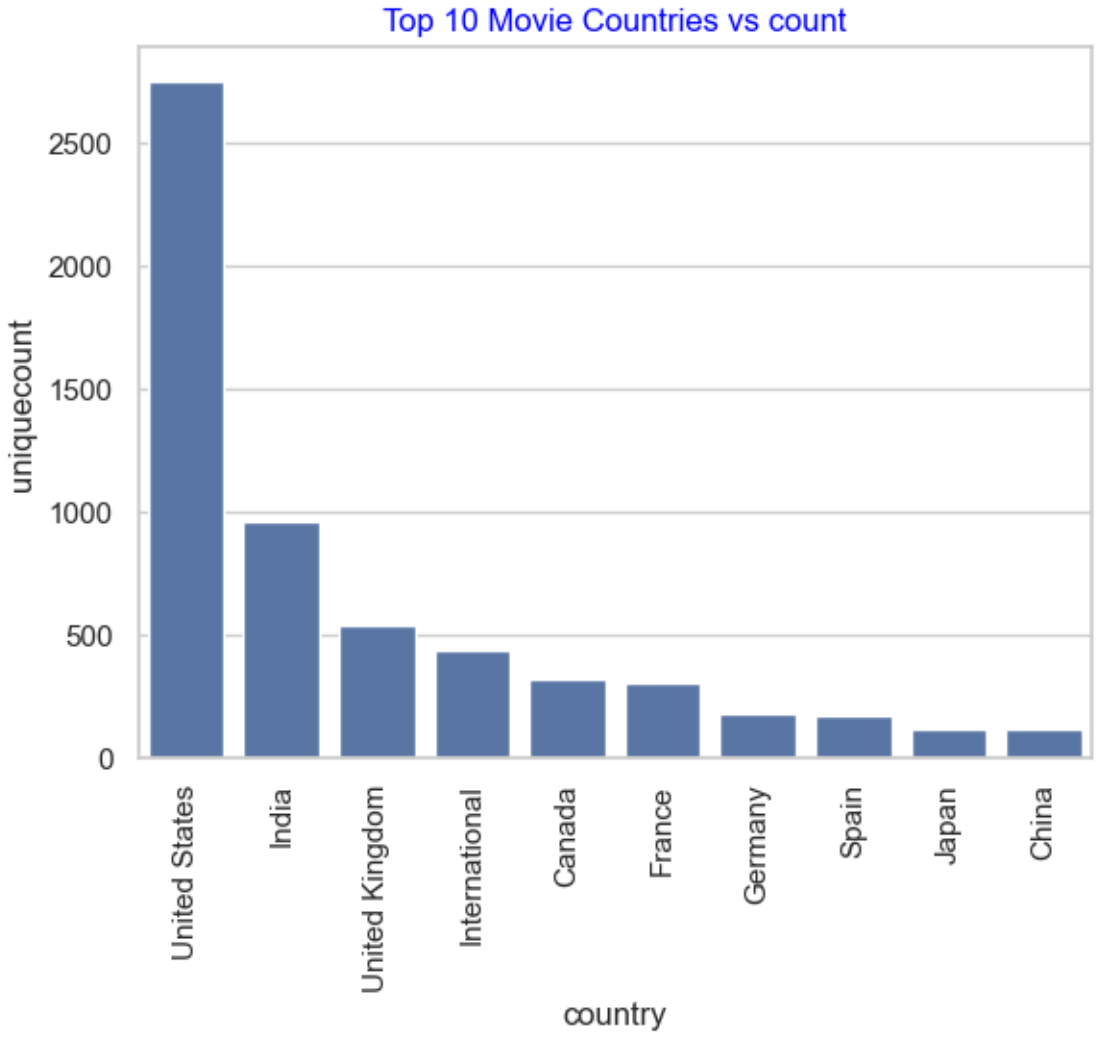
[33]:
```
movie=df[df['type']=='Movie']
group=movie.groupby('country',as_index=False)['title'].nunique()
group=group.sort_values('title',ascending=False)
group.columns=['country','uniquecount']
top10_movies=group.iloc[:10].reset_index().drop(columns='index')
top10_movies.head()
```

[33]:

	country	uniquecount
0	United States	2752
1	India	962
2	United Kingdom	534
3	International	440
4	Canada	319

[34]:
```
sns.set(style="whitegrid")
sns.barplot(data=top10_movies,x='country',y='uniquecount')
plt.title('Top 10 Movie Countries vs count',color='blue')
```

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



2.22 2.b Number of TV Shows by country (Top 10)

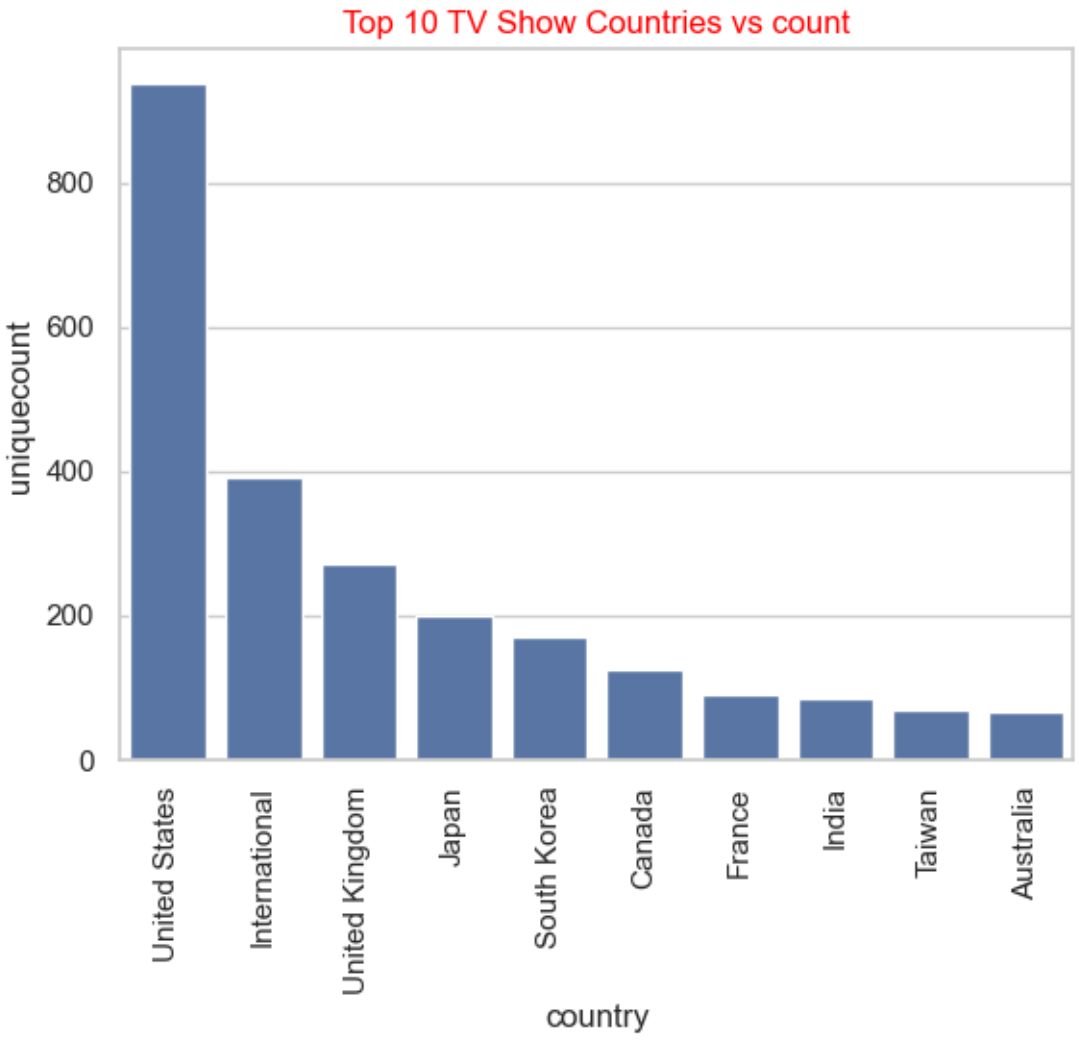
[35]:
```
tv_show=df[df['type']=='TV Show']
group=tv_show.groupby('country',as_index=False)['title'].nunique()
group=group.sort_values('title',ascending=False)
group.columns=['country','uniquecount']
top10_tv_show=group.iloc[:10].reset_index().drop(columns='index')
top10_tv_show.head()
```

[35]:

	country	uniquecount
0	United States	938

```
1    International          391
2  United Kingdom           272
3           Japan           199
4     South Korea           170
```

[36]:
```
sns.set(style="whitegrid")
sns.barplot(data=top10_tv_show,x='country',y='uniquecount')
plt.title('Top 10 TV Show Countries vs count',color='red')
plt.xticks(rotation=90)
plt.show()
```



2.23 Insights: USA leads in both Movie and TV Show count.

2.24 3.a Best week to release Movies and Tv Shows

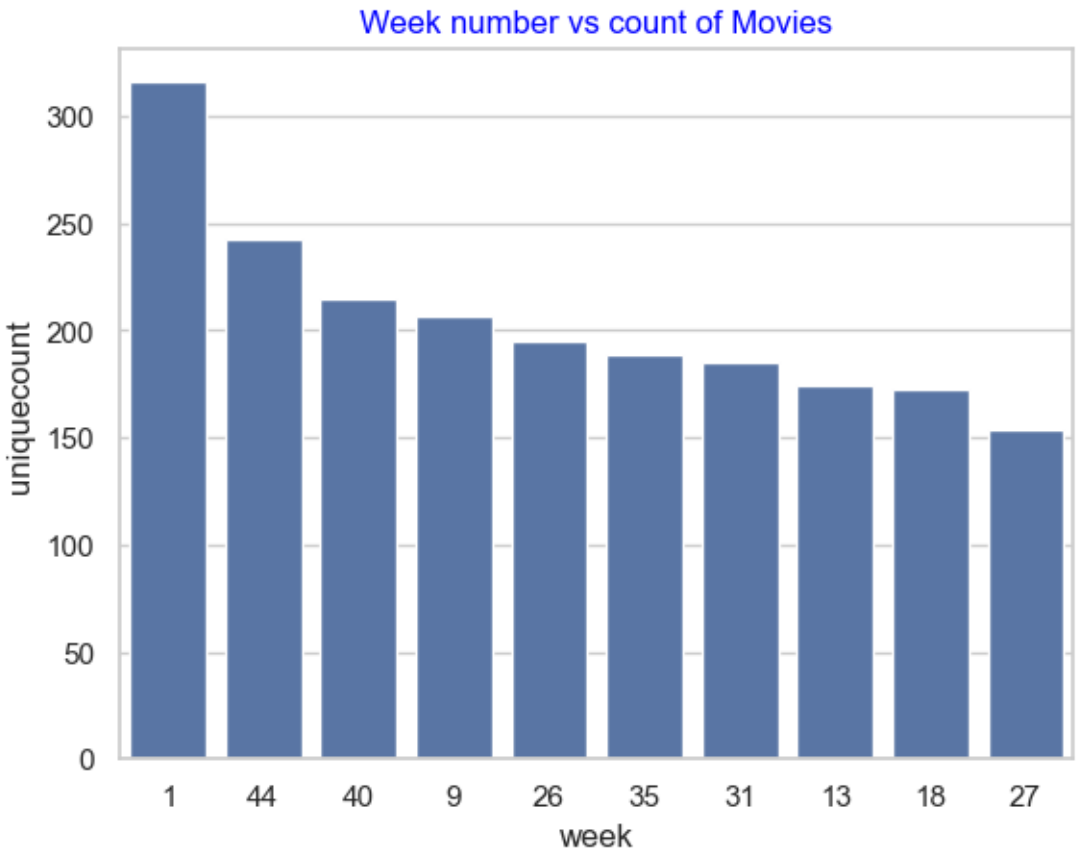
2.25 i)Best Movie Week

[37]:
```
weekmovie=movie.groupby('week_added',as_index=False)['title'].nunique()
weekmovie.columns=['week','uniquecount']
weekmovie = weekmovie.sort_values('uniquecount', ascending=False).iloc[:10, :]
weekmovie.reset_index(inplace=True)
weekmovie.drop(columns=['index'],inplace=True)
weekmovie['week']=weekmovie['week'].astype(int)
weekmovie.head()
```

