Netflix_Data_Wasif

October 29, 2025

0.1 Business Case: Netflix - Data Exploration and Visualisation

- *M N Wasif DSML 29 Oct 2025*

0.2 1. Problem Statement & Basic Metrics

Problem Statement:
Understand Netflix's content library composition (Movies vs. TV Shows), regional production trends, genre preferences, release patterns, and content duration to inform content acquisition, localization, and scheduling strategies.

Importing Libraries and Loading the Dataset

[6]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[7]:
```
df = pd.read_csv('/content/netflix.csv')
df
```

[7]:
```
     show_id     type                  title         director  \
0         s1    Movie   Dick Johnson Is Dead  Kirsten Johnson
1         s2  TV Show          Blood & Water              NaN
2         s3  TV Show              Ganglands  Julien Leclercq
3         s4  TV Show  Jailbirds New Orleans              NaN
4         s5  TV Show           Kota Factory              NaN
…       …       …                     …              …
8802   s8803    Movie                Zodiac    David Fincher
8803   s8804  TV Show            Zombie Dumb              NaN
8804   s8805    Movie             Zombieland  Ruben Fleischer
8805   s8806    Movie                  Zoom    Peter Hewitt
8806   s8807    Movie                Zubaan      Mozez Singh

                                                 cast        country  \
0                                                 NaN  United States
```

```
1     Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban…   South Africa
2     Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi…            NaN
3                                                  NaN            NaN
4     Mayur More, Jitendra Kumar, Ranjan Raj, Alam K…          India
…                                                   …            …
8802  Mark Ruffalo, Jake Gyllenhaal, Robert Downey J…  United States
8803                                               NaN            NaN
8804  Jesse Eisenberg, Woody Harrelson, Emma Stone, …  United States
8805  Tim Allen, Courteney Cox, Chevy Chase, Kate Ma…  United States
8806  Vicky Kaushal, Sarah-Jane Dias, Raaghav Chanan…          India

              date_added  release_year rating   duration  \
0     September 25, 2021          2020  PG-13     90 min
1     September 24, 2021          2021  TV-MA  2 Seasons
2     September 24, 2021          2021  TV-MA   1 Season
3     September 24, 2021          2021  TV-MA   1 Season
4     September 24, 2021          2021  TV-MA  2 Seasons
…                    …           …    …        …
8802   November 20, 2019          2007      R    158 min
8803        July 1, 2019          2018  TV-Y7  2 Seasons
8804    November 1, 2019          2009      R     88 min
8805    January 11, 2020          2006     PG     88 min
8806       March 2, 2019          2015  TV-14    111 min

                                          listed_in  \
0                                       Documentaries
1       International TV Shows, TV Dramas, TV Mysteries
2     Crime TV Shows, International TV Shows, TV Act…
3                               Docuseries, Reality TV
4     International TV Shows, Romantic TV Shows, TV …
…                                                   …
8802                    Cult Movies, Dramas, Thrillers
8803            Kids' TV, Korean TV Shows, TV Comedies
8804                           Comedies, Horror Movies
8805                Children & Family Movies, Comedies
8806    Dramas, International Movies, Music & Musicals

                                           description
0     As her father nears the end of his life, filmm…
1     After crossing paths at a party, a Cape Town t…
2     To protect his family from a powerful drug lor…
3     Feuds, flirtations and toilet talk go down amo…
4     In a city of coaching centers known to train I…
…                                                   …
8802  A political cartoonist, a crime reporter and a…
8803  While living alone in a spooky town, a young g…
8804  Looking to survive in a world taken over by zo…
```

```
8805  Dragged from civilian life, a former superhero…
8806  A scrappy but poor boy worms his way into a ty…

[8807 rows x 12 columns]
```

[8]:
```
df.duplicated().sum()
```

[8]:
```
np.int64(0)
```

[9]:
```
df.isnull().sum()
```

[9]:
```
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
```

[10]:
```
# Replacing nulls with 'missing' string for director, cast, country, and␣
  ↪duration
for col in ['director','cast','country','duration']:
  df[col].fillna('missing', inplace=True)
df.isnull().sum()
```

[10]:
```
show_id          0
type             0
title            0
director         0
cast             0
country          0
date_added      10
release_year     0
rating           4
duration         0
listed_in        0
description      0
dtype: int64
```

[11]:
```
df.shape
```

[11]:
```
(8807, 12)
```

[12]:
```
df.columns
```

[12]:
```
Index(['show_id', 'type', 'title', 'director', 'cast', 'country', 'date_added',
       'release_year', 'rating', 'duration', 'listed_in', 'description'],
      dtype='object')
```

[13]:
```
# data types
df.dtypes
```

[13]:
```
show_id         object
type            object
title           object
director        object
cast            object
country         object
date_added      object
release_year     int64
rating          object
duration        object
listed_in       object
description     object
dtype: object
```

[14]:
```
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      8807 non-null   object
 4   cast          8807 non-null   object
 5   country       8807 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      8807 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
```

#1. Data Shape, Types, Missing Values & Summary

- **Shape**: 8,807 rows × 12 columns

- **Data Types**:
  - 1 numeric (`release_year` as `int64`)
  - 11 object-type (text), later enriched with datetime (`date_added`)
- **Missing Values**:
  - `director`: 2,634 missing
  - `cast`: 825 missing
  - `country`: 831 missing
  - `date_added`: 10 missing
  - `rating`: 4 missing
    → Handled by replacing with `'missing'` or mode

[15]:
```
# Analysis of object data types
df.describe(include = 'object')
```

[15]:
```
        show_id   type   title director     cast        country  \
count      8807   8807    8807     8807     8807           8807
unique     8807      2    8807     4529     7693            749
top       s8807  Movie  Zubaan  missing  missing  United States
freq          1   6131       1     2634      825           2818

              date_added rating  duration                     listed_in  \
count               8797   8803      8807                          8807
unique              1767     17       221                           514
top     January 1, 2020  TV-MA  1 Season  Dramas, International Movies
freq                 109   3207      1793                           362

                                                 description
count                                                   8807
unique                                                  8775
top     Paranormal activity at a lush, abandoned prope…
freq                                                       4
```

[16]:
```
# Analysis of numeric data types
df.describe()
```

[16]:
```
       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
```

[17]:
```
# Value counts in columns
for col in df.columns:
  print(f'{col} : {df[col].nunique()}')
```

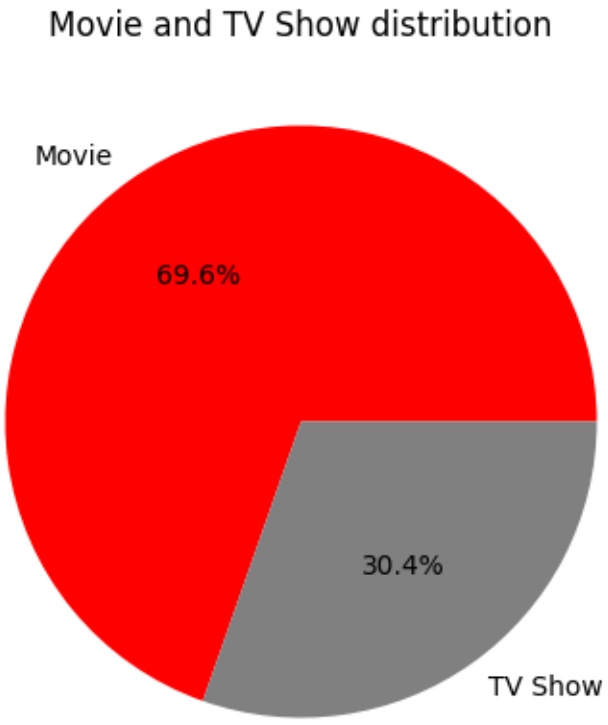
```
show_id : 8807
type : 2
title : 8807
director : 4529
cast : 7693
country : 749
date_added : 1767
release_year : 74
rating : 17
duration : 221
listed_in : 514
description : 8775
```

[58]:
```
# Value counts for type, country, release_year, rating, duration

for col in ['type', 'country', 'release_year', 'rating', 'duration']:
  print(f'Value count in {col} column are :-')
  print(df[col].value_counts())
  print('-'*75)
```

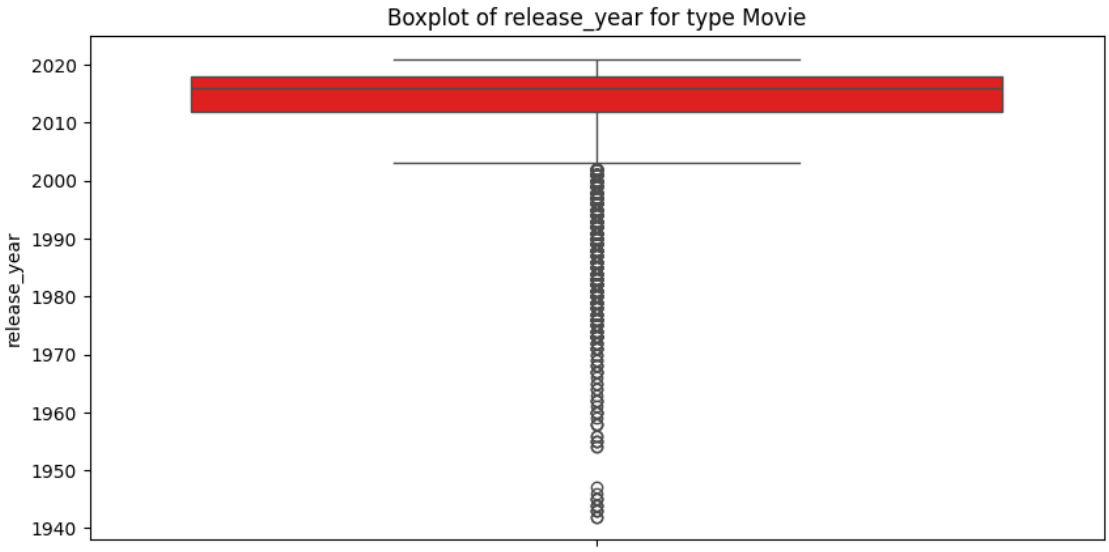
```
Value count in type column are :-
type
Movie      6131
TV Show    2676
Name: count, dtype: int64
---------------------------------------------------------------------------
Value count in country column are :-
country
United States                                          2818
India                                                   972
missing                                                 831
United Kingdom                                          419
Japan                                                   245
                                                       ...
Germany, Canada, United States                            1
Denmark, United Kingdom, South Africa, Sweden, Belgium    1
Serbia, South Korea, Slovenia                             1
United Kingdom, Spain, Belgium                            1
South Africa, United States, Japan                        1
Name: count, Length: 749, dtype: int64
---------------------------------------------------------------------------
Value count in release_year column are :-
```

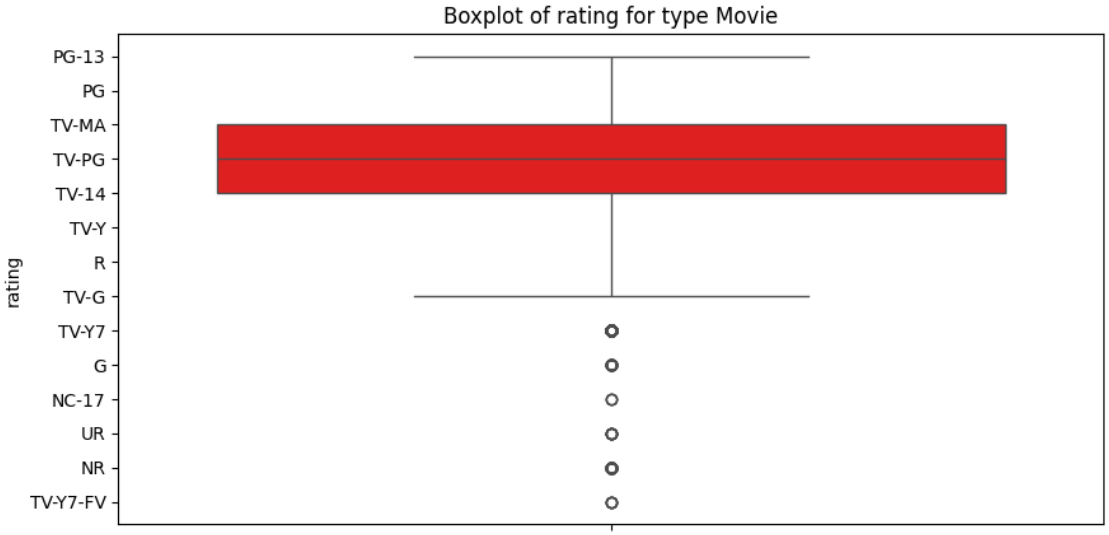
```
release_year
2018    1147
2017    1032
2019    1030
2020     953
2016     902
        …
1961       1
1925       1
1959       1
1966       1
1947       1
Name: count, Length: 74, dtype: int64
--------------------------------------------------------------------------------
Value count in rating column are :-
rating
TV-MA       3207
TV-14       2160
TV-PG        863
R            799
PG-13        490
TV-Y7        334
TV-Y         307
PG           287
TV-G         220
NR            80
G             41
UR            10
TV-Y7-FV       6
NC-17          3
Name: count, dtype: int64
--------------------------------------------------------------------------------
Value count in duration column are :-
duration
1 Season     1793
2 Seasons     425
3 Seasons     199
90 min        152
94 min        146
             …
228 min         1
18 min          1
205 min         1
201 min         1
191 min         1
Name: count, Length: 221, dtype: int64
--------------------------------------------------------------------------------
```

[71]:
```
# Movie and TV Show distribution pie plot
plt.figure(figsize = (10, 5))
plt.pie(df['type'].value_counts(), labels = df['type'].value_counts().index,␣
  ↪autopct = '%.1f%%', colors=['red','grey'])
plt.title('Movie and TV Show distribution')
plt.show()
```



[79]:
```
# Boxplots of release_year, rating of type Movie

for col in ['release_year', 'rating']:
  plt.figure(figsize = (10, 5))
  sns.boxplot(df[df['type'] == 'Movie'][col], color='red')
  plt.title(f'Boxplot of {col} for type Movie')
  plt.show()
```