[37]:

	week	uniquecount
0	1	316
1	44	243
2	40	215
3	9	207
4	26	195

[38]:
```
sns.set(style="whitegrid")
sns.barplot(data=weekmovie, x='week', y='uniquecount', order=weekmovie['week'].
 ↪tolist())
plt.title('Week number vs count of Movies',color='blue')
plt.show()
```



2.26 ii) Best TV Show week

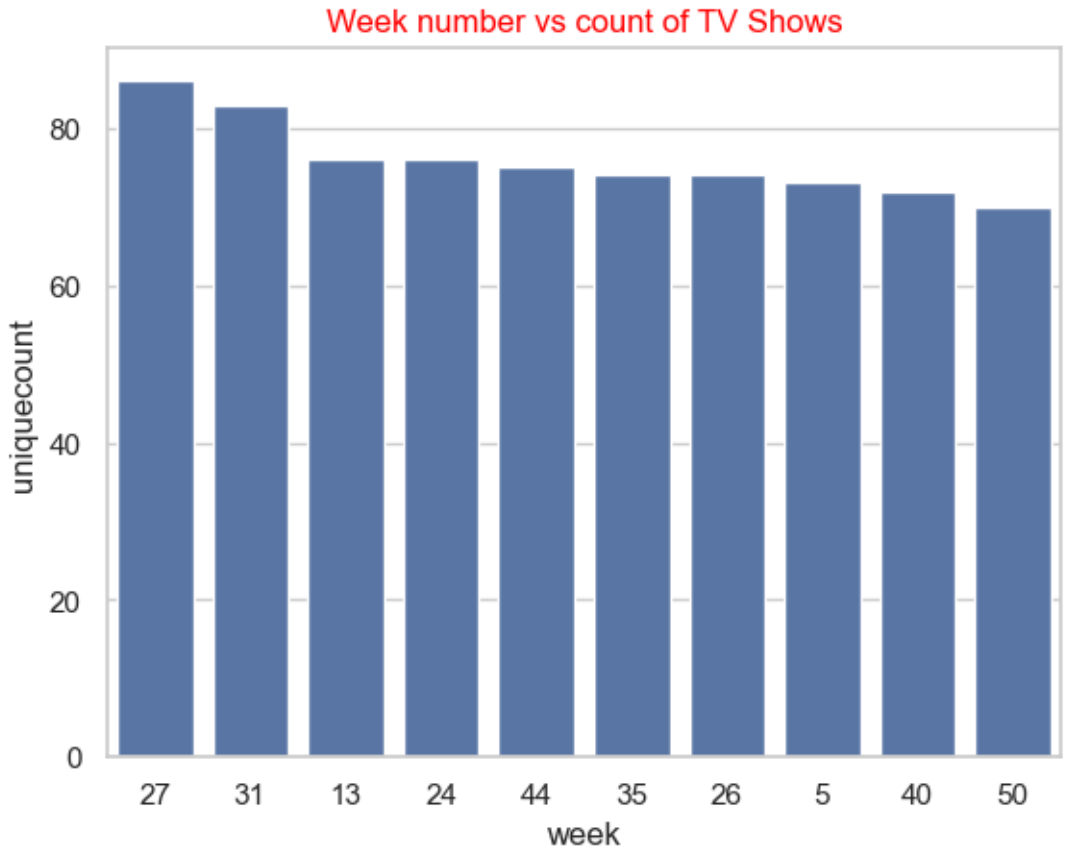
[39]:
```
weektv_show=tv_show.groupby('week_added',as_index=False)['title'].nunique()
weektv_show.columns=['week','uniquecount']
weektv_show = weektv_show.sort_values('uniquecount', ascending=False).iloc[:10,␣
↪:]
weektv_show.reset_index(inplace=True)
weektv_show.drop(columns=['index'],inplace=True)
weektv_show.head()
```

[39]:

	week	uniquecount
0	27	86
1	31	83
2	13	76
3	24	76
4	44	75

[40]:
```
sns.set(style="whitegrid")
```

```
sns.barplot(data=weektv_show, x='week', y='uniquecount',␣
  ↪order=weektv_show['week'].tolist())
plt.title('Week number vs count of TV Shows',color='red')
plt.show()
```



2.27 Insights: Most Movies are added in week 1 and most TV Shows are added in week 27.

2.28 3.b Best month to release Movies and Tv Shows

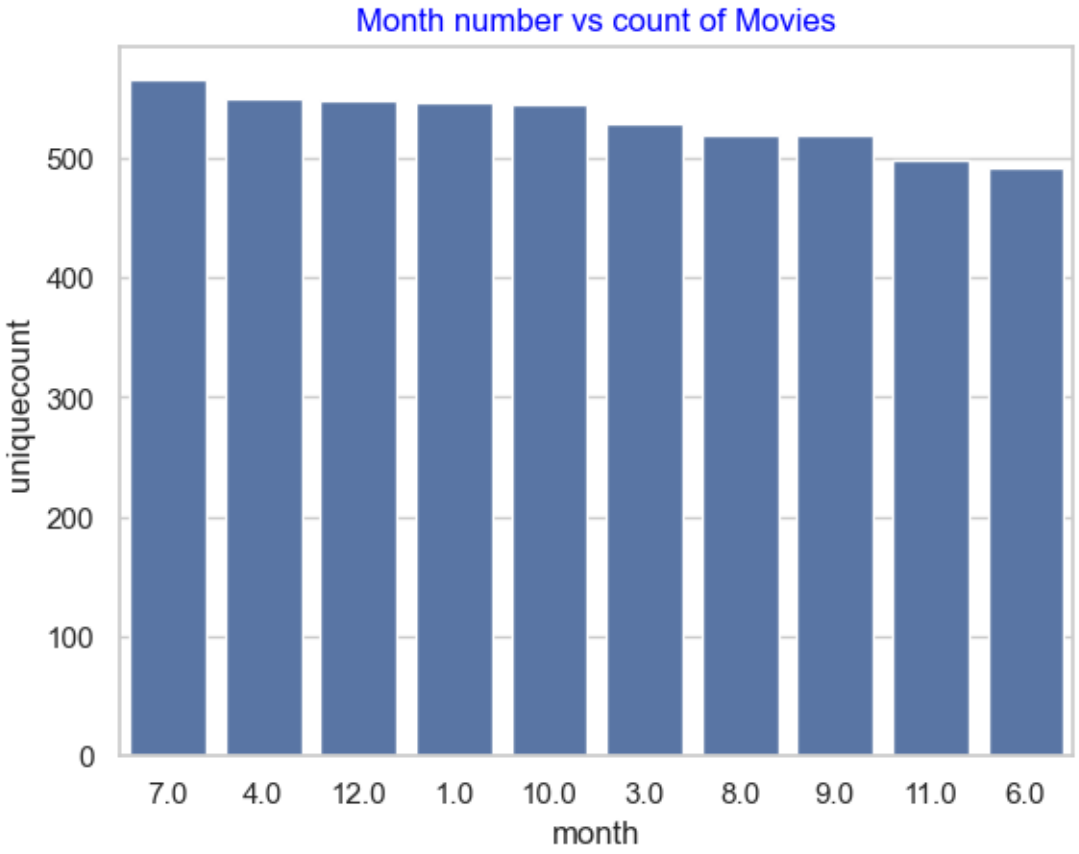
2.29 i)Best Movie Month

[41]:
```
monthmovie=movie.groupby('month_added',as_index=False)['title'].nunique()
monthmovie.columns=['month','uniquecount']
monthmovie = monthmovie.sort_values('uniquecount', ascending=False).iloc[:10, :]
monthmovie.reset_index(inplace=True)
monthmovie.drop(columns=['index'],inplace=True)
monthmovie.head()
```

[41]:

	month	uniquecount
0	7.0	565
1	4.0	550
2	12.0	547
3	1.0	546
4	10.0	545

[42]:
```
sns.set(style="whitegrid")
sns.barplot(data=monthmovie, x='month', y='uniquecount',␣
 ↪order=monthmovie['month'].tolist())
plt.title('Month number vs count of Movies',color='blue')
plt.show()
```



2.30 ii)Best TV Show Month

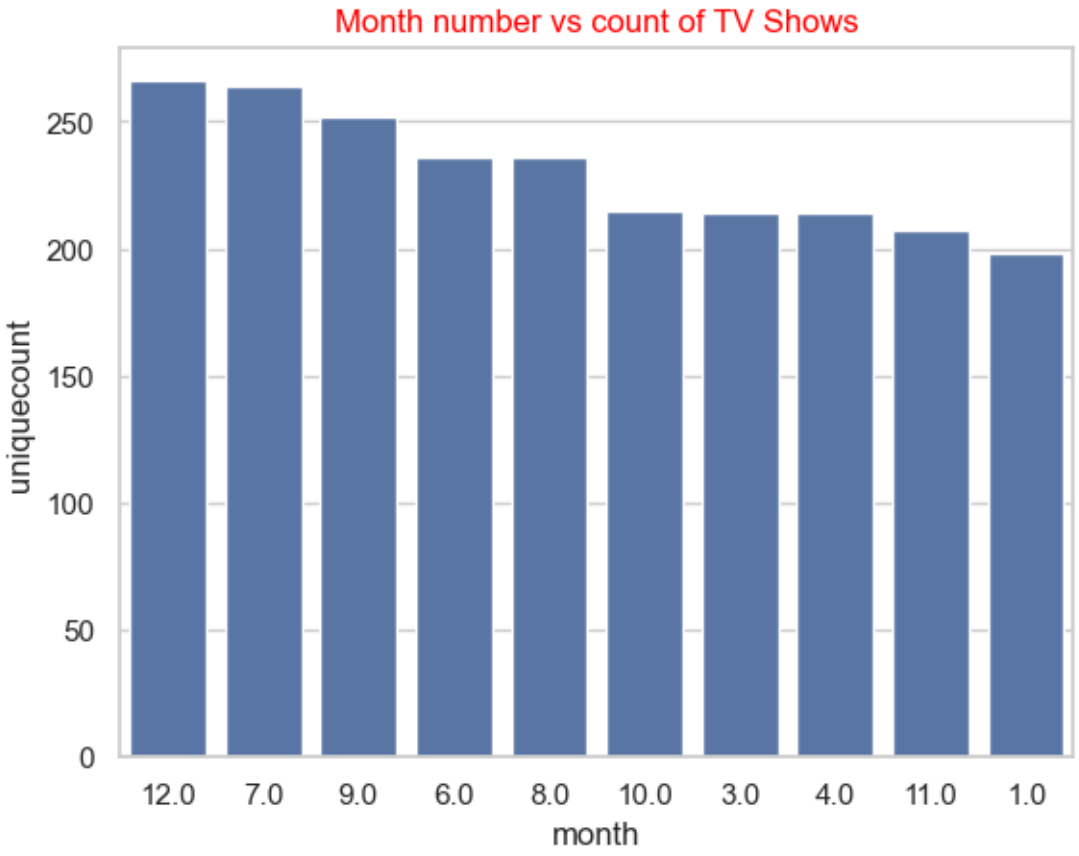
[43]:
```
monthtv_show=tv_show.groupby('month_added',as_index=False)['title'].nunique()
monthtv_show.columns=['month','uniquecount']
monthtv_show = monthtv_show.sort_values('uniquecount', ascending=False).iloc[:
 ↪10, :]
```

```
monthtv_show.reset_index(inplace=True)
monthtv_show.drop(columns=['index'],inplace=True)
monthtv_show.head()
```

[43]:

	month	uniquecount
0	12.0	266
1	7.0	264
2	9.0	252
3	6.0	236
4	8.0	236

[44]:
```
sns.set(style="whitegrid")
sns.barplot(data=monthtv_show, x='month', y='uniquecount',␣
 ↪order=monthtv_show['month'].tolist())
plt.title('Month number vs count of TV Shows',color='red')
plt.show()
```