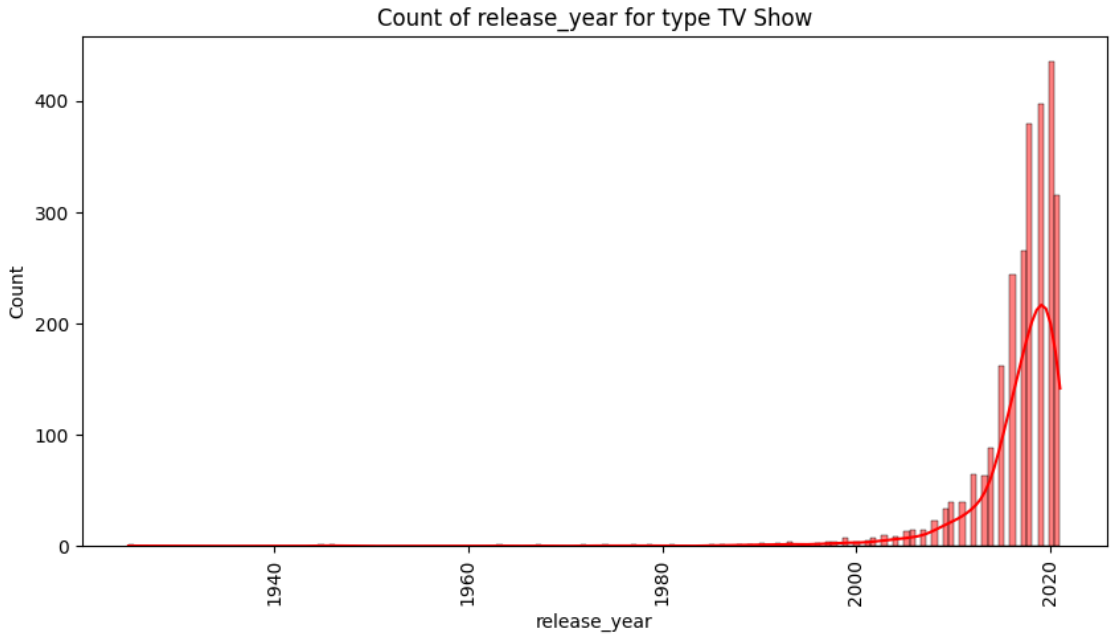


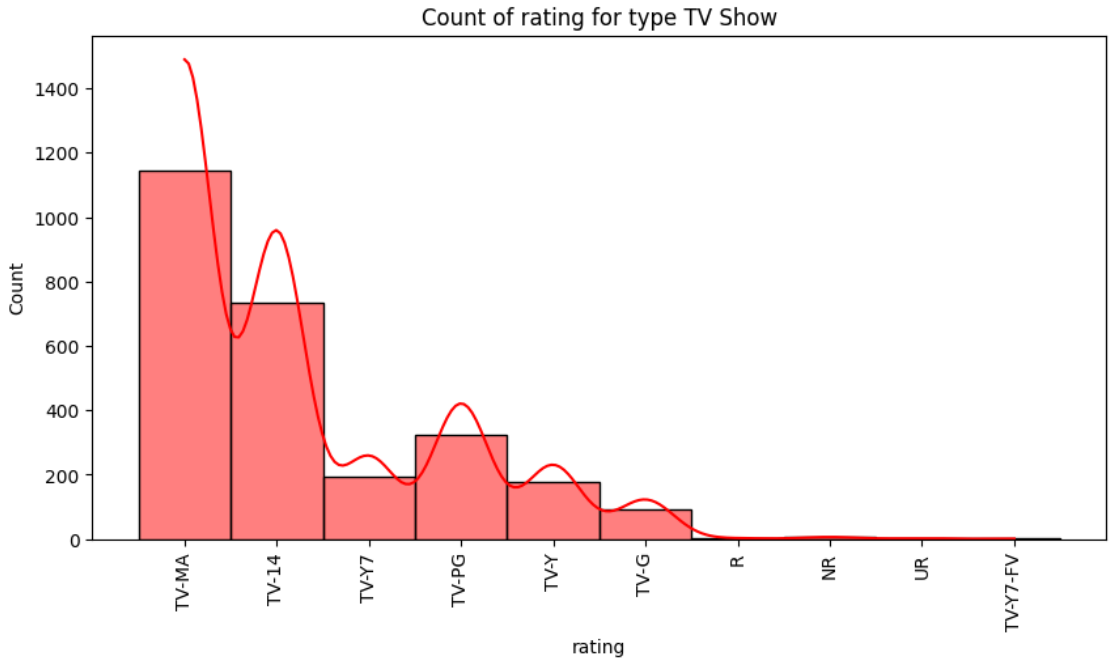
[19]:
```
# Replacing durations in rating by 'UR' (unrated)
df['rating'].fillna('UR', inplace = True)
df['rating'].replace({'66 min': 'UR', '74 min': 'UR','84 min': 'UR'}, inplace =␣
 ↪True)
print(f'Value count in rating column are :-')
print(df['rating'].value_counts())
```

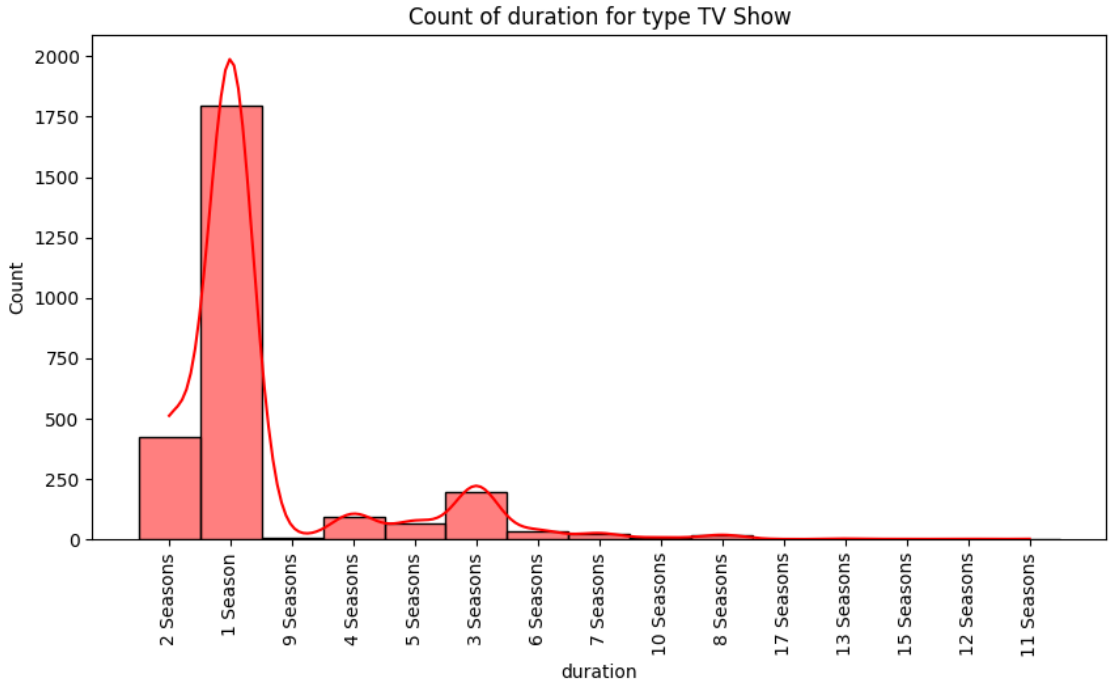
```
Value count in rating column are :-
rating
TV-MA       3207
```

```
TV-14       2160
TV-PG        863
R            799
PG-13        490
TV-Y7        334
TV-Y         307
PG           287
TV-G         220
NR            80
G             41
UR            10
TV-Y7-FV       6
NC-17          3
Name: count, dtype: int64
```

[277]:
```python
# Histogram analysis
for col in ['release_year', 'rating', 'duration']:
  plt.figure(figsize = (10, 5))
  sns.histplot(df[df['type'] == 'TV Show'][col], color = 'red', kde=True)
  plt.xticks(rotation = 90)
  plt.title(f'Count of {col} for type TV Show')
  plt.show()
```

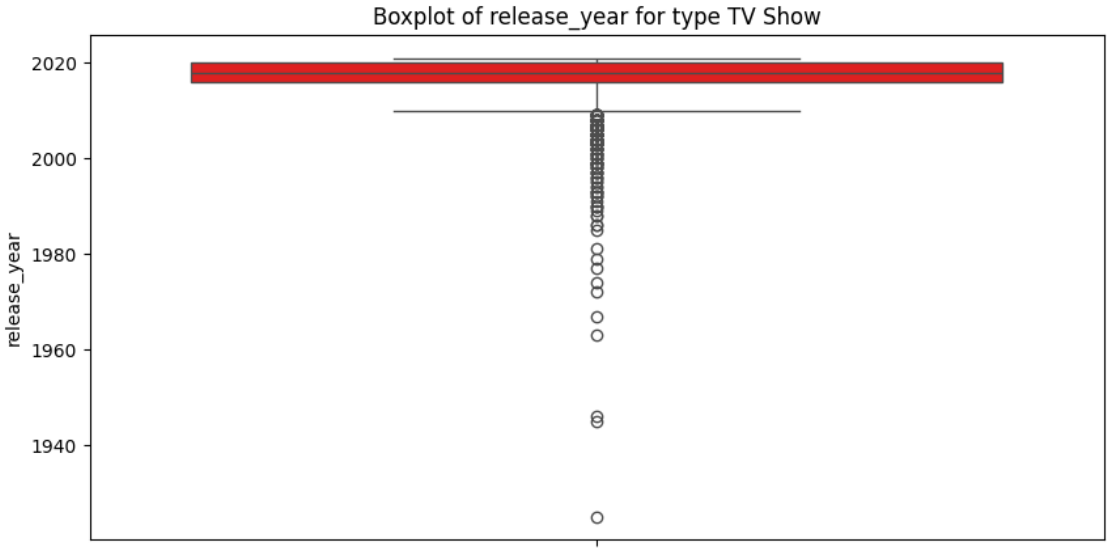


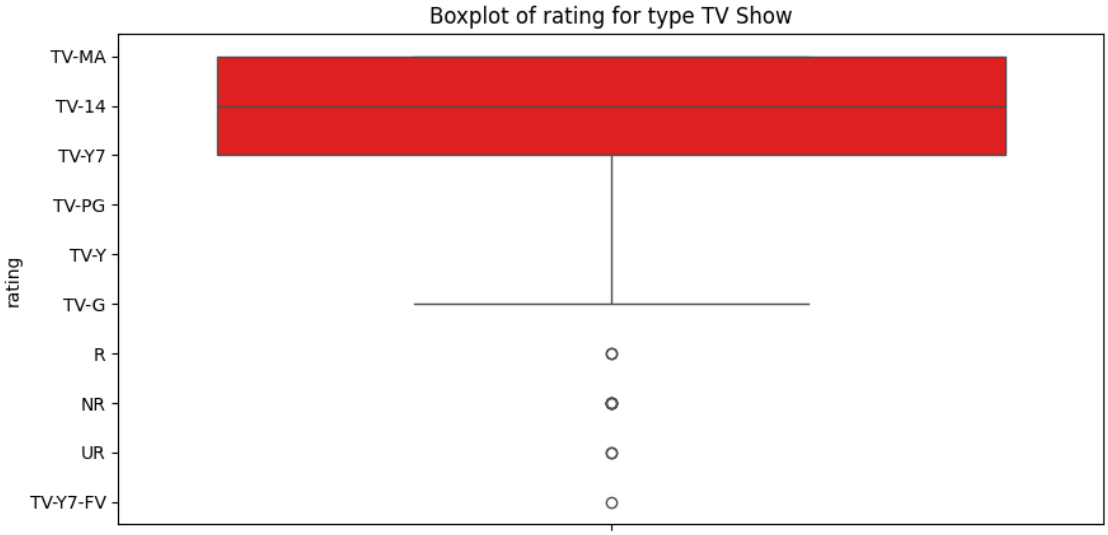


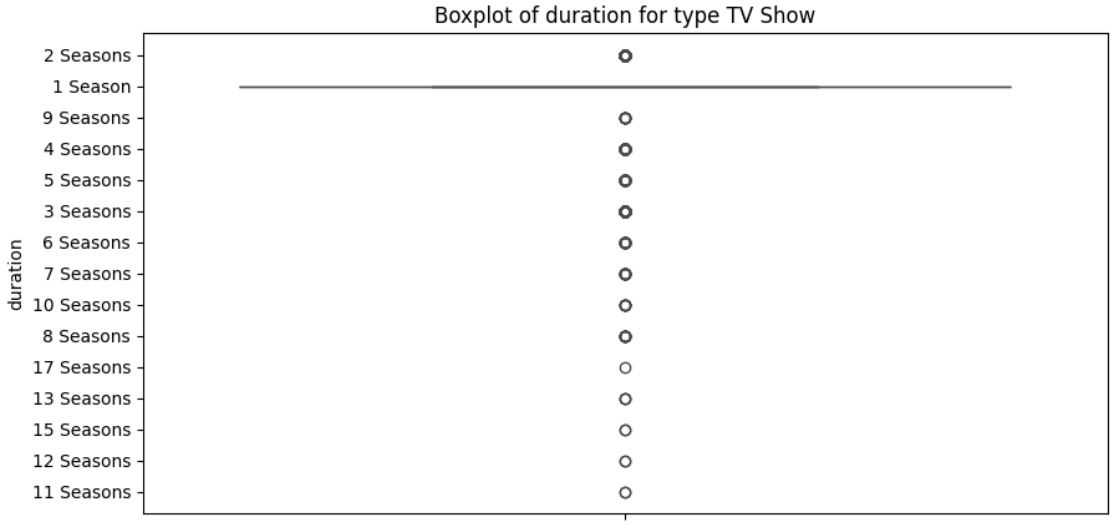


[75]:
```
# Boxplots of release_year, rating, duration of type TV Show
for col in ['release_year', 'rating', 'duration']:
  plt.figure(figsize = (10, 5))
```

```
sns.boxplot(df[df['type'] == 'TV Show'][col], color='red')
plt.title(f'Boxplot of {col} for type TV Show')
plt.show()
```







Basic Metrics: - Total entries: **8,807** - Content split: **6,131 Movies (69.6%)**, **2,676 TV Shows (30.4%)** - Time range: **1925–2021** (majority from 2013–2021) - Top country: **United States (2,818 titles)**, followed by **India (972)** - Most common rating: **TV-MA (3,207)**, indicating mature-audience focus

Statistical Summary:
- Median release year: **2017**
- Mean release year: **2014.18**
- Most frequent duration: **"1 Season" (1,793)** for TV; **"90 min" (152)** for Movies

[20]:
```
df['date_added'].fillna(df['date_added'].mode()[0], inplace = True)
```

[260]:
```
import datetime as dt
df["date_added"] = pd.to_datetime(df['date_added'],format='mixed')

df['weekday_added']=df['date_added'].dt.day_name()
df['month_name_added']=df['date_added'].dt.month_name()
df['year_added'] = df['date_added'].dt.year

df.info()
```

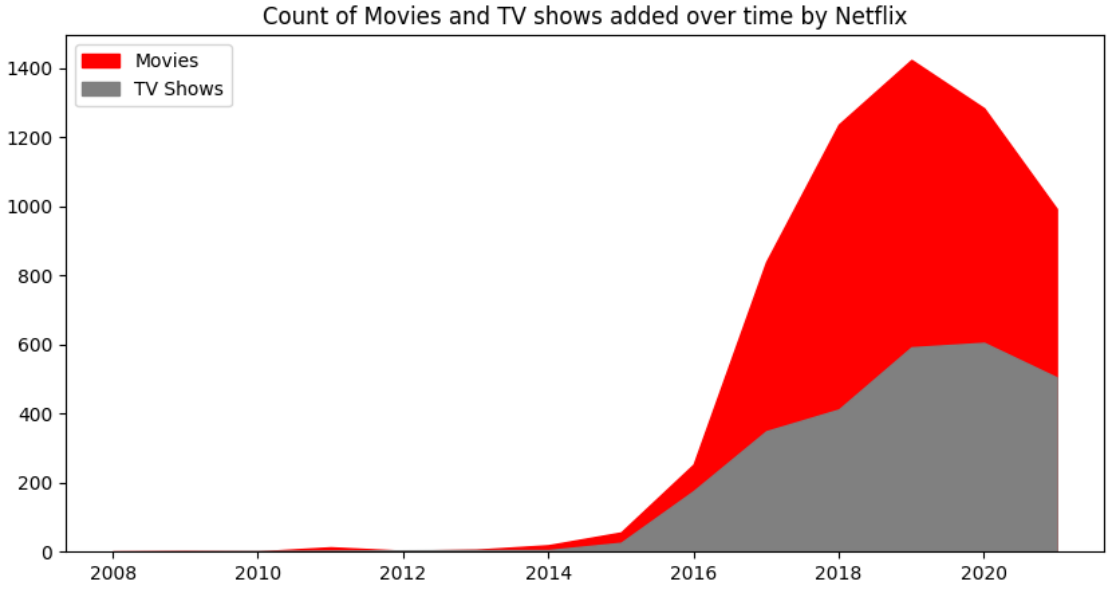
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8807 entries, 0 to 8806
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   show_id           8807 non-null   object
 1   type              8807 non-null   object
 2   title             8807 non-null   object
 3   director          8807 non-null   object
 4   cast              8807 non-null   object
```

```
 5   country           8807 non-null   object
 6   date_added        8807 non-null   datetime64[ns]
 7   release_year      8807 non-null   int64
 8   rating            8807 non-null   object
 9   duration          8807 non-null   object
 10  listed_in         8807 non-null   object
 11  description       8807 non-null   object
 12  weekday_added     8807 non-null   object
 13  month_name_added  8807 non-null   object
 14  year_added        8807 non-null   int32
dtypes: datetime64[ns](1), int32(1), int64(1), object(12)
memory usage: 997.8+ KB
```

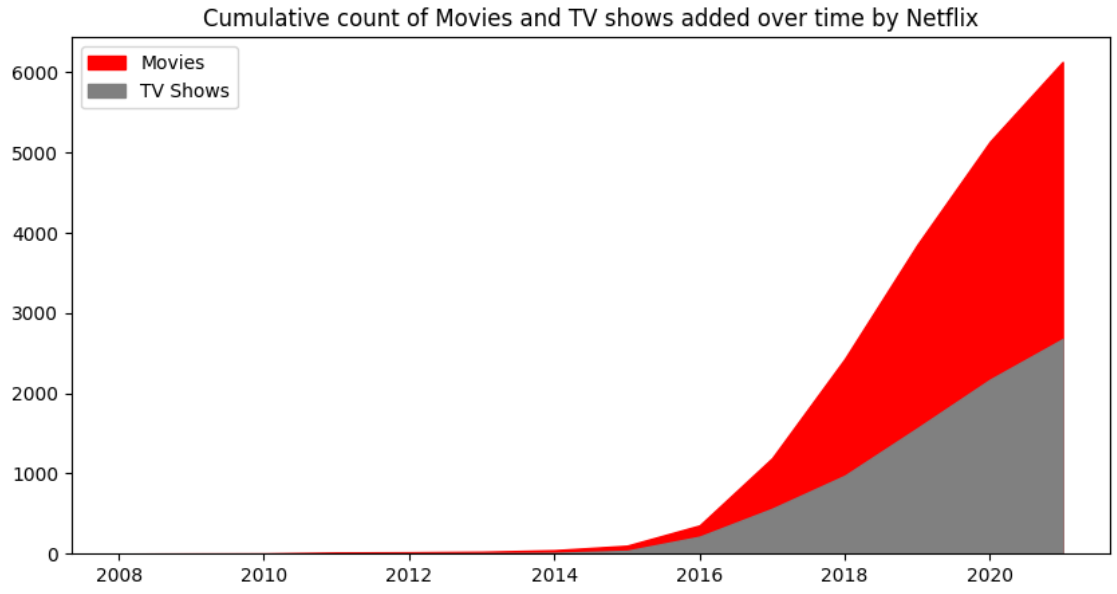
[22]:
```
# List cases where year_added is less than release_year
df[df['year_added'] < df['release_year']].value_counts().sum()
```

[22]:
```
np.int64(14)
```

[117]:
```
# Count of of Movies and TV Show added over time by year_added
movies_sum = df[df['type'] == 'Movie'].groupby('year_added')['title'].count()
tvshow_sum = df[df['type'] == 'TV Show'].groupby('year_added')['title'].count()

plt.figure(figsize = (10, 5))
plt.stackplot(movies_sum.index, movies_sum.values, color = 'red')
plt.stackplot(tvshow_sum.index, tvshow_sum.values, color = 'grey')
plt.legend(['Movies', 'TV Shows'])
plt.title('Count of Movies and TV shows added over time by Netflix')
plt.show()
```



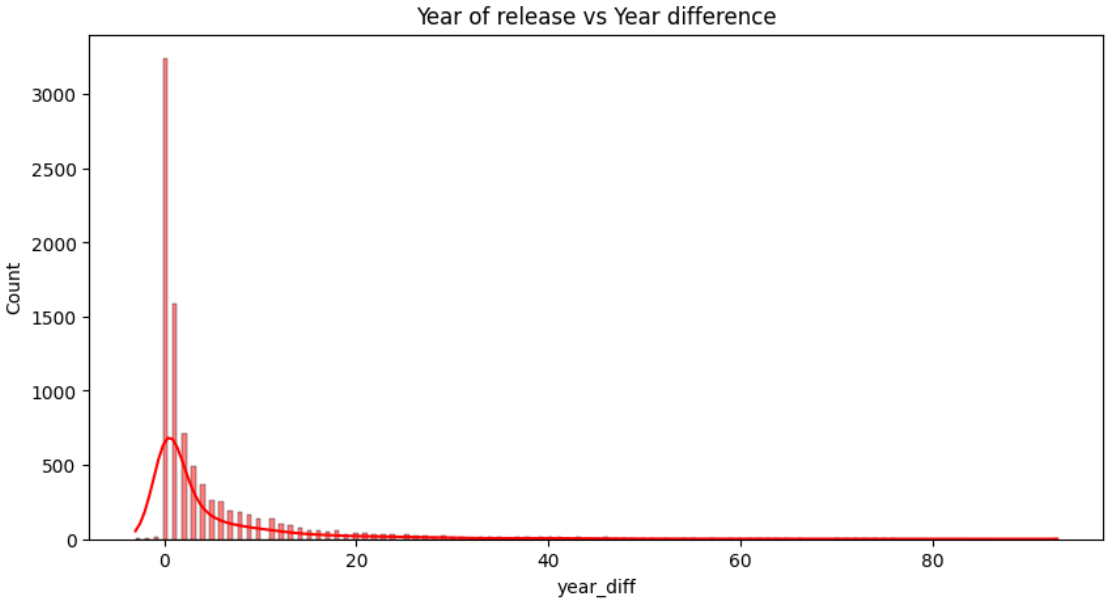
[116]:
```
# Cumulative count of Movies and TV Show added over time by year_added
movie_cumsum = df[df['type'] == 'Movie'].groupby('year_added')['title'].count().
 ↪cumsum()
tvshow_cumsum = df[df['type'] == 'TV Show'].groupby('year_added')['title'].
 ↪count().cumsum()

plt.figure(figsize = (10, 5))
plt.stackplot(movie_cumsum.index, movie_cumsum.values, color = 'red')
plt.stackplot(tvshow_cumsum.index, tvshow_cumsum.values, color = 'grey')
plt.legend(['Movies', 'TV Shows'])
plt.title('Cumulative count of Movies and TV shows added over time by Netflix')
plt.show()
```



[274]:
```
# Calculate difference between the columns having year_added  and release_year␣
 ↪and get the mean difference
df['year_diff'] = df['year_added'] - df['release_year']
print('Mean difference between year added annd year of release:
 ↪',df['year_diff'].mean())
print('Median difference between year added annd year of release:
 ↪',df['year_diff'].median())
print('Mode difference between year added annd year of release:
 ↪',df['year_diff'].mode())
```

```
Mean difference between year added annd year of release: 4.692971499943227
Median difference between year added annd year of release: 1.0
Mode difference between year added annd year of release: 0    0
Name: year_diff, dtype: int64
```

[273]:
```
# Plot the year_diff against count of titles
plt.figure(figsize = (10, 5))
sns.histplot(df['year_diff'], color = 'red', kde=True)
plt.title('Year of release vs Year difference')
plt.show()
```



[23]:
```
# Un-nesting directors, cast, and country columns into multiple rows in new_df
import copy
df_new = copy.deepcopy(df)
```

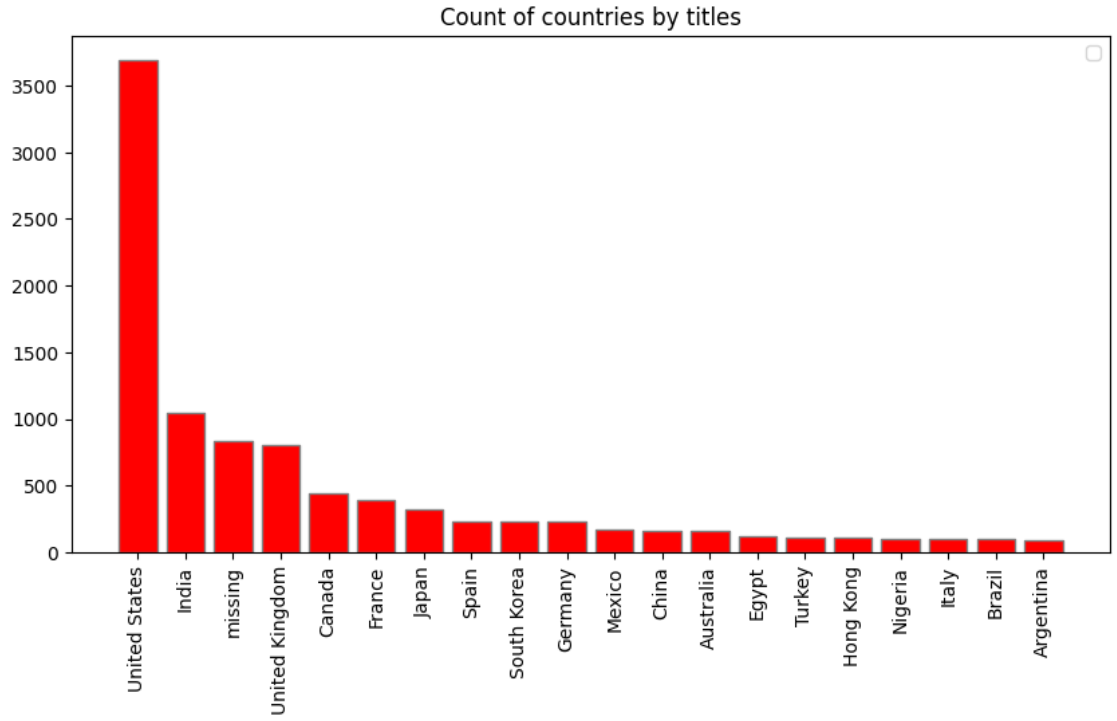
[258]:
```
df_new['director'] = df_new['director'].str.split(', ')
df_new = df_new.explode('director')

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

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

df_new.shape
```

[258]:
```
(89382, 15)
```

[63]:
```
# Count of countries by unique titles in descending order
df_new.groupby('country')['title'].nunique().sort_values(ascending = False).
 ↪head(20)
```

[63]:
```
country
United States     3689
India             1046
missing            831
United Kingdom     804
Canada             445
France             393
Japan              318
Spain              232
South Korea        231
Germany            226
Mexico             169
China              162
Australia          160
Egypt              117
Turkey             113
Hong Kong          105
Nigeria            103
Italy              100
Brazil              97
Argentina           91
Name: title, dtype: int64
```

[107]:
```
# Bar plot of countries by unique titles in descending order
title_country = df_new.groupby('country')['title'].nunique().
 ↪sort_values(ascending = False).head(20)

plt.figure(figsize = (10, 5))
plt.bar(title_country.index, title_country, color = 'red', edgecolor = 'grey')
plt.legend()
plt.xticks(rotation = 90)
plt.title('Count of countries by titles')
plt.show()
```

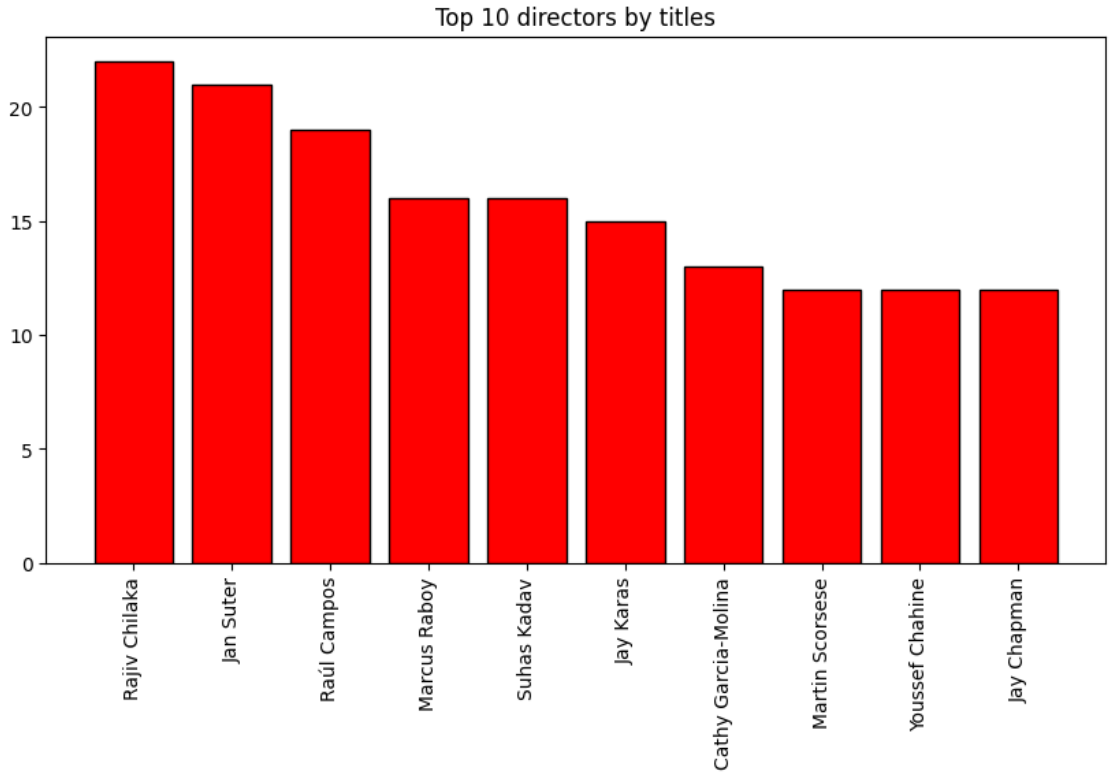


[114]:
```
# Count of unique directors by titles in descending order
df_new.groupby('director')['title'].nunique().sort_values(ascending = False)[1:
 ↪11]
```

[114]:
```
director
Rajiv Chilaka          22
Jan Suter              21
Raúl Campos            19
Marcus Raboy           16
Suhas Kadav            16
Jay Karas              15
Cathy Garcia-Molina    13
Martin Scorsese        12
Youssef Chahine        12
Jay Chapman            12
Name: title, dtype: int64
```

[279]:
```
# Barplot of directors by titles in descending order
title_director = df_new.groupby('director')['title'].nunique().
 ↪sort_values(ascending = False)[1:11]
plt.figure(figsize = (10, 5))
plt.bar(title_director.index, title_director.values,  color ='red', edgecolor =␣
 ↪'black')
```