2.31 Insights: Most Movies are added in July and most TV Shows are added in December.

2.32 4.a Top 10 cast for Movies and TV Shows

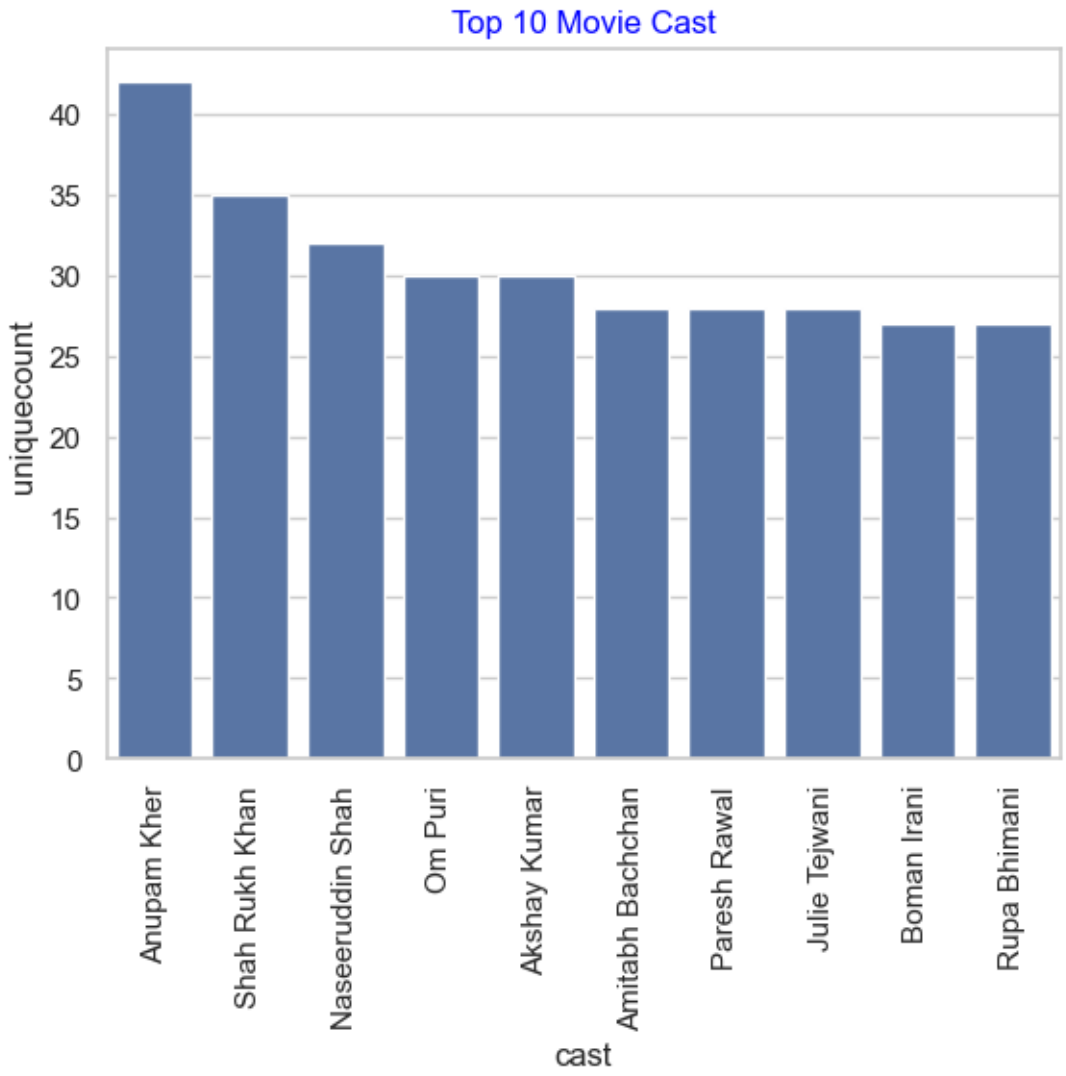
2.33 i)Top 10 cast for Movies

[45]:
```
moviecast = movie.groupby('cast')['title'].nunique().
 ↪sort_values(ascending=False).reset_index()
moviecast.columns=['cast','uniquecount']
moviecast.head()
```

[45]:

	cast	uniquecount
0	Unknown Cast	475
1	Anupam Kher	42
2	Shah Rukh Khan	35
3	Naseeruddin Shah	32
4	Om Puri	30

[46]:
```
moviecast=moviecast[moviecast['cast']!='Unknown Cast'].iloc[:10]
sns.set(style="whitegrid")
sns.barplot(data=moviecast,x='cast',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 Movie Cast',color='blue')
plt.show()
```



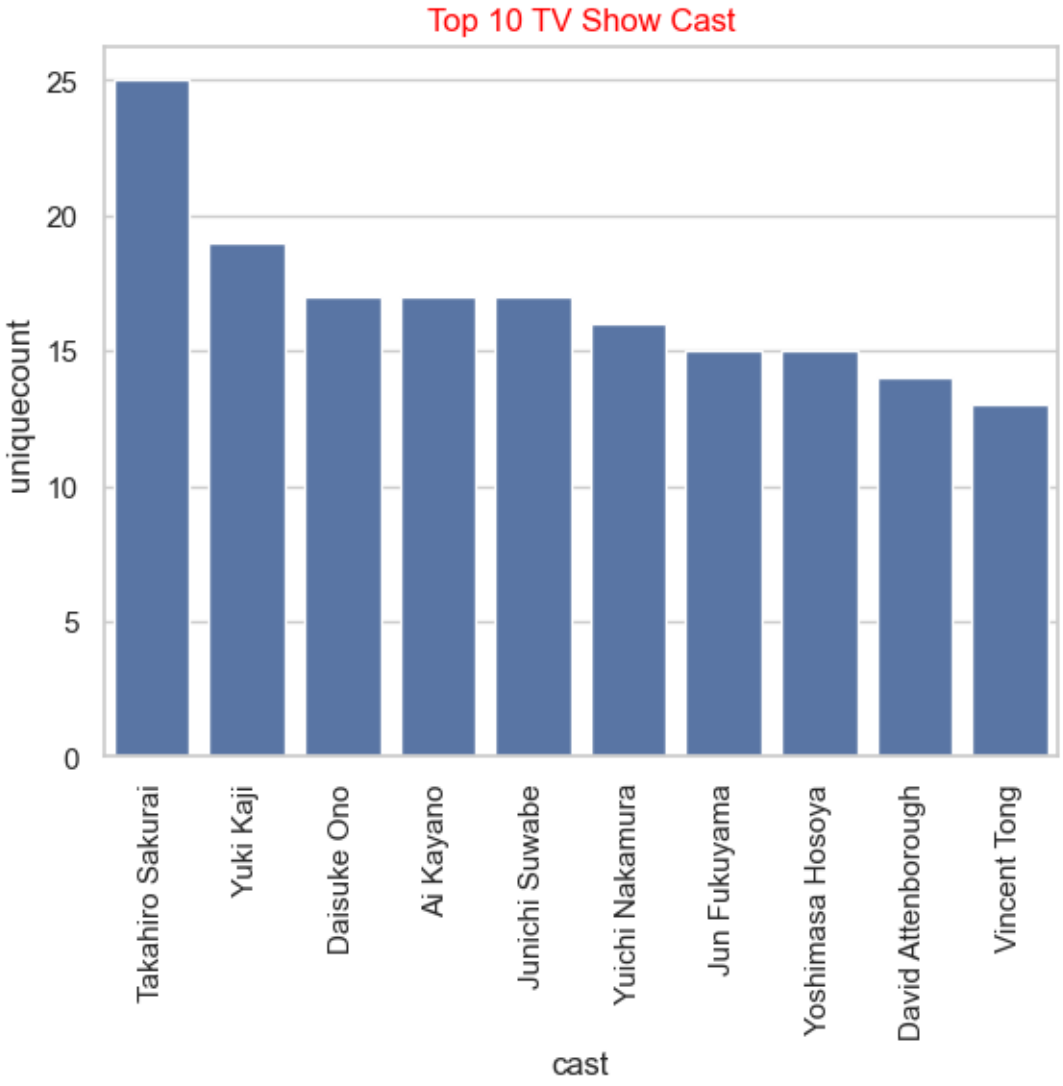
2.34 ii)Top 10 cast for TV Shows

[47]:
```
tv_showcast = tv_show.groupby('cast')['title'].nunique().
 ↪sort_values(ascending=False).reset_index()
tv_showcast.columns=['cast','uniquecount']
tv_showcast.head()
```

[47]:

	cast	uniquecount
0	Unknown Cast	350
1	Takahiro Sakurai	25
2	Yuki Kaji	19
3	Daisuke Ono	17
4	Ai Kayano	17

[48]:
```
tv_showcast=tv_showcast[tv_showcast['cast']!='Unknown Cast'].iloc[:10]
sns.set(style="whitegrid")
sns.barplot(data=tv_showcast,x='cast',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 TV Show Cast',color='red')
plt.show()
```



2.35 4.b Top 10 directors for Movies and TV Shows

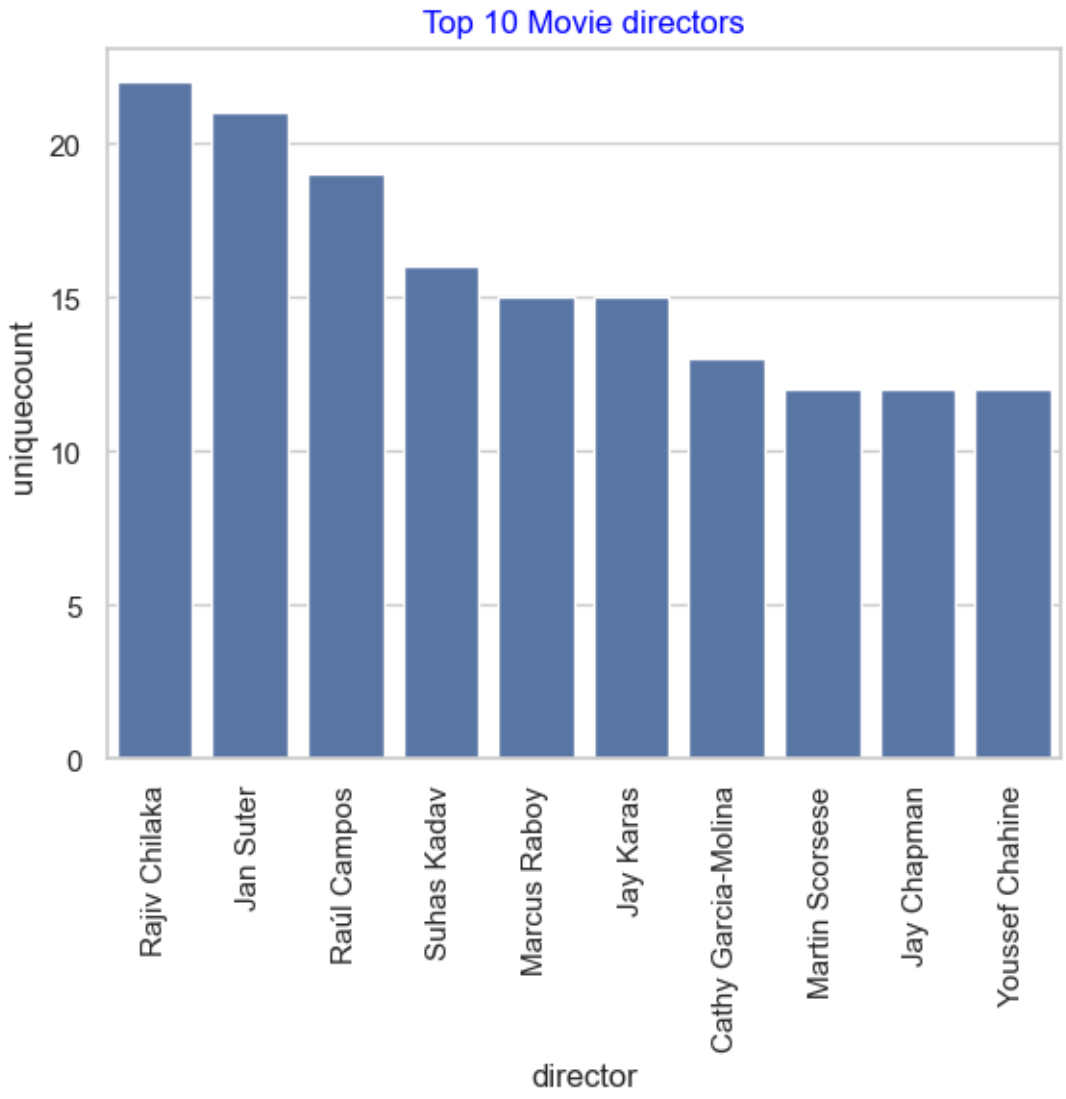
2.36 i)Top 10 directors for Movies

[49]:
```
moviedirector = movie.groupby('director')['title'].nunique().
 ↪sort_values(ascending=False).reset_index()
moviedirector.columns=['director','uniquecount']
moviedirector.head()
```