```
plt.xticks(rotation = 90)
plt.title('Top 10 directors by titles')
plt.show()
```



[280]:
```
# Count of directors by title in descending order of type Movies
df_new[df_new['type'] == 'Movie'].groupby('director')['title'].nunique().
  ↪sort_values(ascending = False)[1:11]
```

[280]:
```
director
Rajiv Chilaka          22
Jan Suter              21
Raúl Campos            19
Suhas Kadav            16
Marcus Raboy           15
Jay Karas              15
Cathy Garcia-Molina    13
Martin Scorsese        12
Jay Chapman            12
Youssef Chahine        12
Name: title, dtype: int64
```

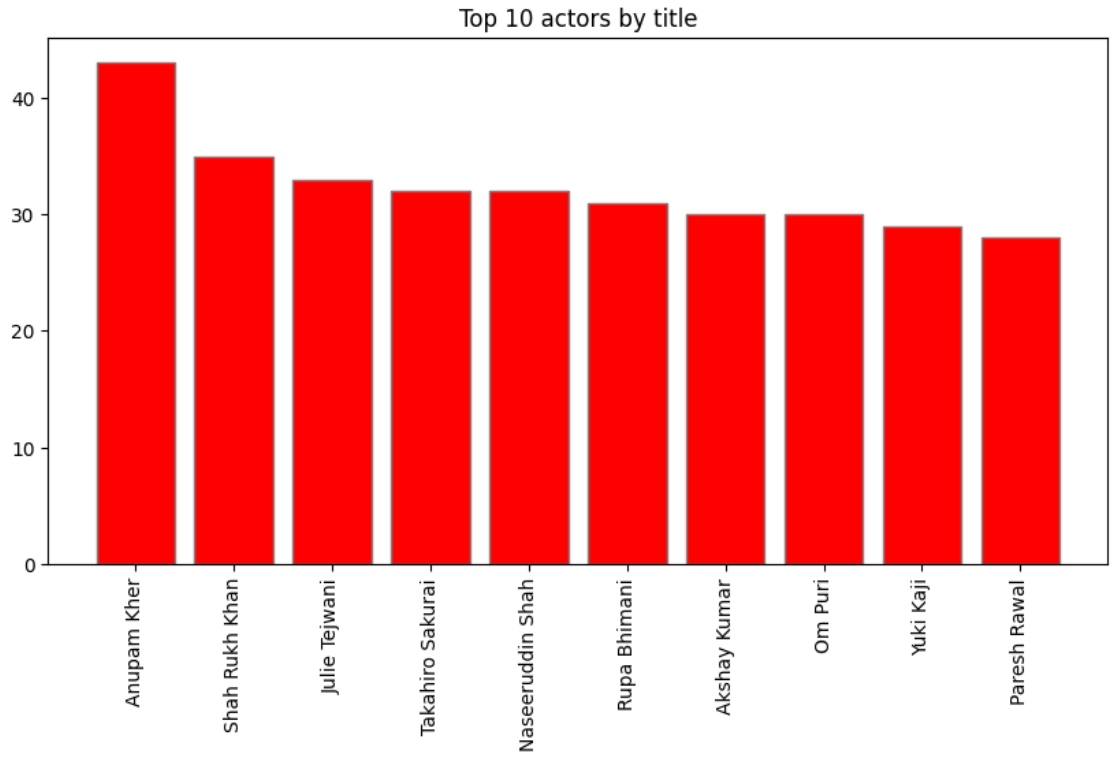
[281]:
```
# Count of directors by title in descending order of type TV Show
df_new[df_new['type'] == 'TV Show'].groupby('director')['title'].nunique().
 ↪sort_values(ascending = False)[1:11]
```

[281]:
```
director
Ken Burns                3
Alastair Fothergill      3
Joe Berlinger            2
Hsu Fu-chun              2
Lynn Novick              2
Rob Seidenglanz          2
Iginio Straffi           2
Shin Won-ho              2
Gautham Vasudev Menon    2
Stan Lathan              2
Name: title, dtype: int64
```

[282]:
```
# Count of unique cast members by titles in descending order
df_new.groupby('cast')['title'].nunique().sort_values(ascending = False)[1:11]
```

[282]:
```
cast
Anupam Kher          43
Shah Rukh Khan       35
Julie Tejwani        33
Takahiro Sakurai     32
Naseeruddin Shah     32
Rupa Bhimani         31
Akshay Kumar         30
Om Puri              30
Yuki Kaji            29
Paresh Rawal         28
Name: title, dtype: int64
```

[285]:
```
# Barplot of actors by titles in descending order
title_cast = df_new.groupby('cast')['title'].nunique().sort_values(ascending =␣
 ↪False)[1:11]
plt.figure(figsize = (10, 5))
plt.bar(title_cast.index, title_cast.values, color = 'red', edgecolor = 'grey')
plt.xticks(rotation = 90)
plt.title('Top 10 actors by title')
plt.show()
```



[283]:
```
# Count of unique cast members by titles in descending order of type Movies
df_new[df_new['type'] == 'Movie'].groupby('cast')['title'].nunique().
 ↪sort_values(ascending = False)[1:11]
```

[283]:
```
cast
Anupam Kher          42
Shah Rukh Khan       35
Naseeruddin Shah     32
Akshay Kumar         30
Om Puri              30
Paresh Rawal         28
Julie Tejwani        28
Amitabh Bachchan     28
Rupa Bhimani         27
Boman Irani          27
Name: title, dtype: int64
```

[284]:
```
# Count of unique cast members by titles in descending order of type TV Show
df_new[df_new['type'] == 'TV Show'].groupby('cast')['title'].nunique().
 ↪sort_values(ascending = False)[1:11]
```

[284]:
```
cast
Takahiro Sakurai      25
Yuki Kaji             19
Daisuke Ono           17
Ai Kayano             17
Junichi Suwabe        17
Yuichi Nakamura       16
Jun Fukuyama          15
Yoshimasa Hosoya      15
David Attenborough    14
Hiroshi Kamiya        13
Name: title, dtype: int64
```

[31]:
```
# Top countries overall
df_new.groupby('country')['title'].nunique().sort_values(ascending = False).
 ↪head(10)
```

[31]:
```
country
United States     3689
India             1046
missing            831
United Kingdom     804
Canada             445
France             393
Japan              318
Spain              232
South Korea        231
Germany            226
Name: title, dtype: int64
```

[32]:
```
# Countries by type == Movie
df_new[df_new['type'] == 'Movie'].groupby('country')['title'].nunique().
 ↪sort_values(ascending = False).head(10)
```

[32]:
```
country
United States     2751
India              962
United Kingdom     532
missing            440
Canada             319
France             303
Germany            182
Spain              171
Japan              119
China              114
Name: title, dtype: int64
```

[33]:
```
# Countries by type == TV Show
df_new[df_new['type'] == 'TV Show'].groupby('country')['title'].nunique().
 ↪sort_values(ascending = False).head(10)
```

[33]:
```
country
United States     938
missing           391
United Kingdom    272
Japan             199
South Korea       170
Canada            126
France             90
India              84
Taiwan             70
Australia          66
Name: title, dtype: int64
```

[36]:
```
# Year of movie release by value_count
df[df['type'] == 'Movie'].groupby('release_year')['title'].count().
 ↪sort_values(ascending = False).head(10)
```

[36]:
```
release_year
2018    767
2017    767
2016    658
2019    633
2020    517
2015    398
2021    277
2014    264
2013    225
2012    173
Name: title, dtype: int64
```

[37]:
```
# Year of TV show release by count
df[df['type'] == 'TV Show'].groupby('release_year')['title'].count().
 ↪sort_values(ascending = False).head(20)
```

[37]:
```
release_year
2020    436
2019    397
2018    380
2021    315
2017    265
2016    244
2015    162
2014     88
```

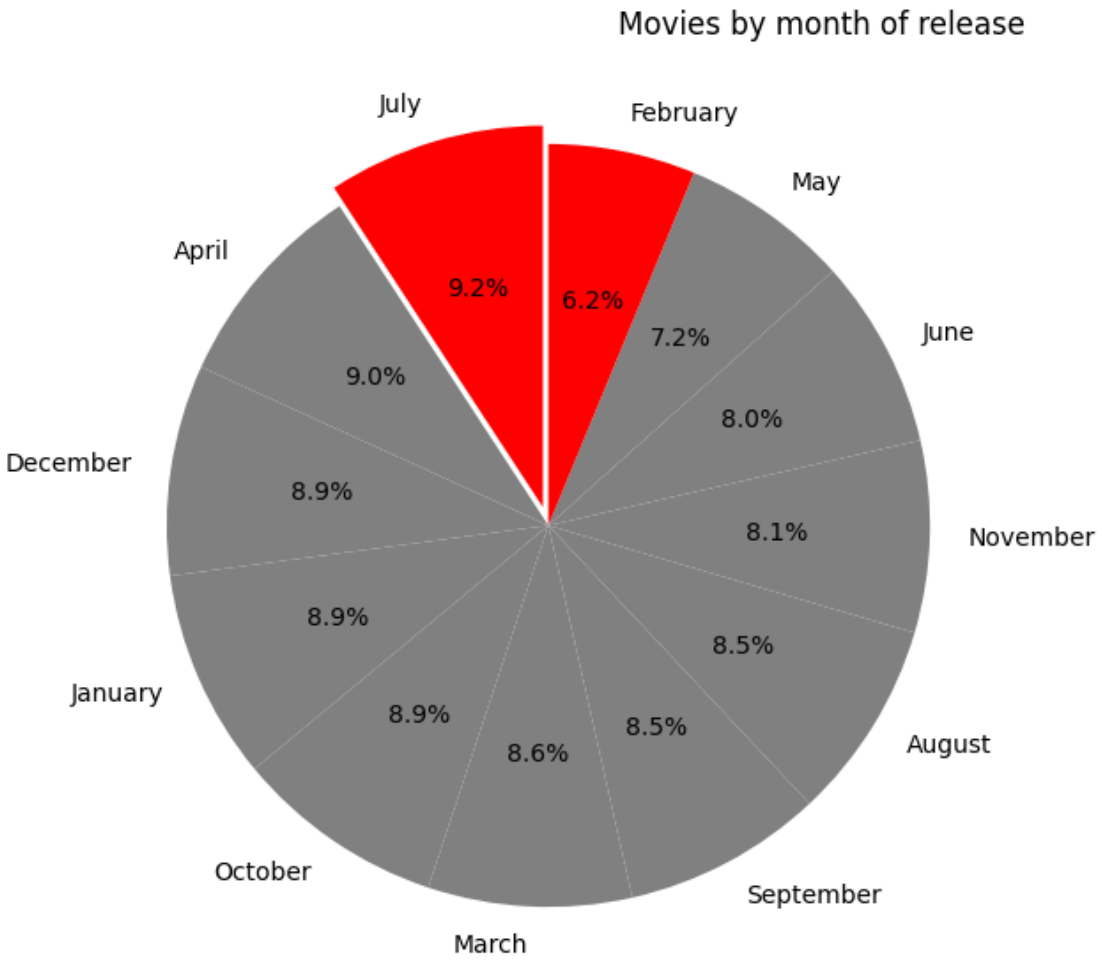
```
2012     64
2013     63
2011     40
2010     40
2009     34
2008     23
2006     14
2007     14
2005     13
2003     10
2004      9
1999      7
Name: title, dtype: int64
```

[38]:
```
# Month of movie release by count
df[df['type'] == 'Movie'].groupby('month_name_added')['title'].count().
 ↪sort_values(ascending = False)
```

[38]:
```
month_name_added
July          565
April         550
December      547
January       546
October       545
March         529
September     519
August        519
November      498
June          492
May           439
February      382
Name: title, dtype: int64
```

[166]:
```
# Pie chart of Movie count  by month of release
movie_month = df[df['type'] == 'Movie'].groupby('month_name_added')['title'].
 ↪count().sort_values(ascending = False)
e = len(movie_month.index) * [0]
e[0] =0.05


plt.figure(figsize = (7, 7))
plt.pie(movie_month.values,
        labels = movie_month.index,
        startangle=90,
        explode= e,
        autopct = '%.1f%%',
```

```
        colors = ['red',␣
 ↪'grey','grey','grey','grey','grey','grey','grey','grey','grey','grey'])
plt.title('Movies by month of release', loc='right')
plt.show()
```

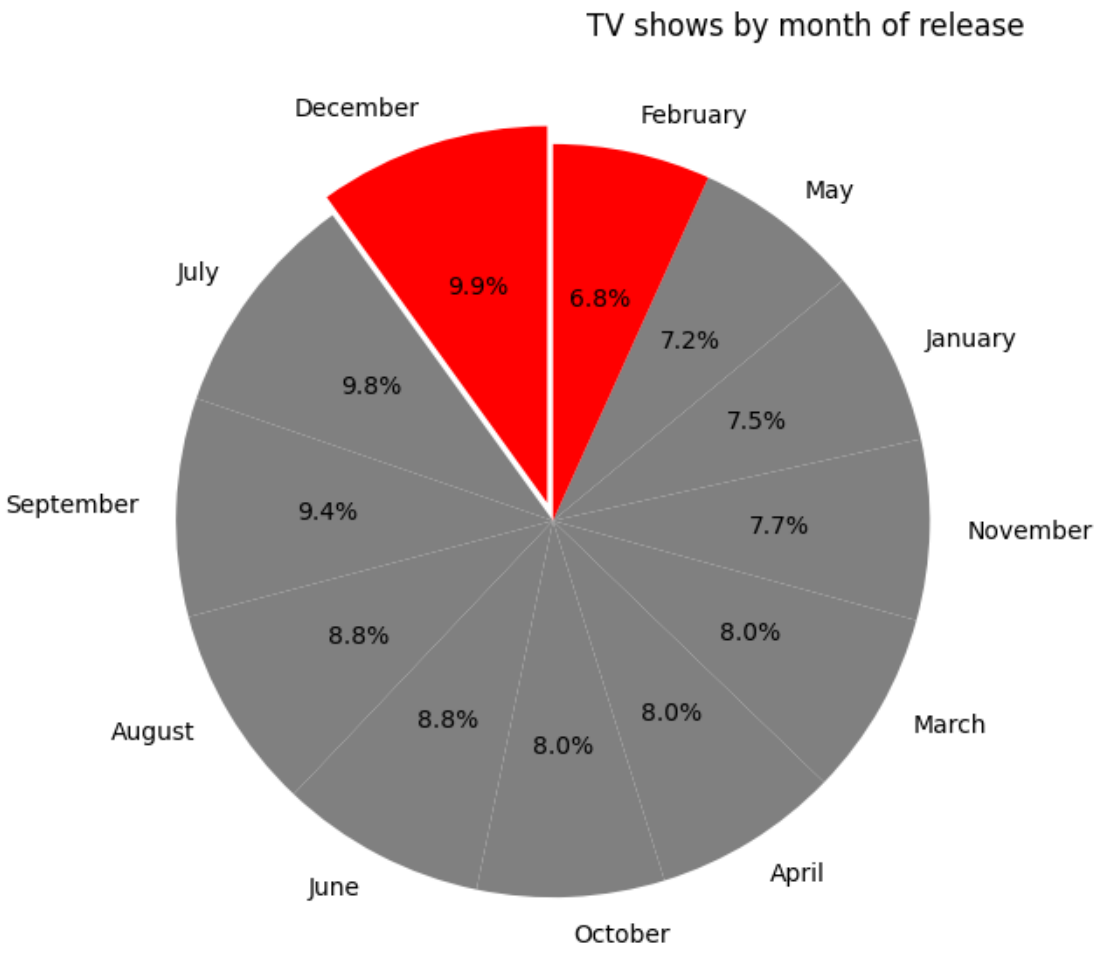


[167]:
```
# Month of TV show release by count
df[df['type'] == 'TV Show'].groupby('month_name_added')['title'].count().
 ↪sort_values(ascending=False)
```

[167]:
```
month_name_added
December     266
July         262
September    251
August       236
June         236
```

```
October      215
April        214
March        213
November     207
January      202
May          193
February     181
Name: title, dtype: int64
```

[168]:
```
# Pie chart of TV Show count  by month of release
tvshow_month = df[df['type'] == 'TV Show'].groupby('month_name_added')['title'].
 ↪count().sort_values(ascending = False)
e = len(tvshow_month.index) * [0]
e[0] =0.05


plt.figure(figsize = (7, 7))
plt.pie(tvshow_month.values,
        labels = tvshow_month.index,
        startangle=90,
        explode= e,
        autopct = '%.1f%%',
        colors = ['red',␣
 ↪'grey','grey','grey','grey','grey','grey','grey','grey','grey','grey'])
plt.title('TV shows by month of release', loc='right')
plt.show()
```

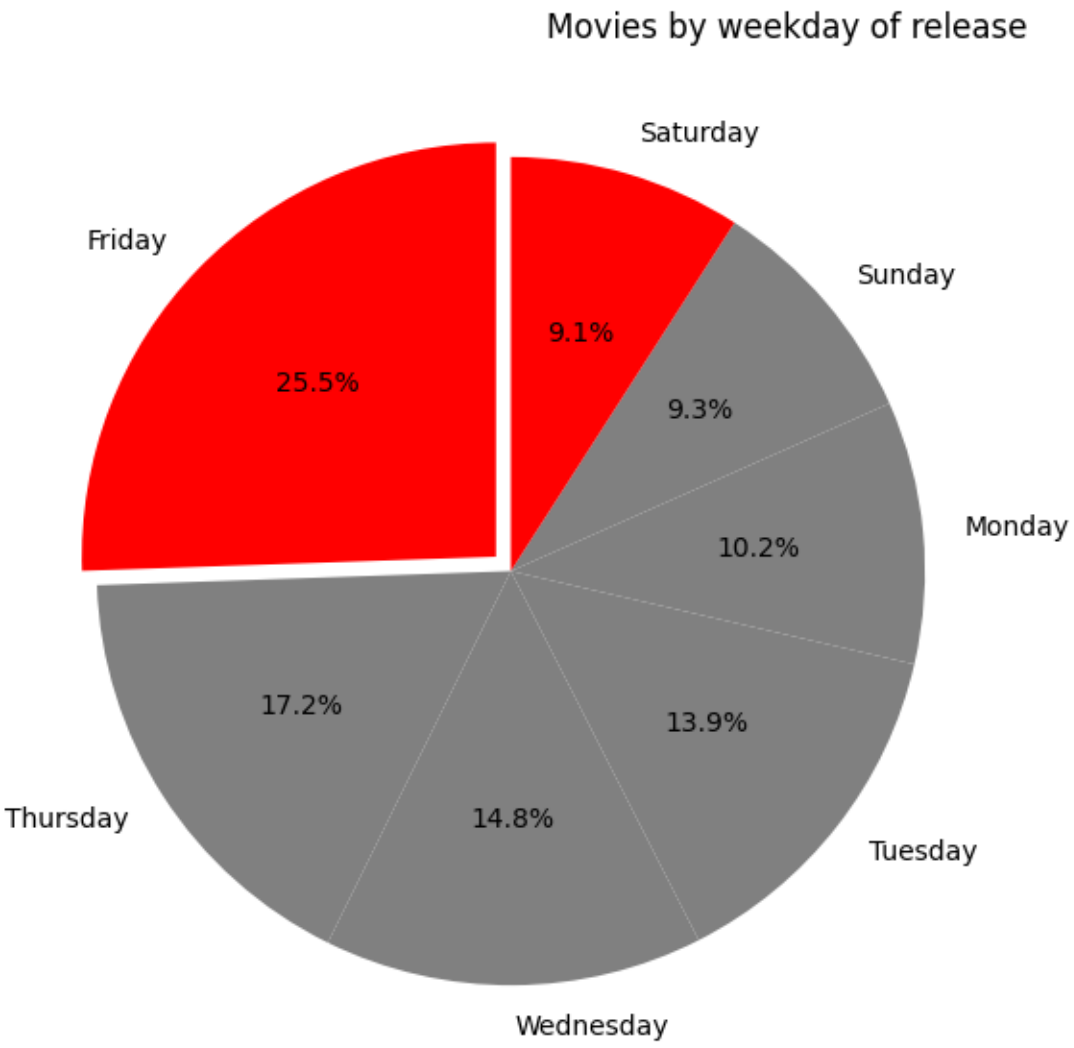


[40]:
```
# Weekday of Movie release by count
df[df['type'] == 'Movie'].groupby('weekday_added')['title'].count().
 ↪sort_values(ascending = False)
```

[40]:
```
weekday_added
Friday       1566
Thursday     1053
Wednesday     906
Tuesday       852
Monday        628
Sunday        569
Saturday      557
Name: title, dtype: int64
```

[170]:
```
# Pie chart of Movies release by weekday
```

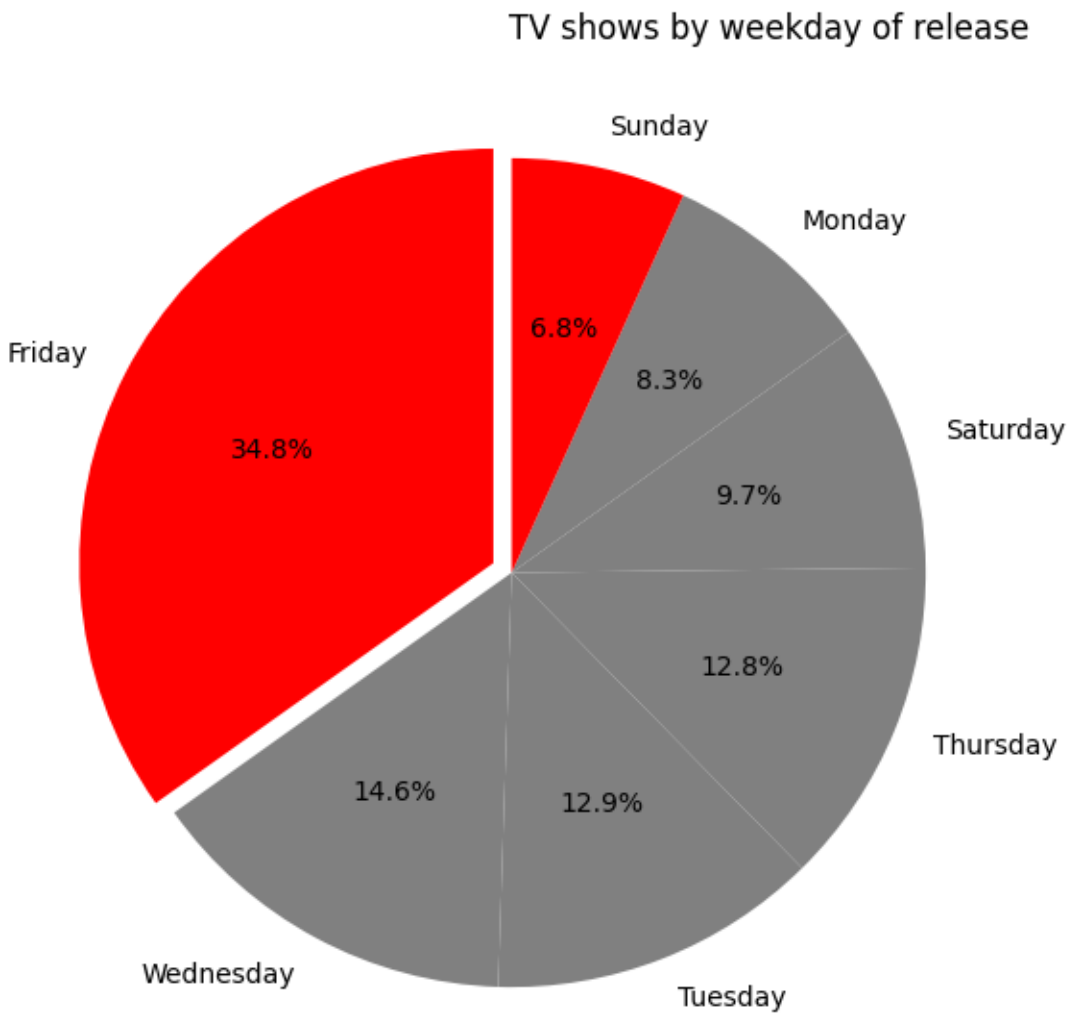
```
movie_weekday = df[df['type'] == 'Movie'].groupby('weekday_added')['title'].
  ↪count().sort_values(ascending=False)
e = len(movie_weekday.index) * [0]
e[0] =0.05

plt.figure(figsize = (7, 7))
plt.pie(movie_weekday.values,
        labels = movie_weekday.index,
        startangle=90,
        explode= e,
        autopct = '%.1f%%',
        colors = ['red', 'grey','grey','grey','grey','grey'])
plt.title('Movies by weekday of release', loc='right')
plt.show()
```



[41]:
```
# Weekday of TV Show release by count
df[df['type'] == 'TV Show'].groupby('weekday_added')['title'].count().
 ↪sort_values(ascending = False)
```

[41]:
```
weekday_added
Friday       932
Wednesday    392
Tuesday      345
Thursday     343
Saturday     259
Monday       223
Sunday       182
Name: title, dtype: int64
```

[171]:
```
# Pie chart of TV show release by weekday
tvshow_weekday = df[df['type'] == 'TV Show'].groupby('weekday_added')['title'].
 ↪count().sort_values(ascending=False)
e = len(tvshow_weekday.index) * [0]
e[0] =0.05

plt.figure(figsize = (7, 7))
plt.pie(tvshow_weekday.values,
        labels = tvshow_weekday.index,
        startangle=90,
        explode= e,
        autopct = '%.1f%%',
        colors = ['red', 'grey','grey','grey','grey','grey'])
plt.title('TV shows by weekday of release', loc='right')
plt.show()
```



[80]:
```
# Un-nesting 'listed_in' columns into multiple rows in df2
df2 = copy.deepcopy(df)

df2['listed_in'] = df2['listed_in'].str.split(', ')
df2 = df2.explode('listed_in')
df2.shape
```

[80]: (19323, 15)

[43]:
```
# Count of categories in listed_in by title
df2.groupby('listed_in')['title'].count().sort_values(ascending = False)
```

[43]:
```
listed_in
International Movies            2752
Dramas                          2427
Comedies                        1674
International TV Shows          1351
Documentaries                    869
Action & Adventure               859
TV Dramas                        763
Independent Movies               756
Children & Family Movies         641
Romantic Movies                  616
TV Comedies                      581
Thrillers                        577
Crime TV Shows                   470
Kids' TV                         451
Docuseries                       395
Music & Musicals                 375
Romantic TV Shows                370
Horror Movies                    357
Stand-Up Comedy                  343
Reality TV                       255
British TV Shows                 253
Sci-Fi & Fantasy                 243
Sports Movies                    219
Anime Series                     176
Spanish-Language TV Shows        174
TV Action & Adventure            168
Korean TV Shows                  151
Classic Movies                   116
LGBTQ Movies                     102
TV Mysteries                      98
Science & Nature TV               92
TV Sci-Fi & Fantasy               84
TV Horror                         75
Anime Features                    71
Cult Movies                       71
Teen TV Shows                     69
Faith & Spirituality              65
Movies                            57
TV Thrillers                      57
Stand-Up Comedy & Talk Shows      56
Classic & Cult TV                 28
TV Shows                          16
Name: title, dtype: int64
```

[44]:
```
# Count of categories in listed_in by title in Movies category
```

```
df2[df2['type'] == 'Movie'].groupby('listed_in')['title'].count().
 ↪sort_values(ascending = False)
```

[44]:
```
listed_in
International Movies        2752
Dramas                      2427
Comedies                    1674
Documentaries                869
Action & Adventure           859
Independent Movies           756
Children & Family Movies     641
Romantic Movies              616
Thrillers                    577
Music & Musicals             375
Horror Movies                357
Stand-Up Comedy              343
Sci-Fi & Fantasy             243
Sports Movies                219
Classic Movies               116
LGBTQ Movies                 102
Anime Features                71
Cult Movies                   71
Faith & Spirituality          65
Movies                        57
Name: title, dtype: int64
```

[45]:
```
# Count of categories in listed_in by title in TV Show category
df2[df2['type'] == 'TV Show'].groupby('listed_in')['title'].count().
 ↪sort_values(ascending=False)
```

[45]:
```
listed_in
International TV Shows          1351
TV Dramas                        763
TV Comedies                      581
Crime TV Shows                   470
Kids' TV                         451
Docuseries                       395
Romantic TV Shows                370
Reality TV                       255
British TV Shows                 253
Anime Series                     176
Spanish-Language TV Shows        174
TV Action & Adventure            168
Korean TV Shows                  151
TV Mysteries                      98
Science & Nature TV               92
TV Sci-Fi & Fantasy               84
```

```
TV Horror                          75
Teen TV Shows                      69
TV Thrillers                       57
Stand-Up Comedy & Talk Shows       56
Classic & Cult TV                  28
TV Shows                           16
Name: title, dtype: int64
```

0.3 3. Non-Graphical Analysis: Value Counts & Uniques

- **Unique values**:
  - `title`: 8,807 (all unique)
  - `director`: 4,529
  - `cast`: 7,693
  - `country`: 749
  - `listed_in` (genres): 514
- **Top categories**:
  - **Genres**: *International Movies (2,752)*, *Dramas (2,427)*, *Comedies (1,674)*
  - **Countries**: US (2,818), India (972), UK (419)
  - **Directors**: Rajiv Chilaka (22), Jan Suter (21)
  - **Actors**: Anupam Kher (43), Shah Rukh Khan (35), Julie Tejwani (33)

  Note: Multi-value fields (`director`, `cast`, `country`, `listed_in`) were **unnested** into separate rows (e.g., one title with 3 actors → 3 rows), enabling granular analysis.

[215]:
```
# Correlation of listed_in vs titles by TV and Movie Shows

listed_in_corr= df2.pivot_table(index = 'rating', columns = 'listed_in', values␣
 ↪= 'title', aggfunc = 'count')