[49]:

	director	uniquecount
0	Unknown Director	188
1	Rajiv Chilaka	22
2	Jan Suter	21
3	Raúl Campos	19
4	Suhas Kadav	16

[50]:
```
moviedirector=moviedirector[moviedirector['director']!='Unknown Director'].
 ↪iloc[:10]
sns.set(style="whitegrid")
sns.barplot(data=moviedirector,x='director',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 Movie directors',color='blue')
plt.show()
```



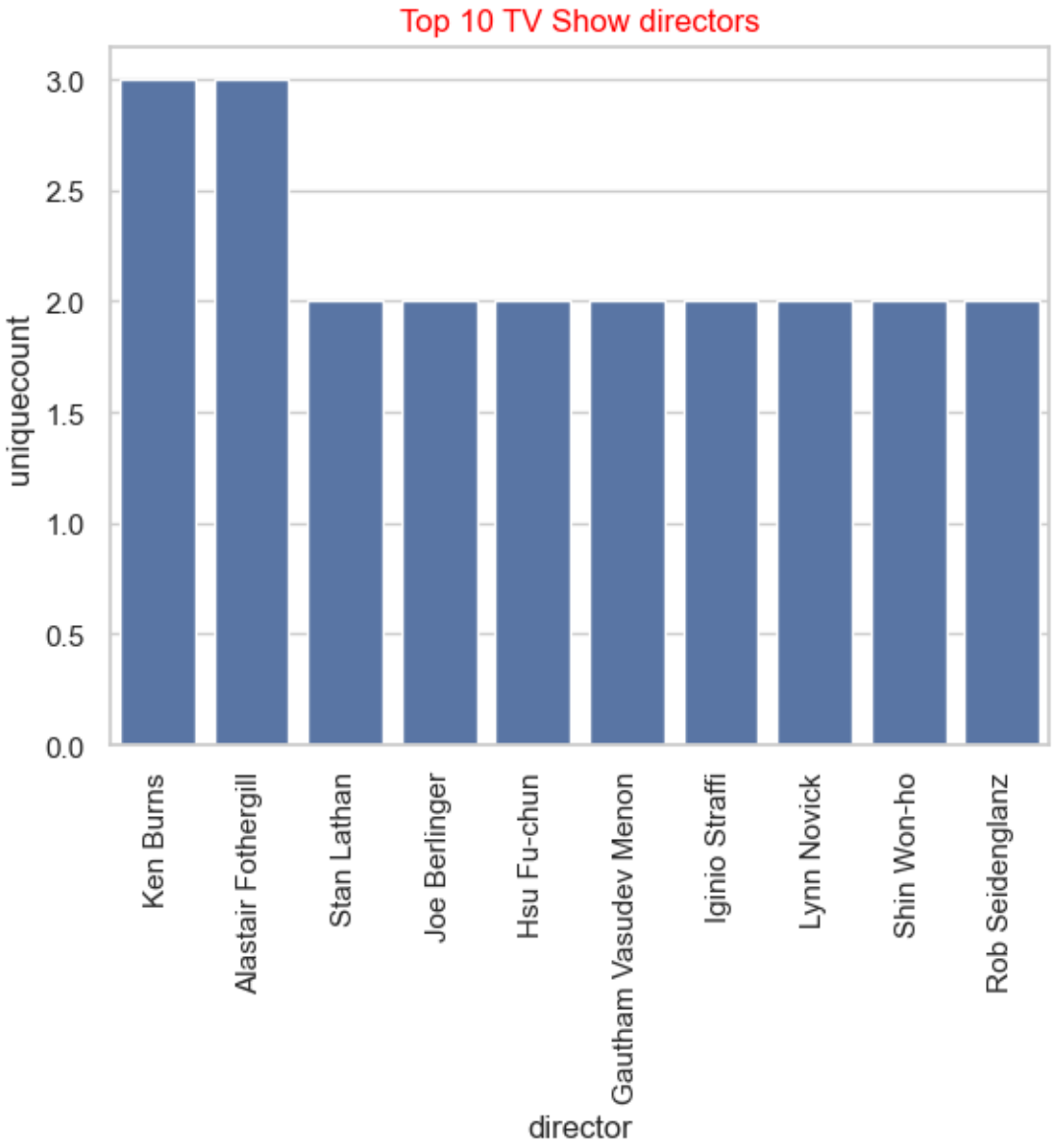
2.37 ii)Top 10 directors for TV Shows

[51]:
```
tv_showdirector = tv_show.groupby('director')['title'].nunique().
↪sort_values(ascending=False).reset_index()
tv_showdirector.columns=['director','uniquecount']
tv_showdirector.head()
```

[51]:

	director	uniquecount
0	Unknown Director	2446
1	Ken Burns	3
2	Alastair Fothergill	3
3	Stan Lathan	2
4	Joe Berlinger	2

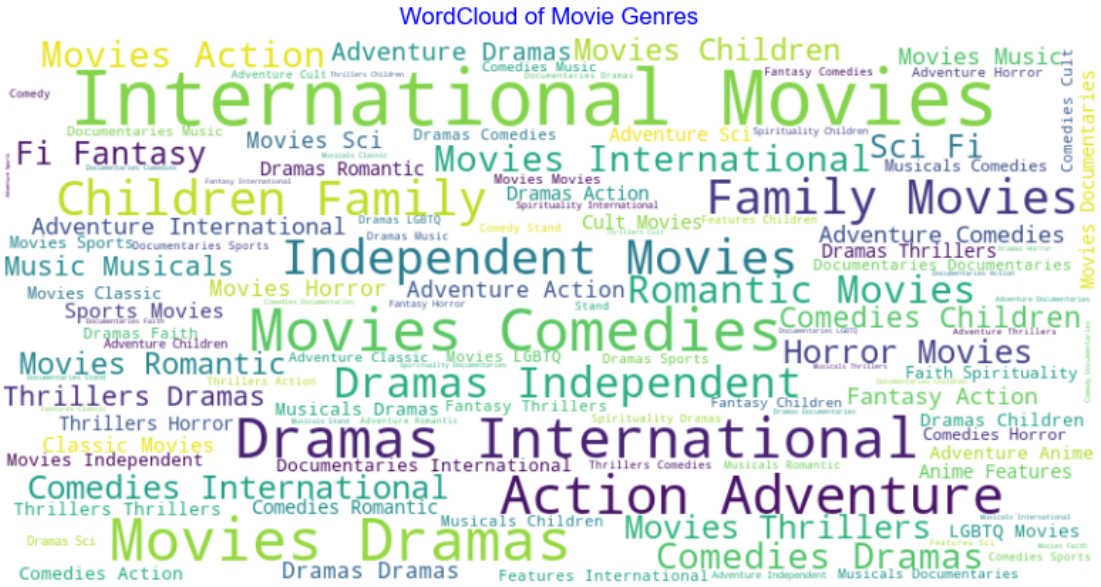
[52]:
```
tv_showdirector=tv_showdirector[tv_showdirector['director']!='Unknown␣
  ↪Director'].iloc[:10]
sns.set(style="whitegrid")
sns.barplot(data=tv_showdirector,x='director',y='uniquecount')
plt.xticks(rotation=90)
plt.title('Top 10 TV Show directors',color='red')
plt.show()
```



2.38 5. Which genre movies are more popular or produced more?

[53]:
```
all_genres = ' '.join(movie['listed_in'].astype(str))
wordcloud = WordCloud(width=800, height=400, background_color='white').
 ↪generate(all_genres)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.title('WordCloud of Movie Genres',color='blue')
plt.axis('off')
plt.show()
```



2.39 Insights: We can conclude that International Movies,Dramas and Comedies are the most produced genres of movies.

2.40 6. After how many days the movie will be added to Netflix after the release of the movie?

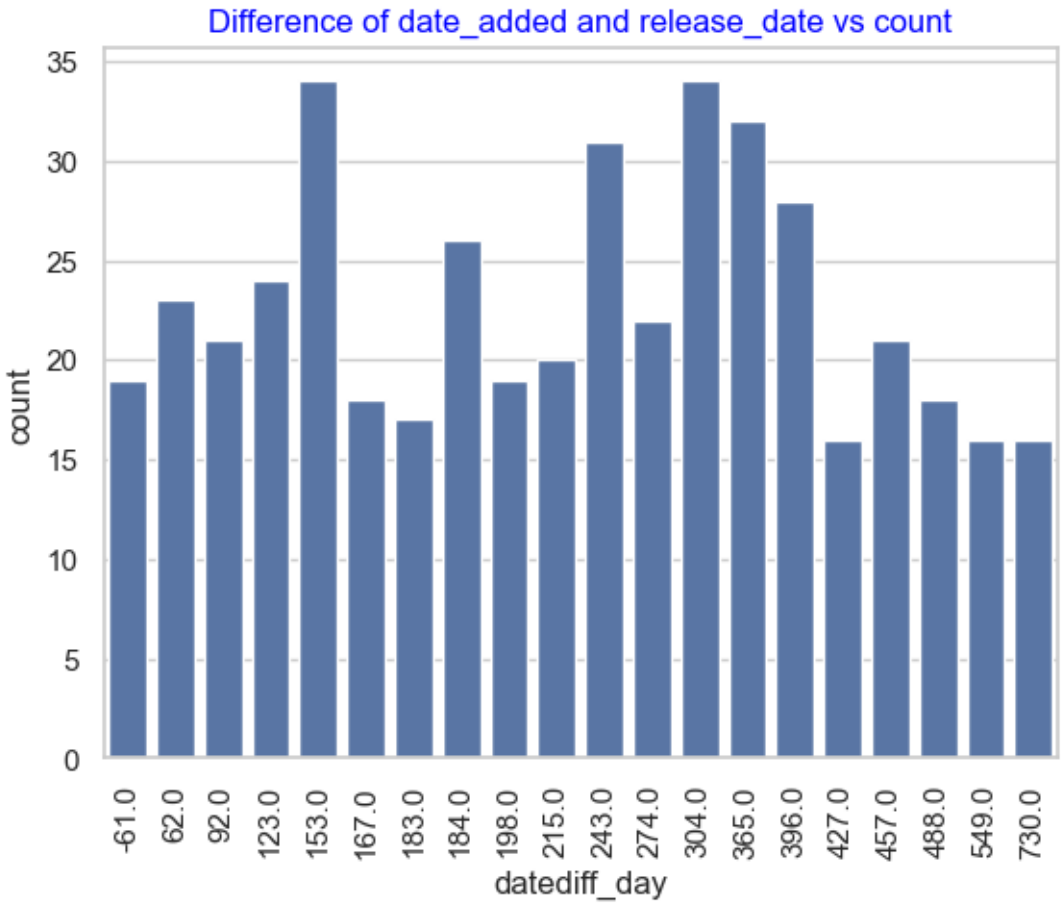
[54]:
```
moviereset=movie.reset_index()
moviediff=moviereset[['show_id','datediff_day']]
moviediff=moviediff.groupby('show_id',as_index=False)['datediff_day'].mean()
predict=moviediff['datediff_day'].value_counts().reset_index().iloc[:20]
median=round((predict.iloc[9,0]+predict.iloc[10,0])/2,2)
mean=predict.iloc[:,0].mean()
print('Median is '+str(median)+' days Mean is '+str(mean)+' days')
predict.head()
```

```
Median is 274.5 days Mean is 277.45 days
```