listed_in_corr.replace(np.nan, 0, inplace = True)
listed_in_corr

listed_in_corr.corr()
```

[215]:
```
listed_in                 Action & Adventure  Anime Features  \
listed_in
Action & Adventure                  1.000000        0.532899
Anime Features                      0.532899        1.000000
Anime Series                        0.604060        0.843710
```

British TV Shows	0.481826	0.763373
Children & Family Movies	-0.340181	0.059797
Classic & Cult TV	0.581371	0.936651
Classic Movies	0.808045	0.429225
Comedies	0.867619	0.829789
Crime TV Shows	0.582408	0.559888
Cult Movies	0.724484	-0.013790
Documentaries	0.646459	0.871840
Docuseries	0.534439	0.827416
Dramas	0.891200	0.747877
Faith & Spirituality	0.362292	0.820333
Horror Movies	0.849606	0.378730
Independent Movies	0.824690	0.474407
International Movies	0.713619	0.834113
International TV Shows	0.647753	0.769966
Kids' TV	-0.343201	-0.105396
Korean TV Shows	0.615047	0.847331
LGBTQ Movies	0.642125	0.497020
Movies	0.032634	0.260634
Music & Musicals	0.738729	0.884641
Reality TV	0.522811	0.929918
Romantic Movies	0.846223	0.859807
Romantic TV Shows	0.659039	0.871543
Sci-Fi & Fantasy	0.806152	0.270642
Science & Nature TV	0.219160	0.825697
Spanish-Language TV Shows	0.527780	0.533660
Sports Movies	0.768427	0.750115
Stand-Up Comedy	0.504804	0.433143
Stand-Up Comedy & Talk Shows	0.544988	0.585150
TV Action & Adventure	0.591442	0.718657
TV Comedies	0.561028	0.724527
TV Dramas	0.650922	0.727705
TV Horror	0.577481	0.553949
TV Mysteries	0.627880	0.633017
TV Sci-Fi & Fantasy	0.590748	0.863594
TV Shows	0.688780	0.724958
TV Thrillers	0.569149	0.554475
Teen TV Shows	0.602859	0.941885
Thrillers	0.904140	0.480009

listed_in	Anime Series	British TV Shows	\
listed_in			
Action & Adventure	0.604060	0.481826	
Anime Features	0.843710	0.763373	
Anime Series	1.000000	0.778865	
British TV Shows	0.778865	1.000000	
Children & Family Movies	-0.089386	-0.086945	

Classic & Cult TV	0.932618	0.890640
Classic Movies	0.328953	0.189768
Comedies	0.866456	0.744238
Crime TV Shows	0.773365	0.882792
Cult Movies	-0.021801	-0.074901
Documentaries	0.865310	0.948533
Docuseries	0.811987	0.982144
Dramas	0.845145	0.795281
Faith & Spirituality	0.438478	0.367900
Horror Movies	0.552965	0.665489
Independent Movies	0.642283	0.750190
International Movies	0.940305	0.866088
International TV Shows	0.907610	0.916844
Kids' TV	0.014615	-0.026033
Korean TV Shows	0.986522	0.782734
LGBTQ Movies	0.621189	0.861301
Movies	0.387940	0.592390
Music & Musicals	0.924034	0.881653
Reality TV	0.842647	0.912860
Romantic Movies	0.854022	0.708860
Romantic TV Shows	0.952703	0.771525
Sci-Fi & Fantasy	0.257234	0.245551
Science & Nature TV	0.498309	0.673614
Spanish-Language TV Shows	0.710558	0.903917
Sports Movies	0.753545	0.860665
Stand-Up Comedy	0.634018	0.853911
Stand-Up Comedy & Talk Shows	0.744216	0.923863
TV Action & Adventure	0.886302	0.927124
TV Comedies	0.892689	0.943900
TV Dramas	0.894952	0.901700
TV Horror	0.762561	0.884454
TV Mysteries	0.842143	0.883604
TV Sci-Fi & Fantasy	0.966512	0.668857
TV Shows	0.891511	0.659293
TV Thrillers	0.762849	0.896296
Teen TV Shows	0.918509	0.786719
Thrillers	0.663690	0.684798

listed_in	Children & Family Movies	Classic & Cult TV	\
listed_in			
Action & Adventure	-0.340181	0.581371	
Anime Features	0.059797	0.936651	
Anime Series	-0.089386	0.932618	
British TV Shows	-0.086945	0.890640	
Children & Family Movies	1.000000	-0.101811	
Classic & Cult TV	-0.101811	1.000000	
Classic Movies	-0.026360	0.355612	

Comedies	-0.111417	0.866759
Crime TV Shows	-0.239650	0.757641
Cult Movies	-0.254603	-0.032727
Documentaries	-0.176738	0.955473
Docuseries	-0.149109	0.924062
Dramas	-0.288216	0.853500
Faith & Spirituality	0.298588	0.591514
Horror Movies	-0.362374	0.538139
Independent Movies	-0.336794	0.643114
International Movies	-0.238573	0.952396
International TV Shows	-0.226231	0.919246
Kids' TV	0.558209	-0.082054
Korean TV Shows	-0.099211	0.947448
LGBTQ Movies	-0.265105	0.658346
Movies	0.292699	0.410736
Music & Musicals	-0.157323	0.965878
Reality TV	-0.110860	0.972565
Romantic Movies	-0.226809	0.880708
Romantic TV Shows	-0.200800	0.954939
Sci-Fi & Fantasy	-0.213718	0.235578
Science & Nature TV	0.051756	0.737408
Spanish-Language TV Shows	-0.210053	0.725313
Sports Movies	-0.090624	0.808821
Stand-Up Comedy	-0.228604	0.637188
Stand-Up Comedy & Talk Shows	-0.222579	0.769343
TV Action & Adventure	-0.170744	0.872817
TV Comedies	-0.116728	0.886668
TV Dramas	-0.239087	0.891236
TV Horror	-0.239677	0.751441
TV Mysteries	-0.249800	0.821637
TV Sci-Fi & Fantasy	-0.105592	0.916985
TV Shows	-0.248823	0.852536
TV Thrillers	-0.212395	0.751967
Teen TV Shows	-0.147184	0.978393
Thrillers	-0.373088	0.637473

listed_in	Classic Movies	Comedies	Crime TV Shows	\
listed_in				
Action & Adventure	0.808045	0.867619	0.582408	
Anime Features	0.429225	0.829789	0.559888	
Anime Series	0.328953	0.866456	0.773365	
British TV Shows	0.189768	0.744238	0.882792	
Children & Family Movies	-0.026360	-0.111417	-0.239650	
Classic & Cult TV	0.355612	0.866759	0.757641	
Classic Movies	1.000000	0.664798	0.205748	
Comedies	0.664798	1.000000	0.763502	
Crime TV Shows	0.205748	0.763502	1.000000	

```
Cult Movies                        0.807464  0.335589        0.012504
Documentaries                      0.385819  0.885837        0.865563
Docuseries                         0.268589  0.795826        0.872584
Dramas                             0.631097  0.966031        0.842966
Faith & Spirituality               0.501894  0.589141        0.104980
Horror Movies                      0.560656  0.753930        0.821396
Independent Movies                 0.560385  0.792206        0.865552
International Movies               0.425206  0.930148        0.871671
International TV Shows             0.319035  0.880455        0.947175
Kids' TV                          -0.381551 -0.256737       -0.176412
Korean TV Shows                    0.346834  0.876369        0.757438
LGBTQ Movies                       0.301711  0.713595        0.936221
Movies                            -0.208259  0.208796        0.443736
Music & Musicals                   0.496732  0.951072        0.832244
Reality TV                         0.329611  0.808188        0.725245
Romantic Movies                    0.606687  0.969361        0.683797
Romantic TV Shows                  0.421988  0.903638        0.746342
Sci-Fi & Fantasy                   0.571169  0.614366        0.382112
Science & Nature TV                0.229055  0.476535        0.293112
Spanish-Language TV Shows          0.160741  0.707865        0.989346
Sports Movies                      0.506558  0.919196        0.874944
Stand-Up Comedy                    0.135375  0.648086        0.975834
Stand-Up Comedy & Talk Shows       0.184407  0.739603        0.990103
TV Action & Adventure              0.241142  0.824815        0.969451
TV Comedies                        0.207183  0.810692        0.952977
TV Dramas                          0.308027  0.870909        0.962489
TV Horror                          0.202062  0.756657        0.999783
TV Mysteries                       0.259903  0.824860        0.989342
TV Sci-Fi & Fantasy                0.381973  0.845739        0.627529
TV Shows                           0.448147  0.864678        0.700359
TV Thrillers                       0.195005  0.747969        0.997321
Teen TV Shows                      0.422484  0.870290        0.663637
Thrillers                          0.624591  0.837753        0.827533

listed_in                    Cult Movies  …  TV Action & Adventure  \
listed_in                                 …
Action & Adventure              0.724484  …               0.591442
Anime Features                 -0.013790  …               0.718657
Anime Series                   -0.021801  …               0.886302
British TV Shows               -0.074901  …               0.927124
Children & Family Movies       -0.254603  …              -0.170744
Classic & Cult TV              -0.032727  …               0.872817
Classic Movies                  0.807464  …               0.241142
Comedies                        0.335589  …               0.824815
Crime TV Shows                  0.012504  …               0.969451
Cult Movies                     1.000000  …              -0.017266
Documentaries                   0.053151  …               0.930609
```

Docuseries	-0.036893	…	0.931402
Dramas	0.391646	…	0.874536
Faith & Spirituality	0.061312	…	0.258402
Horror Movies	0.566169	…	0.761502
Independent Movies	0.497341	…	0.829467
International Movies	0.086099	…	0.930879
International TV Shows	0.011827	…	0.979206
Kids' TV	-0.261071	…	-0.093021
Korean TV Shows	-0.019201	…	0.861980
LGBTQ Movies	0.222006	…	0.894943
Movies	-0.214900	…	0.474849
Music & Musicals	0.143719	…	0.909275
Reality TV	-0.045153	…	0.836793
Romantic Movies	0.291639	…	0.763901
Romantic TV Shows	0.027133	…	0.839516
Sci-Fi & Fantasy	0.624780	…	0.337633
Science & Nature TV	-0.094536	…	0.452160
Spanish-Language TV Shows	-0.005246	…	0.953661
Sports Movies	0.240748	…	0.887232
Stand-Up Comedy	0.022066	…	0.915747
Stand-Up Comedy & Talk Shows	-0.008365	…	0.966637
TV Action & Adventure	-0.017266	…	1.000000
TV Comedies	-0.050545	…	0.991553
TV Dramas	0.019082	…	0.980665
TV Horror	0.012792	…	0.966829
TV Mysteries	0.019572	…	0.978519
TV Sci-Fi & Fantasy	-0.008600	…	0.761821
TV Shows	0.118351	…	0.762516
TV Thrillers	0.017737	…	0.970100
Teen TV Shows	0.003140	…	0.788998
Thrillers	0.563562	…	0.795237

listed_in	TV Comedies	TV Dramas	TV Horror	TV Mysteries	\
listed_in					
Action & Adventure	0.561028	0.650922	0.577481	0.627880	
Anime Features	0.724527	0.727705	0.553949	0.633017	
Anime Series	0.892689	0.894952	0.762561	0.842143	
British TV Shows	0.943900	0.901700	0.884454	0.883604	
Children & Family Movies	-0.116728	-0.239087	-0.239677	-0.249800	
Classic & Cult TV	0.886668	0.891236	0.751441	0.821637	
Classic Movies	0.207183	0.308027	0.202062	0.259903	
Comedies	0.810692	0.870909	0.756657	0.824860	
Crime TV Shows	0.952977	0.962489	0.999783	0.989342	
Cult Movies	-0.050545	0.019082	0.012792	0.019572	
Documentaries	0.928039	0.940079	0.863454	0.898884	
Docuseries	0.932995	0.916142	0.873221	0.885579	
Dramas	0.855689	0.915210	0.838176	0.886847	

Faith & Spirituality	0.257886	0.291874	0.101627	0.181890
Horror Movies	0.727661	0.764623	0.823302	0.800461
Independent Movies	0.801239	0.831466	0.866601	0.853965
International Movies	0.925020	0.970573	0.864947	0.928707
International TV Shows	0.971651	0.997560	0.943092	0.978788
Kids' TV	0.001269	-0.199664	-0.179670	-0.194058
Korean TV Shows	0.877081	0.894966	0.746493	0.835858
LGBTQ Movies	0.869704	0.859675	0.941111	0.896007
Movies	0.554564	0.398963	0.445751	0.413829
Music & Musicals	0.910678	0.939427	0.826400	0.888693
Reality TV	0.850760	0.844301	0.722300	0.775044
Romantic Movies	0.754706	0.826725	0.675888	0.761990
Romantic TV Shows	0.839547	0.898466	0.736351	0.831542
Sci-Fi & Fantasy	0.299910	0.368231	0.382687	0.382965
Science & Nature TV	0.480949	0.431906	0.294430	0.334305
Spanish-Language TV Shows	0.938687	0.928302	0.991839	0.961636
Sports Movies	0.868859	0.894698	0.875084	0.884913
Stand-Up Comedy	0.895847	0.884894	0.979558	0.934258
Stand-Up Comedy & Talk Shows	0.953593	0.947799	0.991754	0.971485
TV Action & Adventure	0.991553	0.980665	0.966829	0.978519
TV Comedies	1.000000	0.970779	0.949848	0.965196
TV Dramas	0.970779	1.000000	0.958460	0.989846
TV Horror	0.949848	0.958460	1.000000	0.986654
TV Mysteries	0.965196	0.989846	0.986654	1.000000
TV Sci-Fi & Fantasy	0.772052	0.805480	0.614181	0.726182
TV Shows	0.774463	0.846863	0.687946	0.793029
TV Thrillers	0.957839	0.951594	0.997775	0.980534
Teen TV Shows	0.796454	0.837184	0.655012	0.751065
Thrillers	0.766296	0.818971	0.826114	0.833812

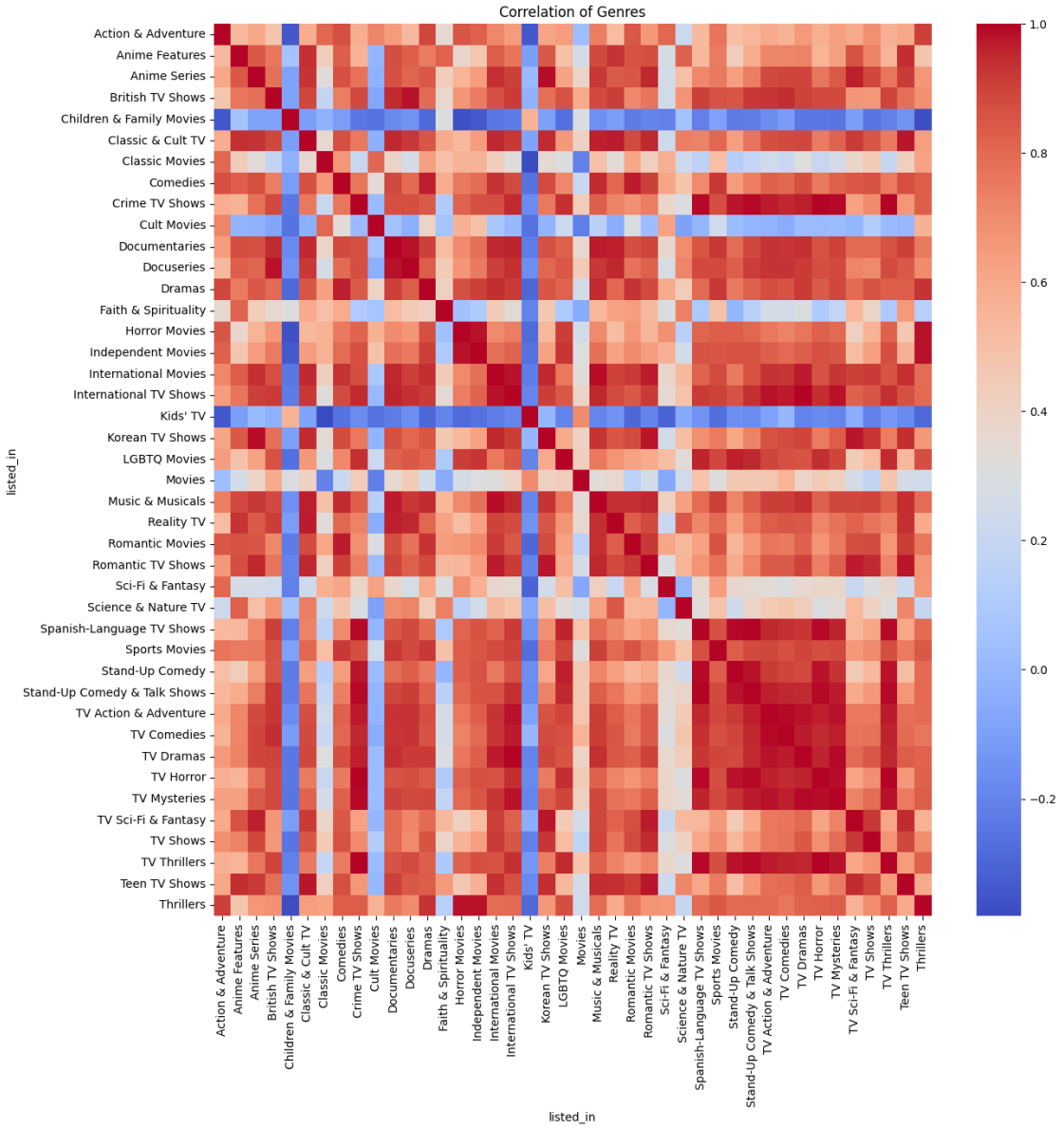
listed_in	TV Sci-Fi & Fantasy	TV Shows	TV Thrillers	\
listed_in				
Action & Adventure	0.590748	0.688780	0.569149	
Anime Features	0.863594	0.724958	0.554475	
Anime Series	0.966512	0.891511	0.762849	
British TV Shows	0.668857	0.659293	0.896296	
Children & Family Movies	-0.105592	-0.248823	-0.212395	
Classic & Cult TV	0.916985	0.852536	0.751967	
Classic Movies	0.381973	0.448147	0.195005	
Comedies	0.845739	0.864678	0.747969	
Crime TV Shows	0.627529	0.700359	0.997321	
Cult Movies	-0.008600	0.118351	0.017737	
Documentaries	0.804020	0.801843	0.863137	
Docuseries	0.721750	0.707706	0.879223	
Dramas	0.795929	0.856612	0.831883	
Faith & Spirituality	0.536223	0.385659	0.093736	
Horror Movies	0.420546	0.560640	0.826108	

Independent Movies	0.516668	0.635539	0.871094
International Movies	0.903683	0.918904	0.855846
International TV Shows	0.826341	0.853456	0.937278
Kids' TV	-0.041732	-0.209109	-0.130076
Korean TV Shows	0.976825	0.925523	0.742704
LGBTQ Movies	0.448487	0.522129	0.948772
Movies	0.261042	0.179357	0.484269
Music & Musicals	0.889982	0.896036	0.823729
Reality TV	0.820873	0.772873	0.726360
Romantic Movies	0.871661	0.879898	0.662845
Romantic TV Shows	0.968290	0.946886	0.722514
Sci-Fi & Fantasy	0.209815	0.301308	0.372834
Science & Nature TV	0.527996	0.401968	0.310387
Spanish-Language TV Shows	0.545322	0.608934	0.994484
Sports Movies	0.657739	0.701227	0.872568
Stand-Up Comedy	0.452573	0.540836	0.982670
Stand-Up Comedy & Talk Shows	0.592821	0.656846	0.993494
TV Action & Adventure	0.761821	0.762516	0.970100
TV Comedies	0.772052	0.774463	0.957839
TV Dramas	0.805480	0.846863	0.951594
TV Horror	0.614181	0.687946	0.997775
TV Mysteries	0.726182	0.793029	0.980534
TV Sci-Fi & Fantasy	1.000000	0.922387	0.606727
TV Shows	0.922387	1.000000	0.673343
TV Thrillers	0.606727	0.673343	1.000000
Teen TV Shows	0.950703	0.891698	0.646531
Thrillers	0.564905	0.693564	0.825298

listed_in	Teen TV Shows	Thrillers
listed_in		
Action & Adventure	0.602859	0.904140
Anime Features	0.941885	0.480009
Anime Series	0.918509	0.663690
British TV Shows	0.786719	0.684798
Children & Family Movies	-0.147184	-0.373088
Classic & Cult TV	0.978393	0.637473
Classic Movies	0.422484	0.624591
Comedies	0.870290	0.837753
Crime TV Shows	0.663637	0.827533
Cult Movies	0.003140	0.563562
Documentaries	0.906559	0.754069
Docuseries	0.845923	0.701440
Dramas	0.836024	0.932218
Faith & Spirituality	0.652136	0.133021
Horror Movies	0.465177	0.981162
Independent Movies	0.569796	0.982594
International Movies	0.935690	0.794870