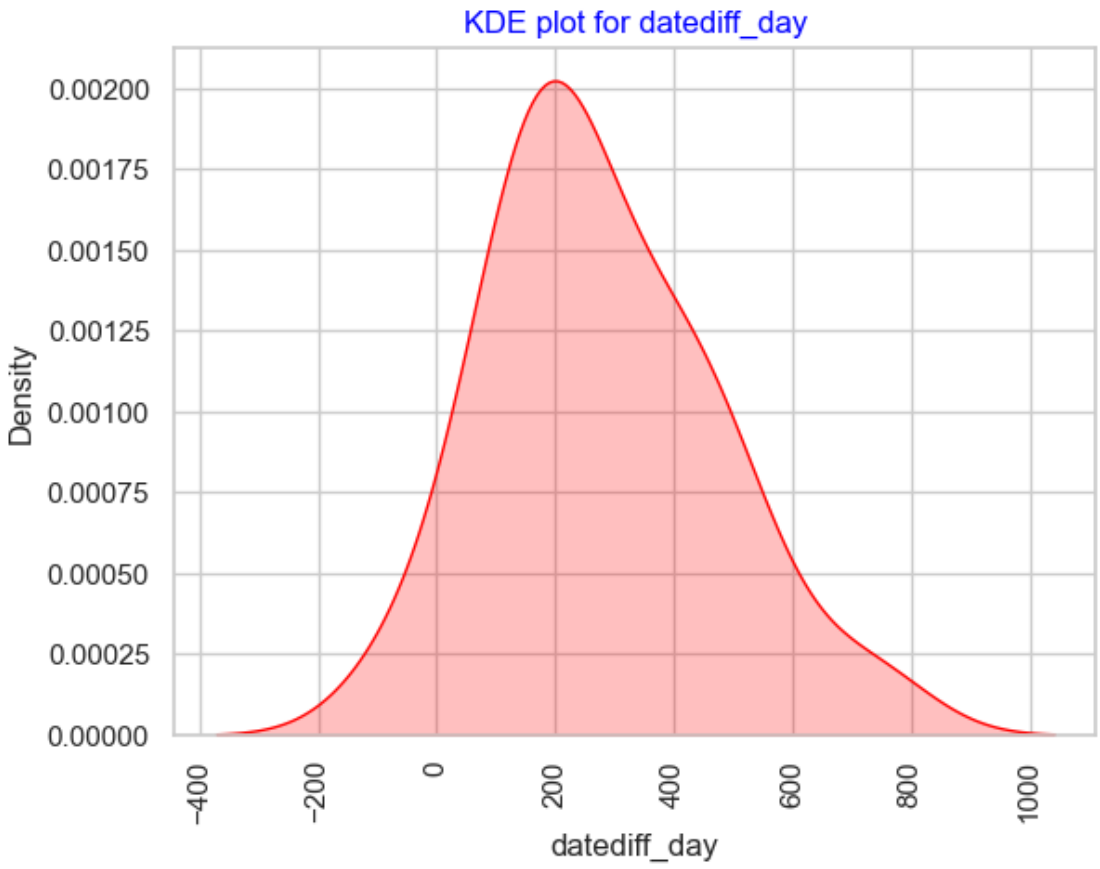
[54]:

	datediff_day	count
0	304.0	34
1	153.0	34
2	365.0	32
3	243.0	31
4	396.0	28

[55]:
```
sns.set(style="whitegrid")
sns.barplot(data=predict, x='datediff_day', y='count')
plt.title('Difference of date_added and release_date vs count',color='blue')
plt.xticks(rotation=90)
plt.show()
```

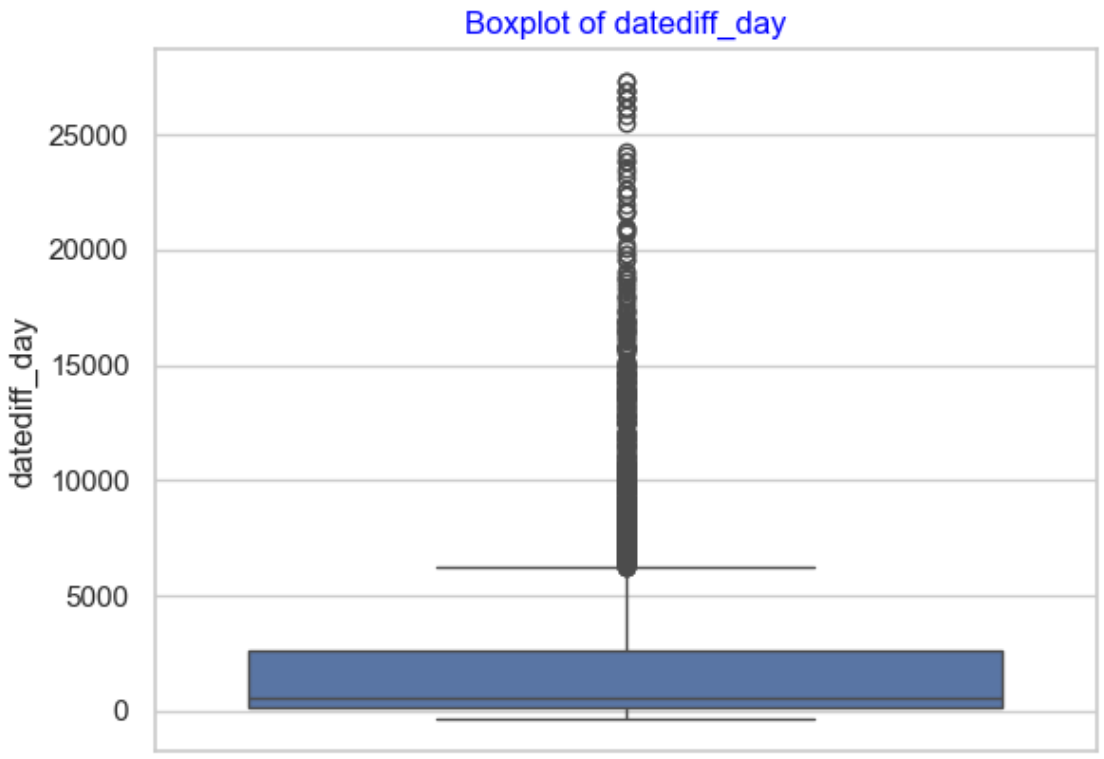


[56]:
```
sns.set(style="whitegrid")
sns.kdeplot(data=predict, x='datediff_day', color='red', fill=True)
plt.title('KDE plot for datediff_day',color='blue')
plt.xticks(rotation=90)
plt.show()
```



2.41 Insights: Distribution is bimodal with peaks at 153 days and 304 days and the mean and median are both close to 280 days which is about 10 months for the top 20 most frequent datediff_day s.We can predict that within 10 months of the movie release it will be added to Netflix.

[57]:
```
boxpredict=movie.drop_duplicates(subset=['title','datediff_day'])
sns.set(style="whitegrid")
sns.boxplot(data=boxpredict,y='datediff_day')
plt.title('Boxplot of datediff_day',color='blue')
plt.show()
```

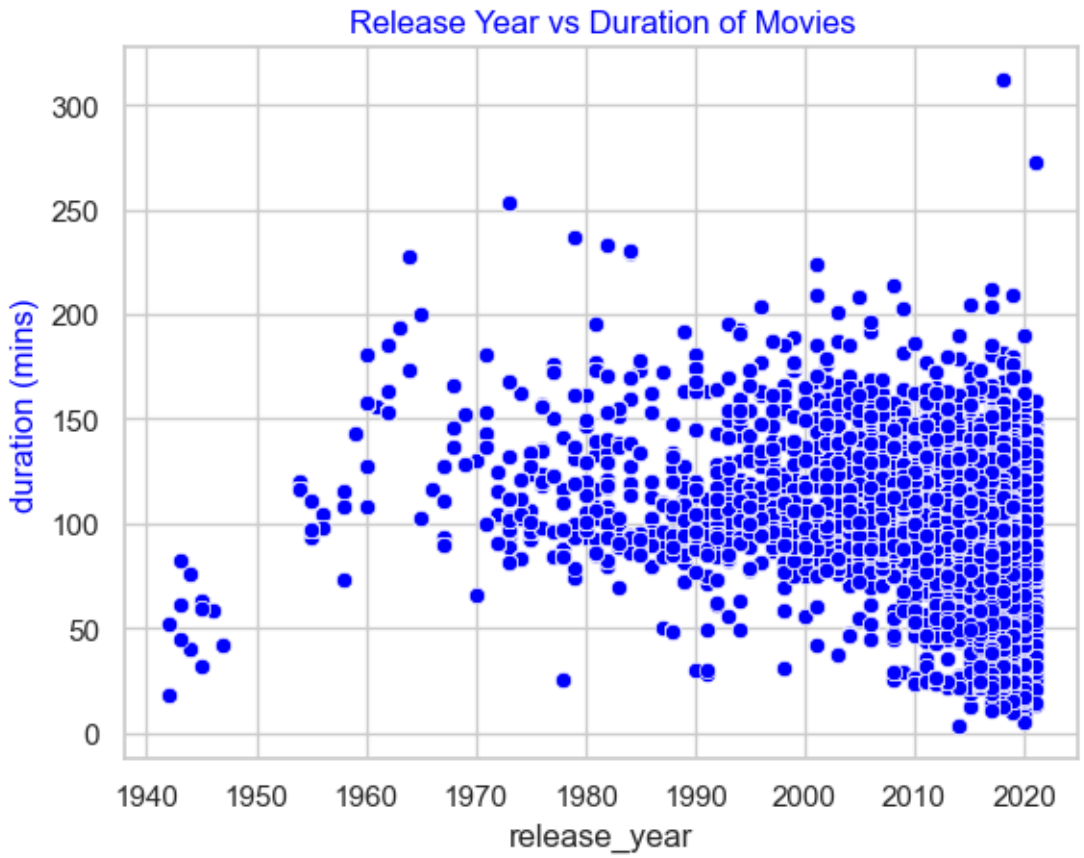


2.42 **There are a lot of outliers for movie releases in the higher end which shows that the difference between release_date and movie_added date depends a lot on the demand and popularity of the movies.**

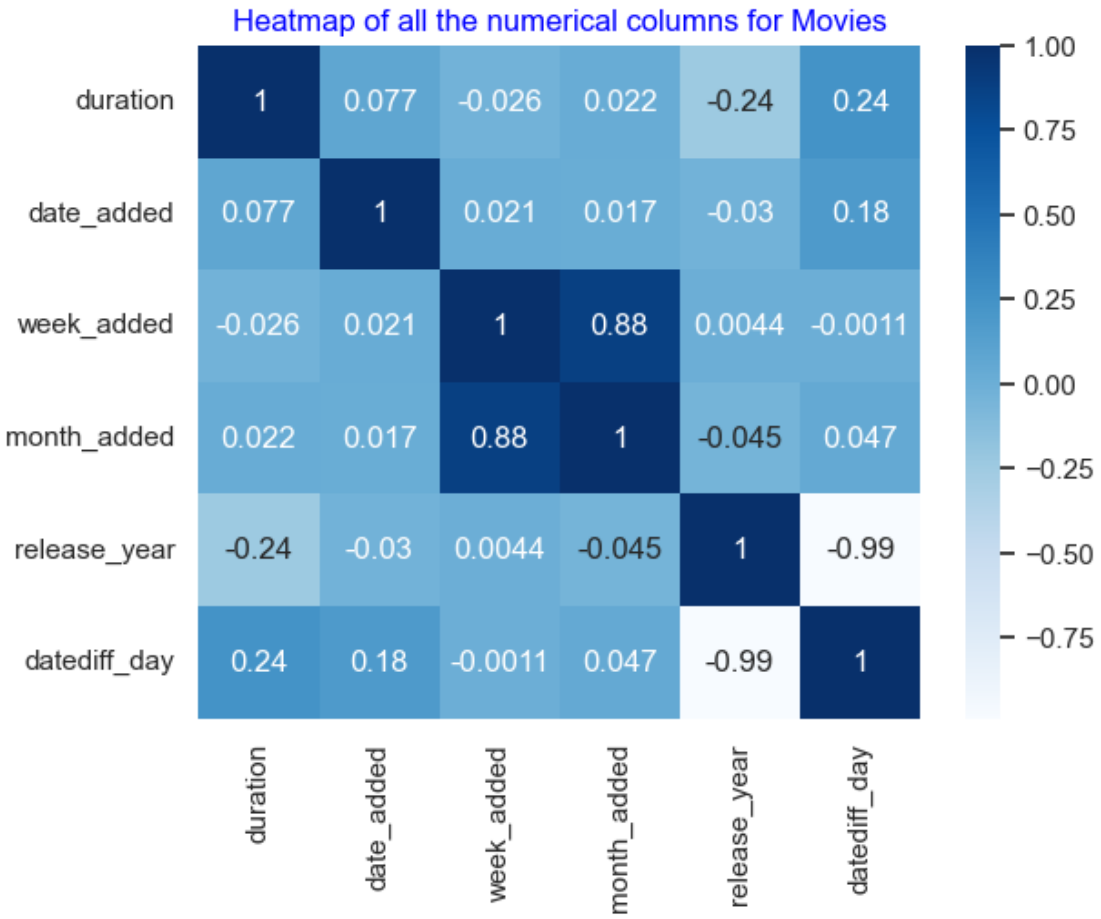
2.43 **7. Is Duration of Movies or TV Shows getting shorter with time?**

[58]:
```
moviecopy = movie.copy(deep=False)
moviecopy['duration'] = moviecopy['duration'].str.extract('(\d+)', expand=False)
moviecopy['duration'] = pd.to_numeric(moviecopy['duration'])
```

[59]:
```
sns.set(style="whitegrid")
sns.scatterplot(data=moviecopy,x='release_year',y='duration',color='blue')
plt.title('Release Year vs Duration of Movies',color='blue')
plt.ylabel('duration (mins)',color='blue')
plt.show()
```

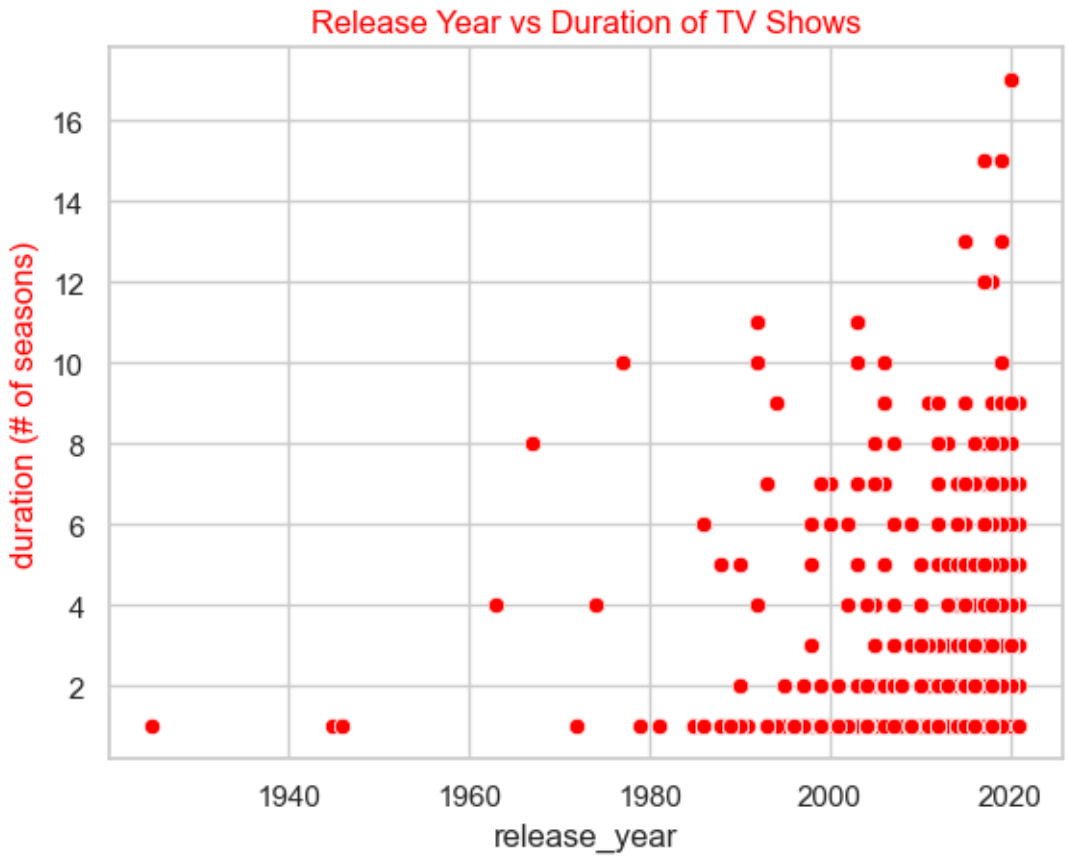


[60]:
```
moviecopy=moviecopy[['duration','date_added','week_added','month_added','release_year','datedi
movie_corr=moviecopy.corr()
sns.heatmap(movie_corr,cmap='Blues',annot=True)
plt.title('Heatmap of all the numerical columns for Movies',color='blue')
plt.show()
```

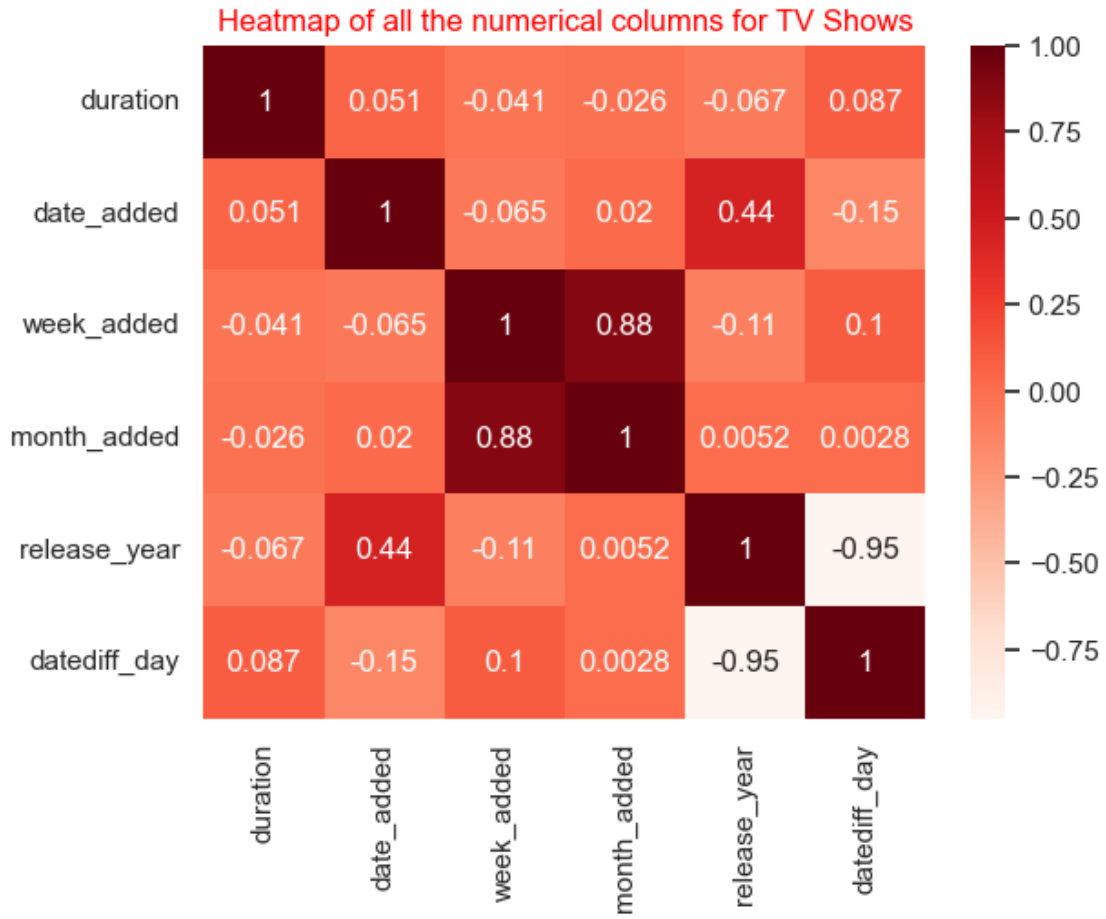


[61]:
```
tv_show_copy=tv_show.copy(deep=False)
tv_show_copy['duration'] = tv_show_copy['duration'].str.extract('(\d+)',␣
↪expand=False)
tv_show_copy['duration'] = pd.to_numeric(tv_show_copy['duration'])
```

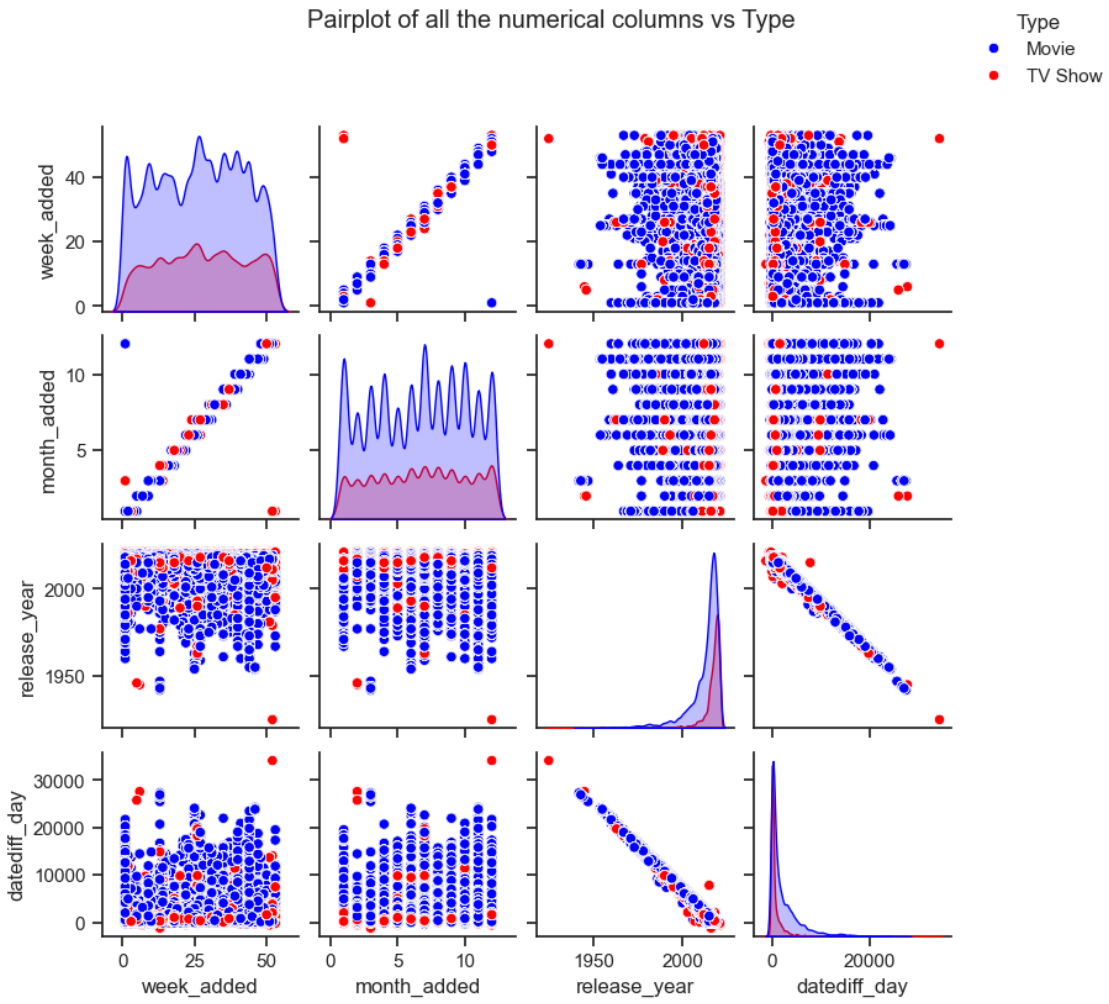
[62]:
```
sns.set(style="whitegrid")
sns.scatterplot(data=tv_show_copy,x='release_year',y='duration',color='red')
plt.ylabel('duration (# of seasons)',color='red')
plt.title('Release Year vs Duration of TV Shows',color='red')
plt.show()
```