```
International TV Shows             0.868124   0.803779
Kids' TV                          -0.177952  -0.285652
Korean TV Shows                    0.943912   0.657219
LGBTQ Movies                       0.539129   0.873587
Movies                             0.259723   0.244059
Music & Musicals                   0.944901   0.791100
Reality TV                         0.939804   0.593472
Romantic Movies                    0.908722   0.762755
Romantic TV Shows                  0.976153   0.673748
Sci-Fi & Fantasy                   0.232826   0.660192
Science & Nature TV                0.717197   0.200291
Spanish-Language TV Shows          0.609663   0.799059
Sports Movies                      0.747814   0.847251
Stand-Up Comedy                    0.513205   0.796106
Stand-Up Comedy & Talk Shows       0.663244   0.801606
TV Action & Adventure              0.788998   0.795237
TV Comedies                        0.796454   0.766296
TV Dramas                          0.837184   0.818971
TV Horror                          0.655012   0.826114
TV Mysteries                       0.751065   0.833812
TV Sci-Fi & Fantasy                0.950703   0.564905
TV Shows                           0.891698   0.693564
TV Thrillers                       0.646531   0.825298
Teen TV Shows                      1.000000   0.591007
Thrillers                          0.591007   1.000000

[42 rows x 42 columns]
```

[226]:
```
plt.figure(figsize = (14, 14))
sns.heatmap(listed_in_corr.corr(), annot = False, cmap='coolwarm')
plt.title('Correlation of Genres')
plt.show()
```



[46]:
```
# Duration of Movies
df[df['type'] == 'Movie'].groupby('duration')['title'].count().
 ↪sort_values(ascending = False)
```

[46]:
```
duration
90 min     152
97 min     146
93 min     146
94 min     146
91 min     144
           ...
```

```
253 min      1
43 min       1
5 min        1
8 min        1
9 min        1
Name: title, Length: 206, dtype: int64
```

[47]:
```
# Duration of TV Shows
df[df['type'] == 'TV Show'].groupby('duration')['title'].count().
 ↪sort_values(ascending = False)
#
```

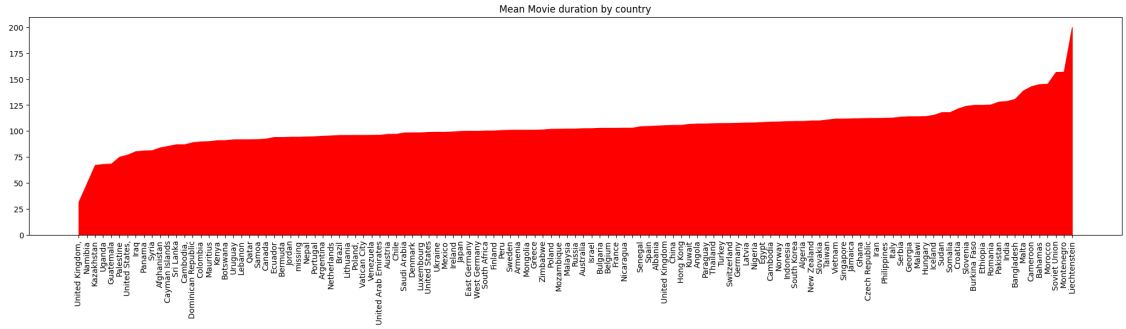
[47]:
```
duration
1 Season      1793
2 Seasons      425
3 Seasons      199
4 Seasons       95
5 Seasons       65
6 Seasons       33
7 Seasons       23
8 Seasons       17
9 Seasons        9
10 Seasons       7
13 Seasons       3
12 Seasons       2
15 Seasons       2
11 Seasons       2
17 Seasons       1
Name: title, dtype: int64
```

[229]:
```
# Mean duration of movies by country in df_new
df_movies = df_new[(df_new['type'] == 'Movie') & (df_new['duration'] !=␣
 ↪'missing')].copy()
df_movies['duration_minutes'] = df_movies['duration'].str.replace(' min', '').
 ↪astype(int)
df_movies.groupby('country')['duration_minutes'].mean().sort_values(ascending =␣
 ↪False)
```

[229]:
```
country
Liechtenstein      200.000000
Montenegro         157.000000
Soviet Union       156.636364
Morocco            145.413043
Bahamas            145.000000
                         …
Guatemala           68.333333
Uganda              68.000000
```

```
Kazakhstan          67.000000
Namibia             49.250000
United Kingdom,     31.600000
Name: duration_minutes, Length: 123, dtype: float64
```

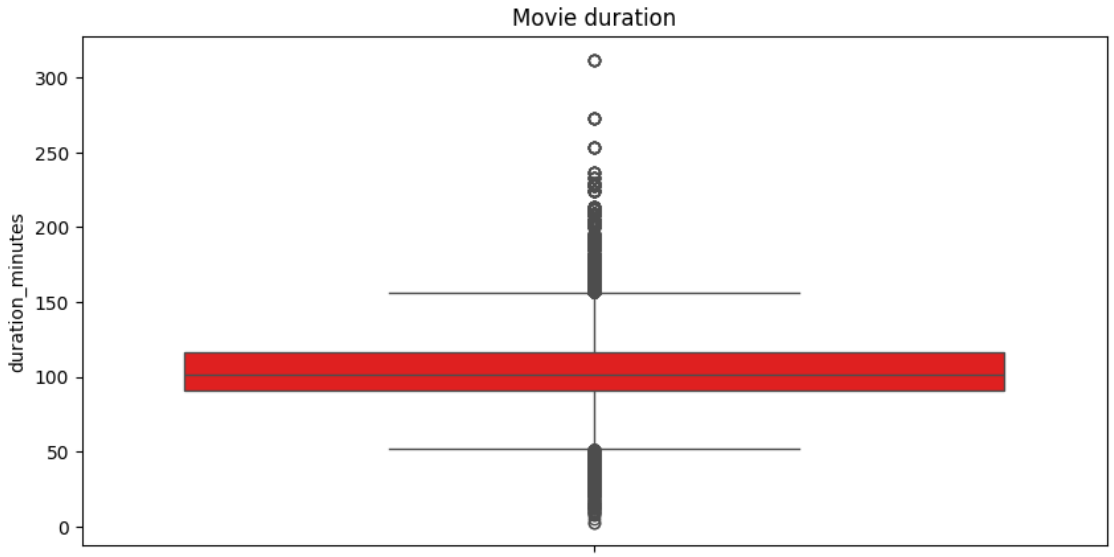
[246]:
```
# Stackplot of mean Movie duration by country
mean_duration = df_movies.groupby('country')['duration_minutes'].mean().
 ↪sort_values()
plt.figure(figsize = (25, 5))
plt.stackplot(mean_duration.index, mean_duration.values, color = 'red',␣
 ↪baseline='zero')
plt.xticks(rotation = 90)
plt.title('Mean Movie duration by country')
plt.show()
```



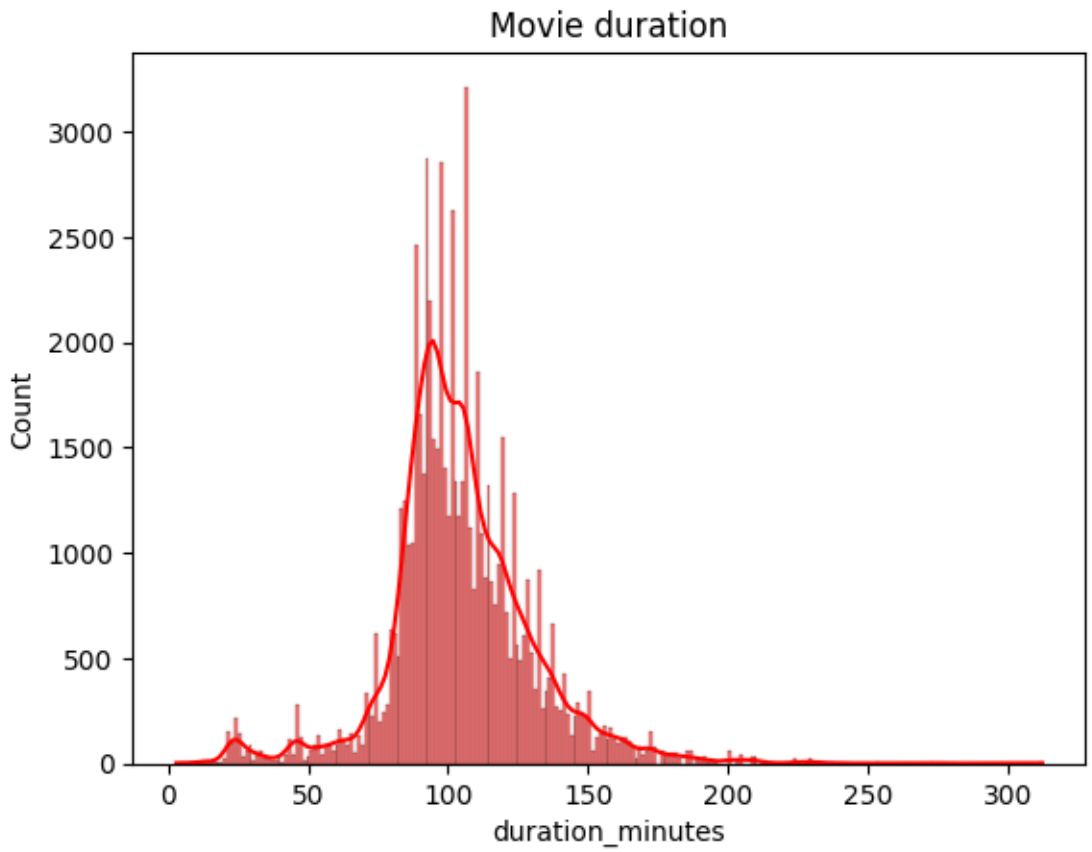
[295]:
```
# Mean duration of movies
df_movies['duration_minutes'].mean()
```

[295]:
```
np.float64(104.50364997015748)
```

[78]:
```
# Boxplot of duration of Movie
plt.figure(figsize = (10, 5))
sns.boxplot(df_movies[df_movies['type'] == 'Movie']['duration_minutes'],␣
 ↪color='red')
plt.title('Movie duration')
plt.show()
```



[256]:
```
# Histplot of duration of Movie
sns.histplot(df_movies[df_movies['type'] == 'Movie']['duration_minutes'],␣
 ↪color='red', kde=True)
plt.title('Movie duration')
plt.show()
```



[175]:
```
# Mean duration of TV Show by country
df_tv = df_new[(df_new['type'] == 'TV Show') & (df_new['duration'] !=␣
 ↪'missing')].copy()
df_tv['duration_seasons'] = df_tv['duration'].str.replace(' Seasons', '').str.
 ↪replace(' Season', '').astype(int)
df_tv.groupby('country')['duration_seasons'].mean().sort_values(ascending =␣
 ↪False)
```

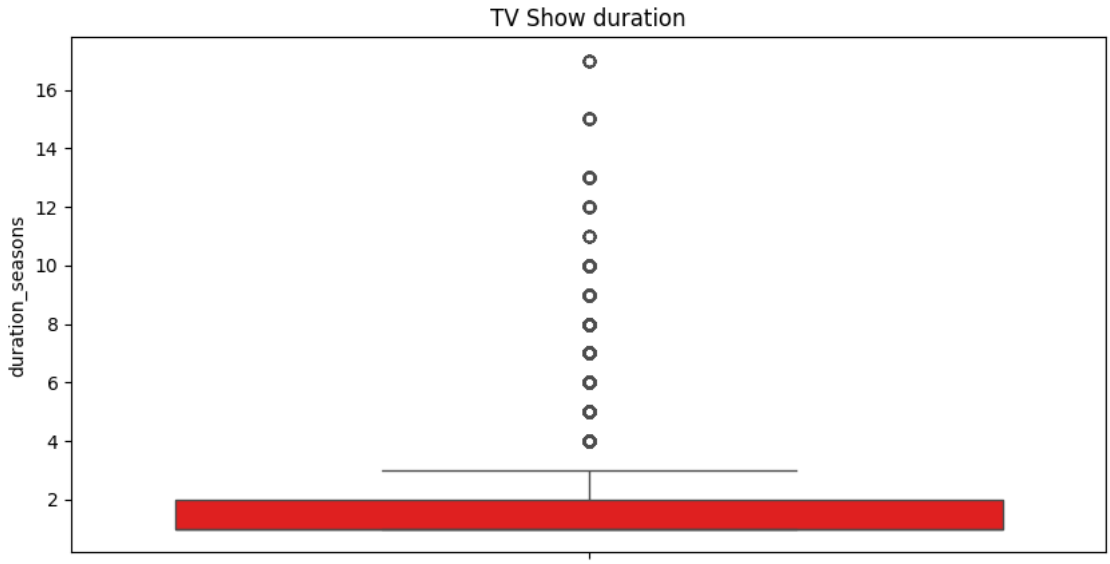
[175]:
```
country
Malta                   4.000000
Canada                  3.087638
United Arab Emirates    3.000000
Hungary                 3.000000
United States           2.708505
                            …
Puerto Rico             1.000000
Mauritius               1.000000
Syria                   1.000000
Switzerland             1.000000
```

```
West Germany            1.000000
Name: duration_seasons, Length: 67, dtype: float64
```

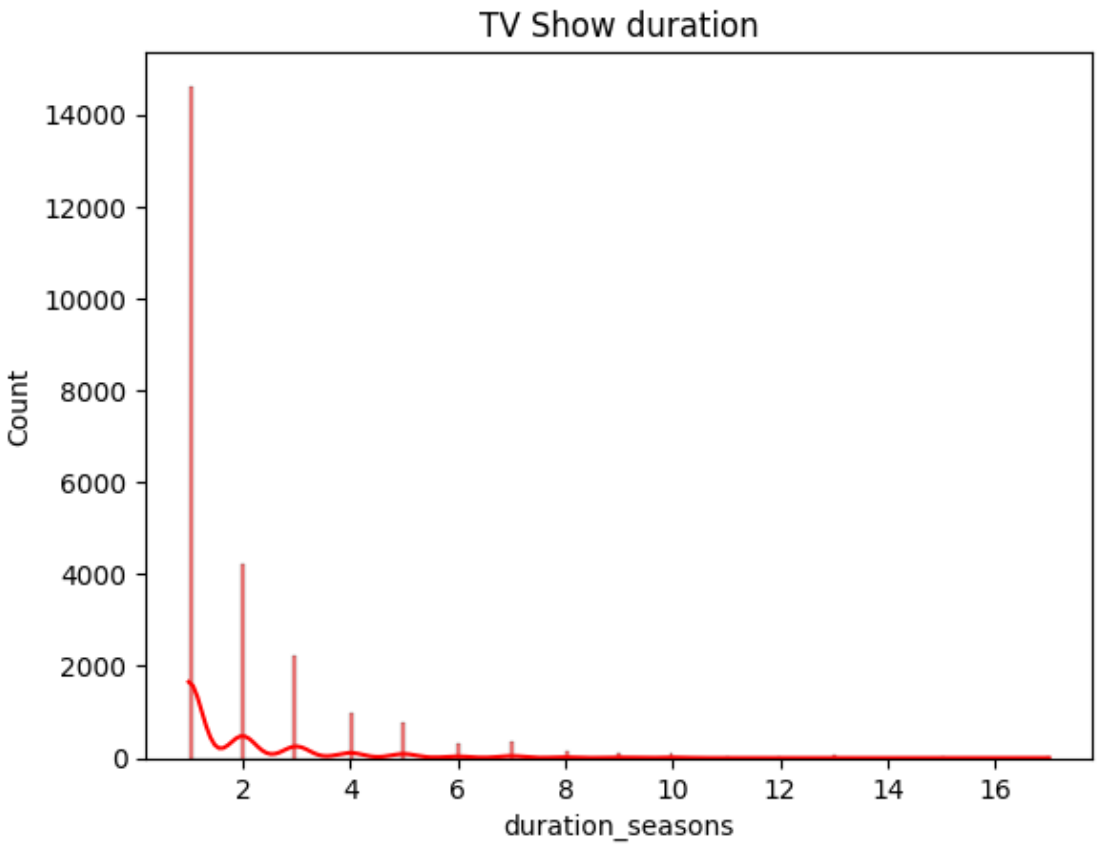
[296]:
```
# Mean duration of TV shows
df_tv['duration_seasons'].mean()
```

[296]:
```
np.float64(1.9726660009985022)
```

[298]:
```
# Boxplot of duration of TV Show
plt.figure(figsize = (10, 5))
sns.boxplot(df_tv['duration_seasons'], color='red')
plt.title('TV Show duration')
plt.show()
```



[300]:
```
# Histplot of duration of TV Shows
sns.histplot(df_tv['duration_seasons'], color='red', kde=True)
plt.title('TV Show duration')
plt.show()
```



0.4 4. Visual Analysis

0.4.1 4.1 Continuous Variables – Univariate

- `release_year`:
  - Histogram shows sharp rise from 2015–2020, peaking in **2018**
  - Boxplot confirms concentration in 2013–2019 (IQR), with older outliers (1925–1960s)
- `duration` **(converted to numeric)**:
  - Movie durations: **Right-skewed**, peak at **90–100 min**, median ~99 min
  - TV Show seasons: **Highly right-skewed**, 75% are **1–2 seasons**, long tail up to 17 seasons

0.4.2 4.2 Categorical Variables – Bivariate

- **Boxplots by** `type`:
  - Confirmed **Movies dominate recent releases** (2016–2020)
  - **TV Shows grew steadily post-2017**, with 2020 as peak year (436)
- **Genre vs. Type**:

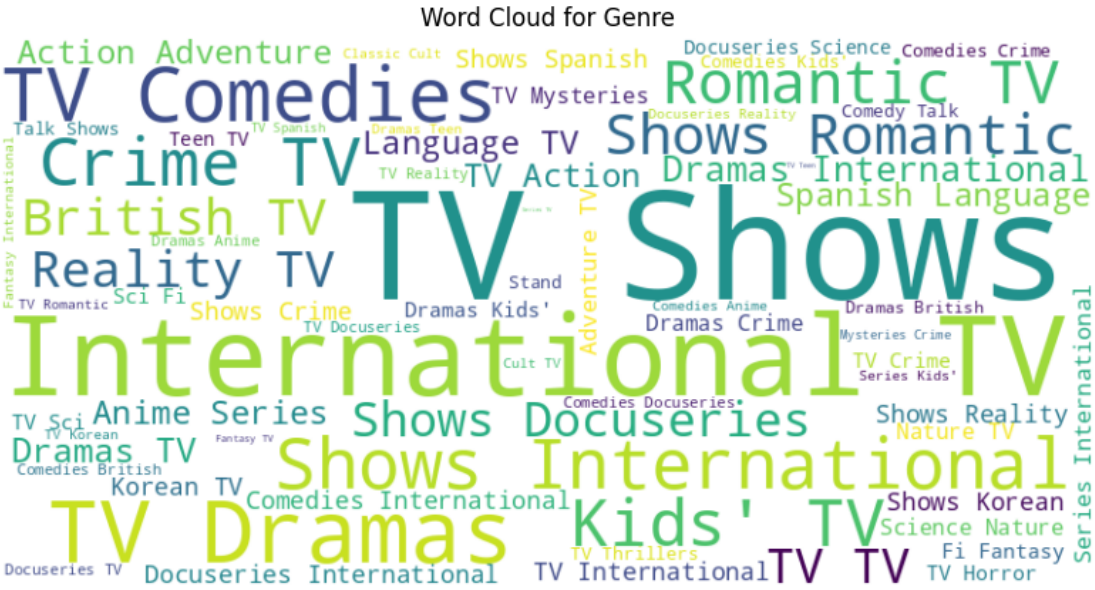
  - *International Movies*, *Dramas*, *Comedies* → Movie-heavy
  - *International TV Shows*, *TV Dramas*, *Crime TV* → TV-heavy
- **Country vs. Type**:
  - **India**: Strong in Movies (962) vs. TV (84)
  - **Japan/South Korea**: Balanced or TV-leaning
  - **US**: Dominates both categories

0.5 5. Missing Values & Outliers

- **Missing Values**:
  - Strategically imputed: `'missing'` for categorical, **mode** for `date_added`
  - No deletion → preserved sample size
- **Outliers**:
  - **Temporal**: Titles released before 1980 (e.g., 1925) — valid but rare
  - **Duration**: Movies >180 min (e.g., *Zodiac*: 158 min) and TV shows >10 seasons — real outliers but meaningful (e.g., legacy series)
  - **No aggressive trimming** — retained for completeness

[50]:
```
import wordcloud as wc
```

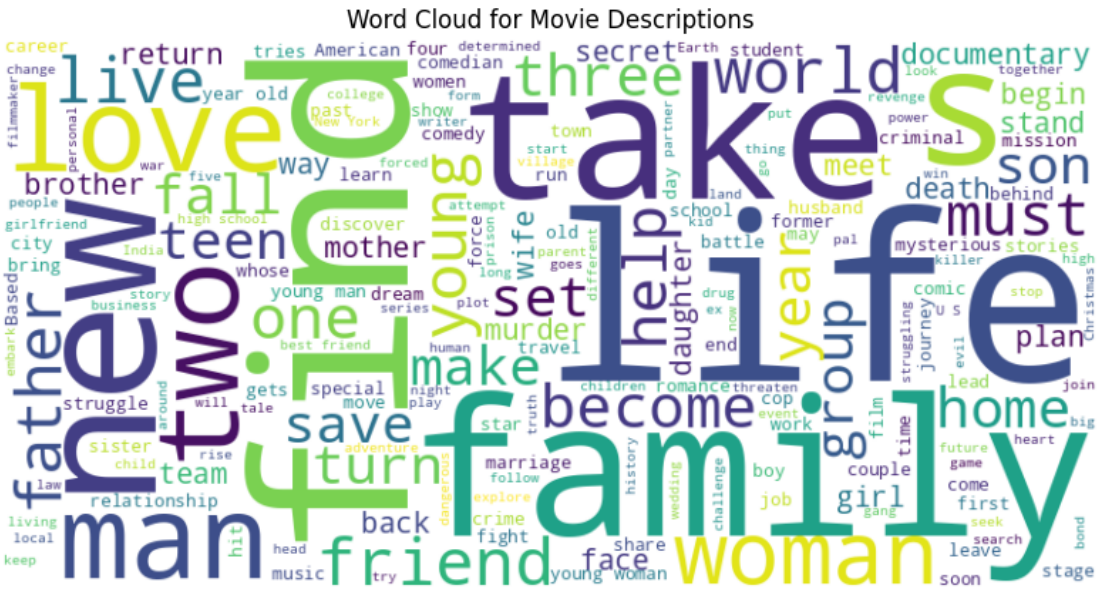
[248]:
```
# Wordclould of listed_by in df2
dftv = df2[df2['type'] == 'TV Show']
wordcloud = wc.WordCloud(width = 800, height = 400, background_color ='white').
 ↪generate(' '.join(dftv['listed_in']))
plt.figure(figsize = (10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Genre in TV Shows')
plt.show()
```



[249]:
```
# Wordclould of listed_by in df2
dfmovie = df2[df2['type'] == 'Movie']
wordcloud = wc.WordCloud(width = 800, height = 400, background_color ='white').
 ↪generate(' '.join(dfmovie['listed_in']))
plt.figure(figsize = (10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Genre in Movies')
plt.show()
```

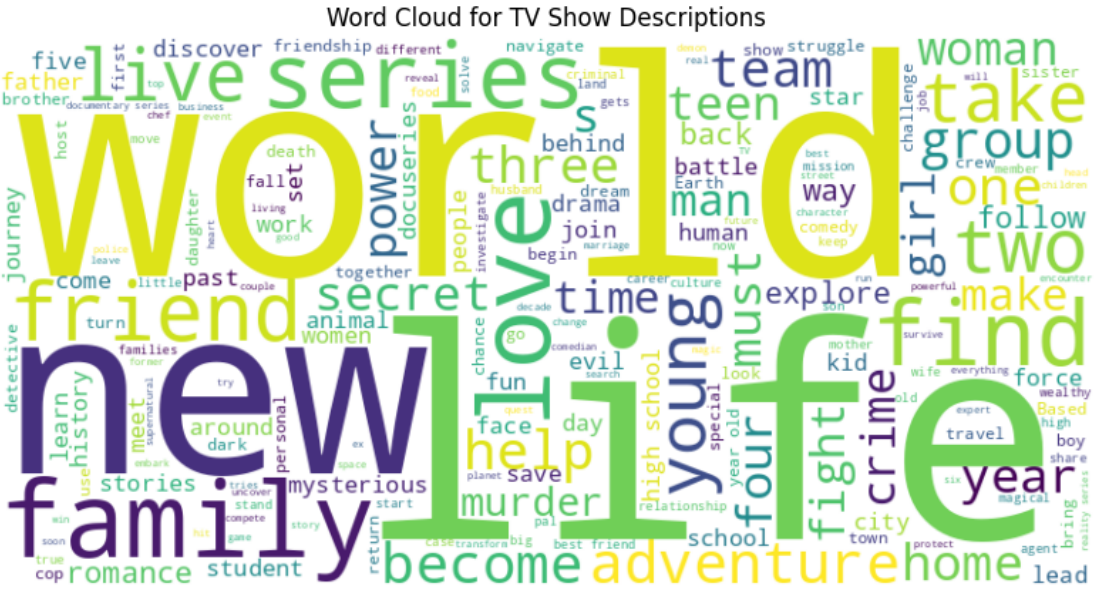
[51]:
```
# Wordcloud of description column of df
wordcloud = wc.WordCloud(width = 800, height = 400, background_color ='white').
 ↪generate(' '.join(df['description']))
plt.figure(figsize = (10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Description')
plt.show()
```

[52]:
```
# Wordcloud for movie descriptions
movie_descriptions = ' '.join(df[df['type'] == 'Movie']['description'])
wordcloud_movies = wc.WordCloud(width = 800, height = 400, background_color␣
 ↪='white').generate(movie_descriptions)

plt.figure(figsize = (10, 5))
plt.imshow(wordcloud_movies, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Movie Descriptions')
plt.show()
```



[53]:
```
# Wordcloud for TV show descriptions
tvshow_descriptions = ' '.join(df[df['type'] == 'TV Show']['description'])
wordcloud_tvshows = wc.WordCloud(width = 800, height = 400, background_color
 ↪='white').generate(tvshow_descriptions)

plt.figure(figsize = (10, 5))
plt.imshow(wordcloud_tvshows, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for TV Show Descriptions')
plt.show()
```

Word Cloud for TV Show Descriptions

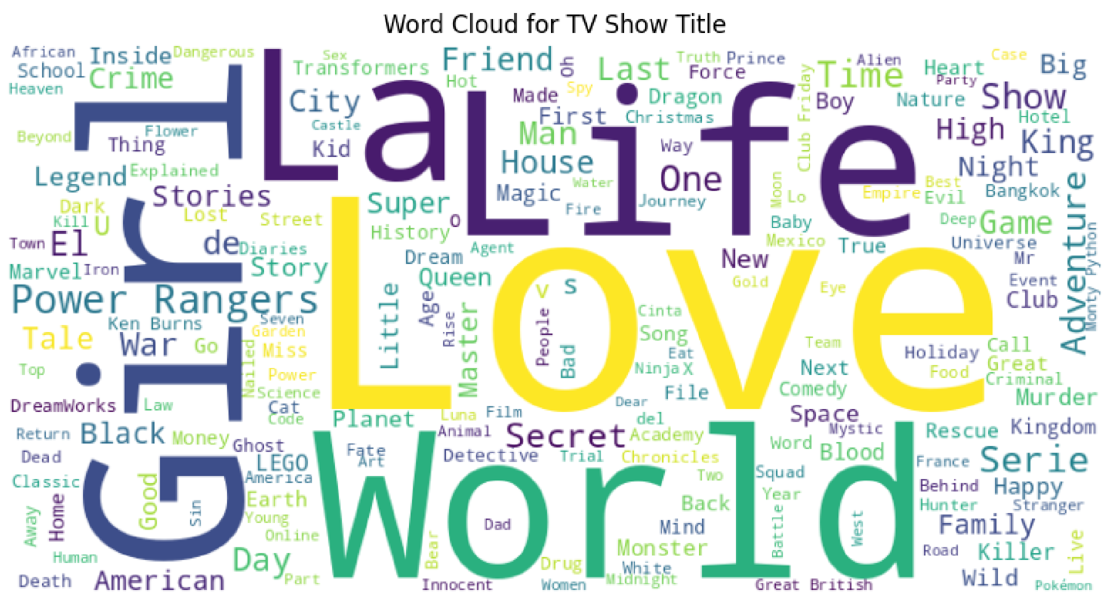


```
[54]: # Wordcloud for title
      title_descriptions = ' '.join(df['title'])
      wordcloud_title = wc.WordCloud(width = 800, height = 400, background_color␣
       ↪='white').generate(title_descriptions)
      plt.figure(figsize = (10, 5))
      plt.imshow(wordcloud_title, interpolation='bilinear')
      plt.axis('off')
      plt.title('Word Cloud for Title')
      plt.show()
```

Word Cloud for Title