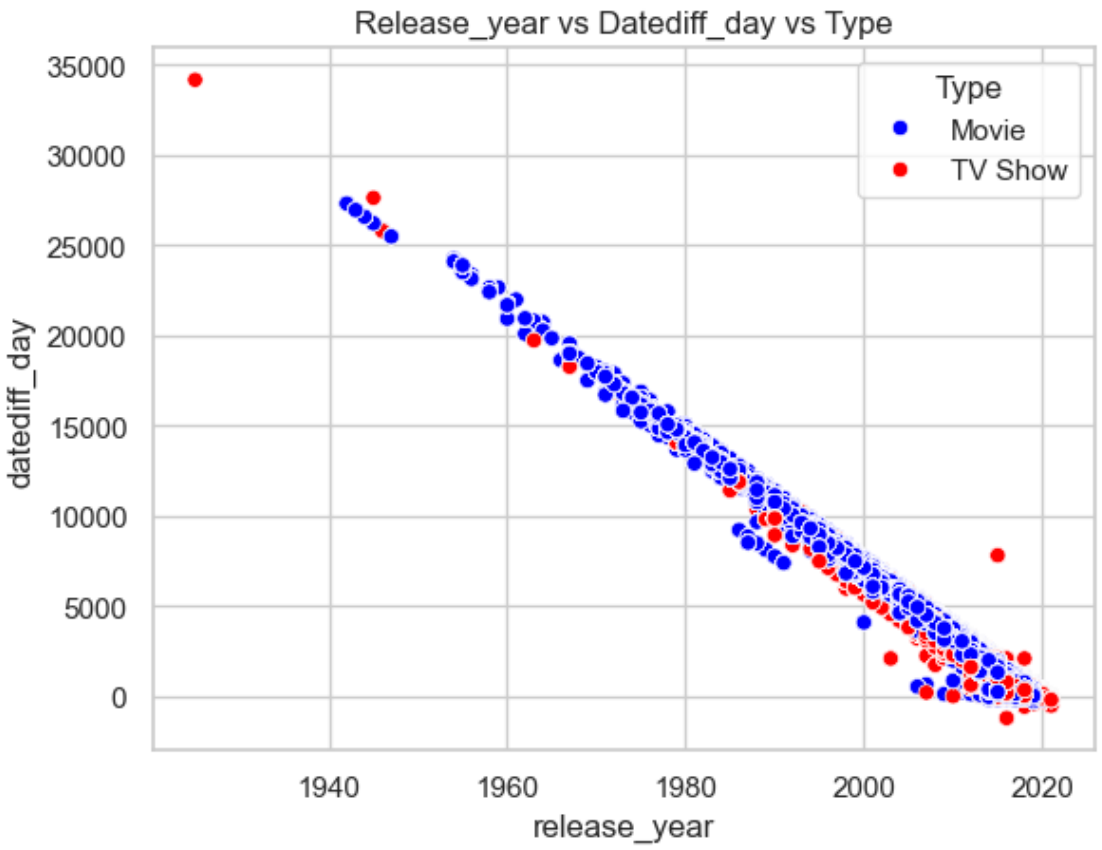
[63]:
```
tv_show_copy=tv_show_copy[['duration','date_added','week_added','month_added','release_year','
tv_show_corr=tv_show_copy.corr()
sns.heatmap(tv_show_corr,cmap='Reds',annot=True)
plt.title('Heatmap of all the numerical columns for TV Shows',color='red')
plt.show()
```



[64]:
```
dfcopy=df[['duration','date_added','week_added','month_added','release_year','datediff_day','t
sns.set(style="ticks", color_codes=True)
g = sns.pairplot(dfcopy,hue='type', height=2,palette={'Movie':'blue','TV Show':
 ↪'red'})
sns.move_legend(g,title='Type',loc='upper right')
plt.suptitle("Pairplot of all the numerical columns vs Type", y=1.02)
plt.subplots_adjust(top=0.9)
plt.show()
```



[65]:
```
sns.set(style="whitegrid")
sns.
 ↪scatterplot(data=df,x='release_year',y='datediff_day',hue='type',palette={'Movie':
 ↪'blue','TV Show':'red'})
plt.title('Release_year vs Datediff_day vs Type')
plt.legend(title='Type')
plt.show()
```



2.44 **Insights: We cannot conclude that Movies or TV Shows duration and release_year are strongly correlated. No the Movies or TV Show s are not getting shorter.We can only conclude that datediff_day is decreasing with increase in release_year for both Movies and TV Shows so shows are added faster after release with passing of time.**

2.45 **8. Is the number of movies released per year increasing with time?**

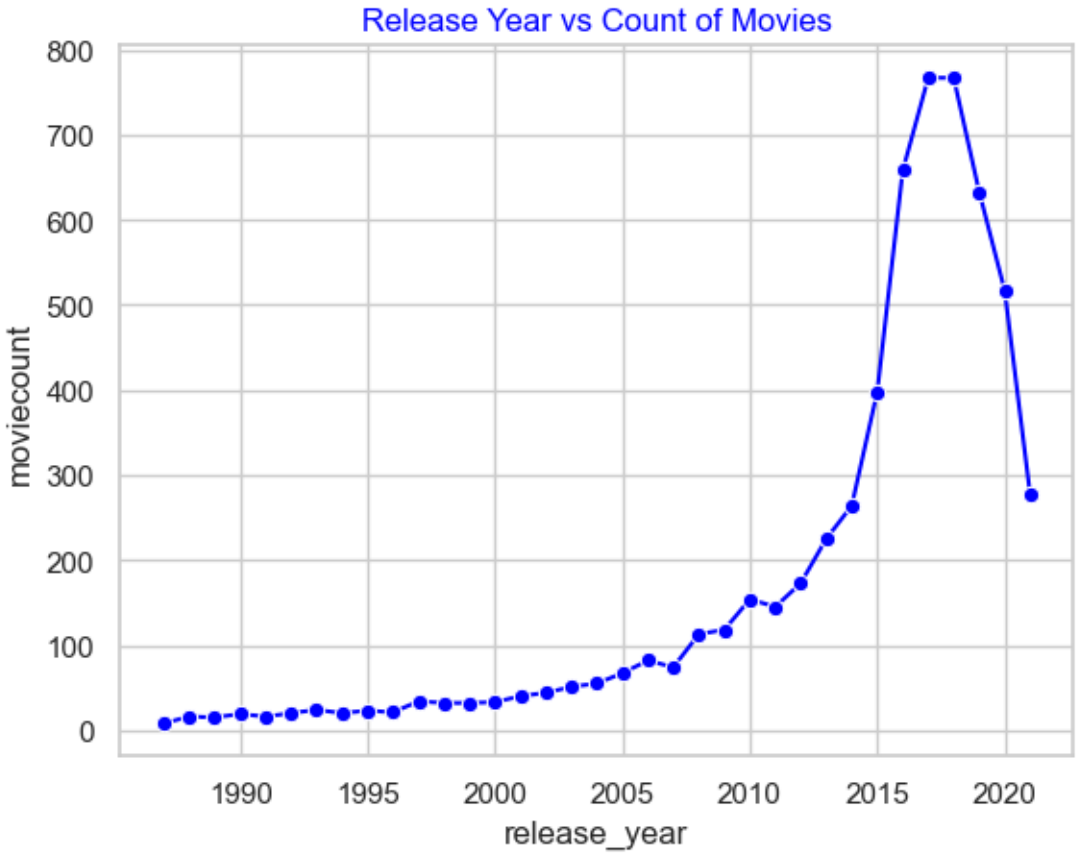
[66]:
```
moviecopy = movie.copy(deep=False).reset_index()
moviecopy=moviecopy.drop_duplicates(subset=['show_id','release_year'])
last35movie=moviecopy.groupby('release_year',as_index=False)['title'].count().
  ↪iloc[-35:].reset_index()
last35movie.drop(columns='index',inplace=True)
last35movie.columns=['release_year','moviecount']
last35movie.head()
```

[66]:

	release_year	moviecount
0	1987	8
1	1988	16
2	1989	15

```
3          1990          19
4          1991          16
```

[67]:
```
sns.set(style="whitegrid")
sns.
 ↪lineplot(data=last35movie,x='release_year',y='moviecount',color='blue',marker='o')
plt.title('Release Year vs Count of Movies',color='blue')
plt.show()
```



2.46 Insights: In last 35 years number of movies released each year has increased before peaking in 2019-2020 and after then there is a drop.

2.47 9. Is Netflix focusing more on TV Shows recently ?

2.48 Added 'date_added_year' by extracting year from 'date_added' column

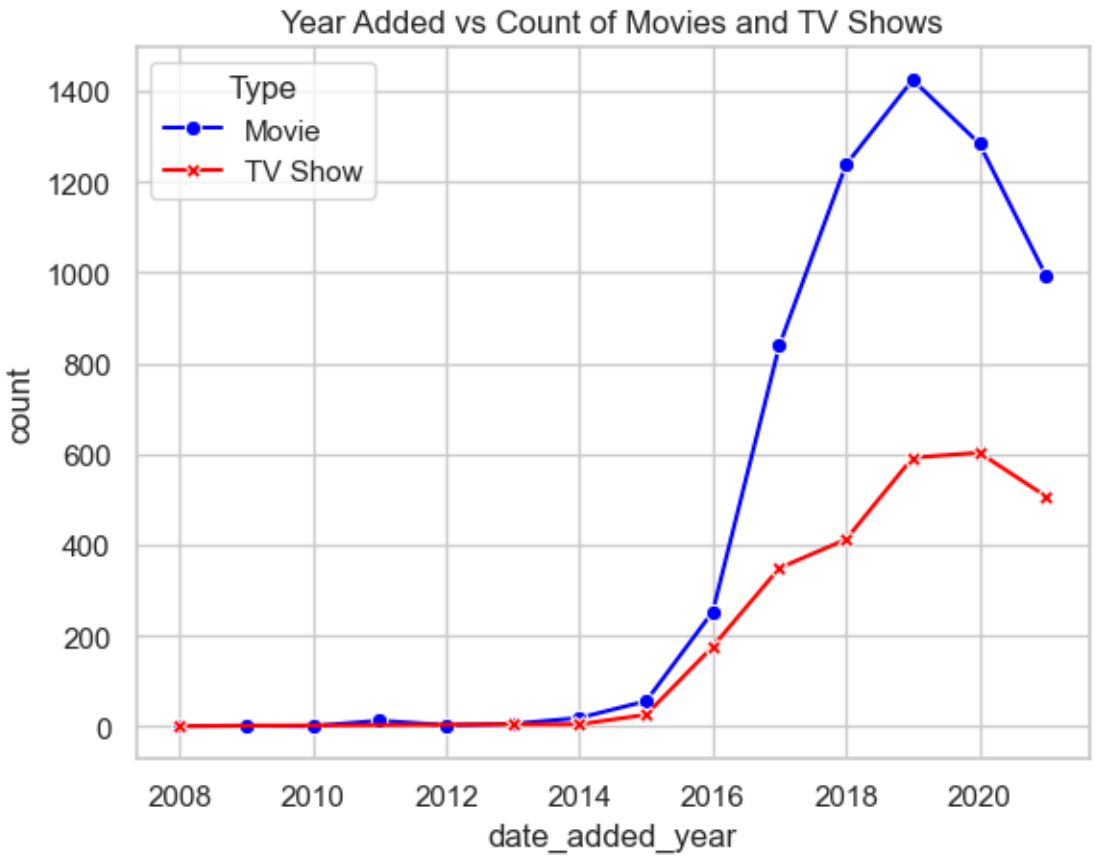
[68]:
```
dfcopy=df.copy(deep=False).reset_index()
dfcopy['date_added_year']=dfcopy['date_added'].dt.year
dfcopy.drop_duplicates(subset=['show_id','date_added','type'],inplace=True)
```

```
dfcopy=dfcopy.groupby(['type','date_added_year'],as_index=False)['show_id'].
 ↪count()
dfcopy.rename(columns={'show_id':'count'},inplace=True)
dfcopy.sort_values('count',ascending=False).reset_index().
 ↪drop(columns='index',inplace=True)
dfcopy.head()
```

[68]:

	type	date_added_year	count
0	Movie	2008	1
1	Movie	2009	2
2	Movie	2010	1
3	Movie	2011	13
4	Movie	2012	3

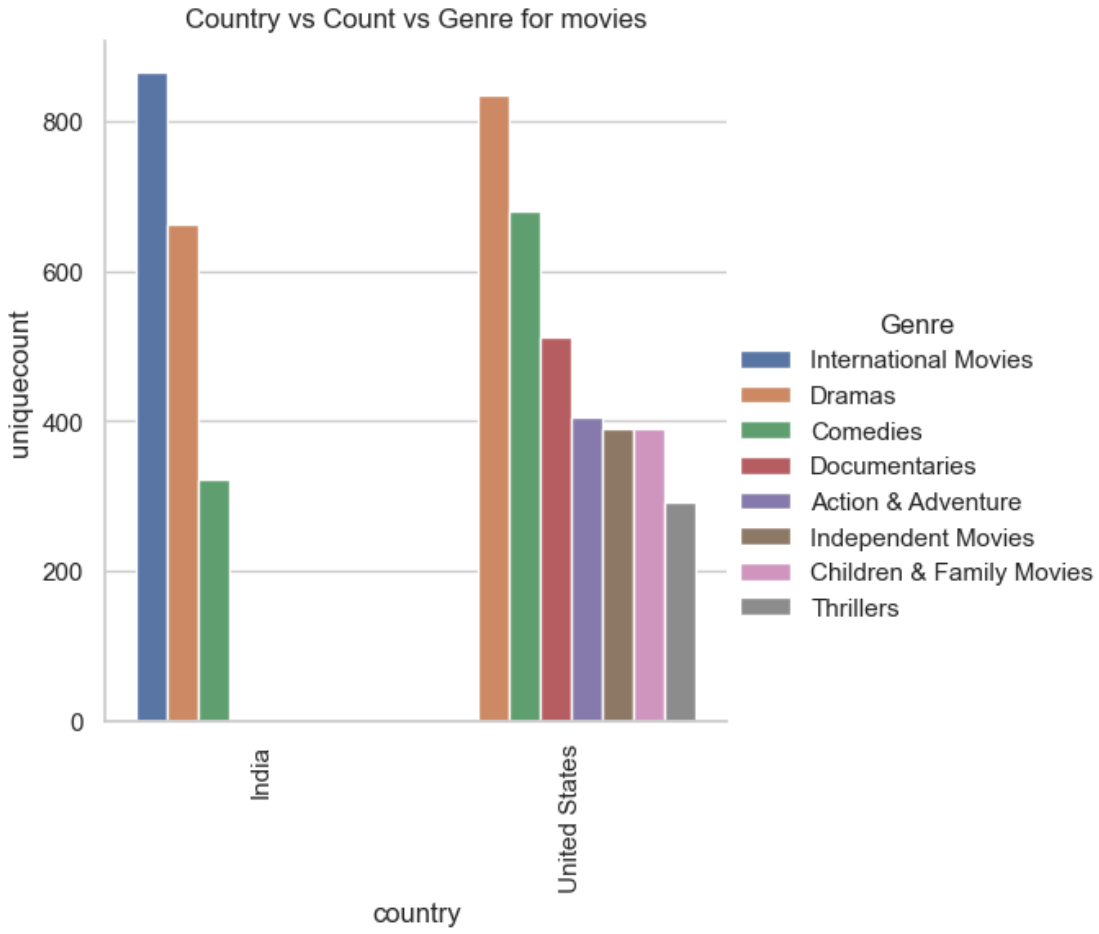
[71]:
```
import warnings
warnings.filterwarnings("ignore", category=UserWarning, message="The figure␣
 ↪layout has changed to tight")
sns.set(style="whitegrid")
sns.lineplot(data=dfcopy,x='date_added_year',y='count',style='type',hue='type',
             markers=True,dashes=False,palette={'Movie': 'blue', 'TV Show':␣
 ↪'red'})
plt.legend(title='Type',loc='upper left')
plt.title('Year Added vs Count of Movies and TV Shows')
plt.show()
```



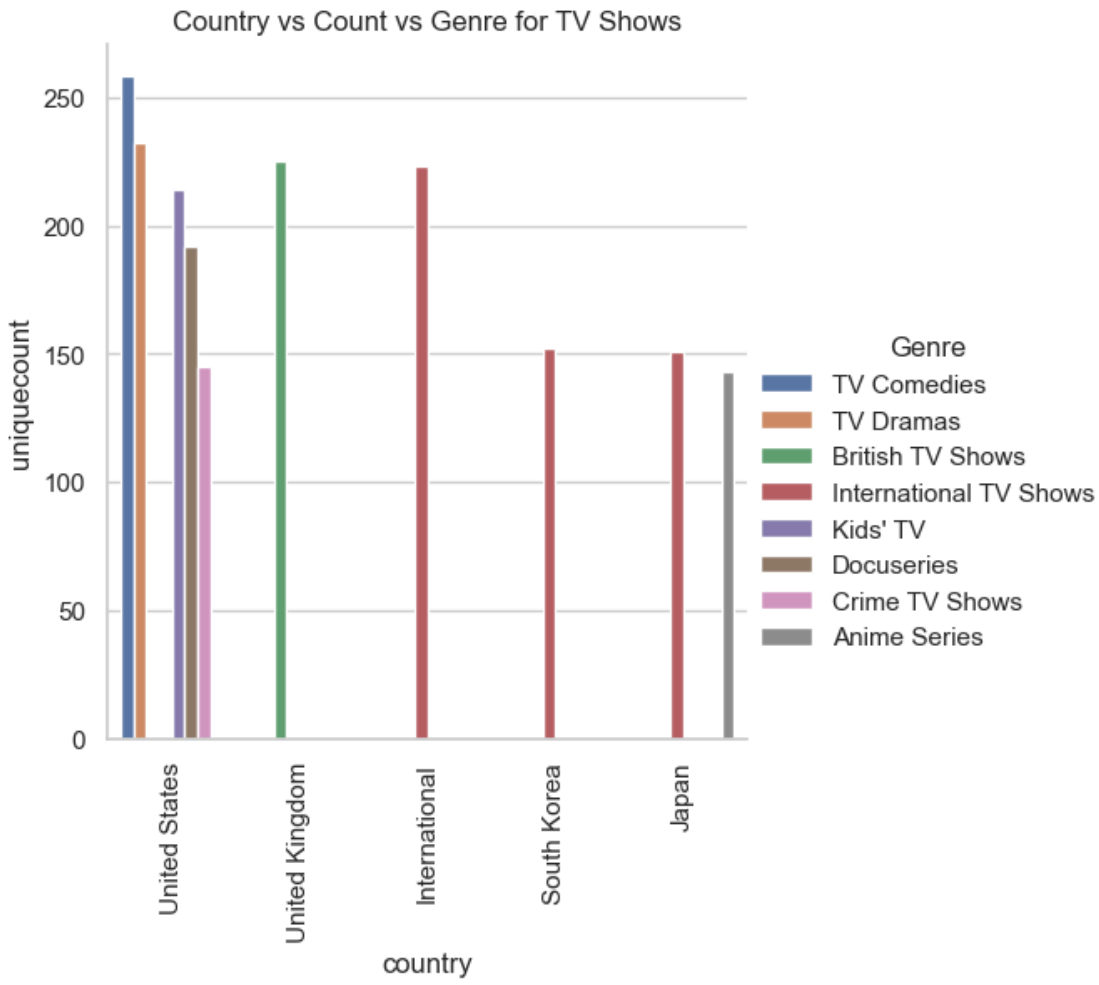
2.49 **Insights: The number of movies and TV Shows added per year is both similar increasing curves from 2015 to 2019 and then decreasing.Between movies and TV shows more number of movies are added each year so Netflix is not focusing more on TV Shows recently.**

2.50 **10. What content is available in what countries?**

[74]:
```
group = movie.groupby(['country', 'listed_in'], as_index=False)['title'].
  ↪nunique().sort_values('title', ascending=False).reset_index().iloc[:, 1:]
group = group.rename(columns={'listed_in': 'genre','title':'uniquecount'}).
  ↪iloc[:10]
sns.set(style="whitegrid")
g=sns.catplot(kind='bar',data=group,x='country',y='uniquecount',hue='genre')
sns.move_legend(g,title='Genre',loc='center right')
plt.title('Country vs Count vs Genre for movies')
plt.xticks(rotation=90)
plt.show()
```



[75]:
```
group = tv_show.groupby(['country', 'listed_in'], as_index=False)['title'].
  ↪nunique().sort_values('title', ascending=False).reset_index().iloc[:, 1:]
group = group.rename(columns={'listed_in': 'genre','title':'uniquecount'}).
  ↪iloc[:10]
sns.set(style="whitegrid")
g=sns.catplot(kind='bar',data=group,x='country',y='uniquecount',hue='genre')
sns.move_legend(g,title='Genre',loc='center right')
plt.title('Country vs Count vs Genre for TV Shows')
plt.xticks(rotation=90)
plt.show()
```



2.51 Insights: International movies and dramas are popular available movie genres available in India whereas Dramas and Comedies are more popular movie genres in USA. As for TV Shows in USA TV Comedies and TV Dramas are available,in UK,British TV Shows are available.International TV shows are available in South Korea,Japan and internationally.Need additional stream or viewership data to make suggestions about making shows available in certain country.

3 11. Recommendations

3.1 Insights:

1. **Duration Distribution:**
   - Distribution of Movie Duration is unimodal and slightly right-skewed, with a peak at 90 minutes.
   - TV Shows have a peak around 1 season, with a median of 2-3 seasons.
2. **Geographical Trends:**

- USA leads in both Movie and TV Show count.

3. **Release Timing:**
   - Most Movies are added in week 1, and most TV Shows are added in week 27.
   - July is the peak month for adding Movies whereas for TV Shows it is December.
4. **Genre Production:**
   - Most produced genres for Movies are International Movies, Dramas, and Comedies.
   - For TV Shows, it's International TV Shows and TV Dramas.
5. **Datediff Distribution:**
   - Datediff distribution is bimodal, with peaks at 153 days and 304 days.
   - Predictions suggest movies will be added within 10 months of release.
6. **Outliers:**
   - Outliers observed in Movie duration and datediff, indicating demand-driven variations.
7. **Duration Trends:**
   - No strong correlation between Movie/TV Show duration and release_year.
   - Movies and TV Shows are not getting consistently shorter.
8. **Temporal Trends:**
   - In the last 35 years, the number of movies released per year increased before saturating in 2019-2020, followed by a decline.
   - Similar trends observed in the number of movies and TV Shows added vs year which is increasing from 2015-2019 then dropping.
   - Between movies and TV Shows more movies are added each year.

3.2 Recommendations:

1. **Content Duration Strategy:**
   - Recognize the diversity in Movie and TV Show durations, and tailor content length based on genre and audience expectations.
   - Movies of duration close to 2 hrs and TV Shows with 1-4 seasons suggested.
2. **Geographic Focus:**
   - Given USA's dominance, consider tailoring content or marketing strategies for the American audience.
   - Could introduce region specific discounts to increase viewerships.
3. **Optimal Release Timing:**
   - For Movies, consider releasing in Week 1 and July, to potentially maximize viewership.
   - For TV shows, Week 27 and December seem to be popular, aligning releases with these times may attract more audience.
4. **Best Cast and Director:**
   - For future projects include casts from the top 10 cast members for both Movie and TV Shows.
   - For future projects include directors from the top 10 directors for both Movie and TV Shows.
5. **Targeting Genres:**
   - Focus on producing more International Movies, Dramas, and Comedies, as these genres have shown popularity.
   - For TV Shows, prioritize International TV Shows and TV Dramas.
6. **Datediff Strategy:**
   - Plan content releases with an understanding of the bimodal datediff distribution.
   - Strategic planning and adding within 10 months of movie release might align with view-

ership patterns.

7. **Outlier Considerations:**
   - Analyze outliers in duration and datediff_day for potential insights into audience preferences and trends.
   - For example long or short length movies might have specific audience.
   - Add date of movies and TV Shows could be decided based on demand or popularity.
8. **Adaptation to Temporal Trends:**
   - Consider the temporal trends in the number of releases when planning content production schedules.
   - Find out why after 2019-2020 there is a decline in number of movies released as well as number of movies added and solve the problem.
   - As there is a higher number of movies added each year compared to TV shows, consider a balanced approach or strategically allocate resources based on the observed trend.

[ ]: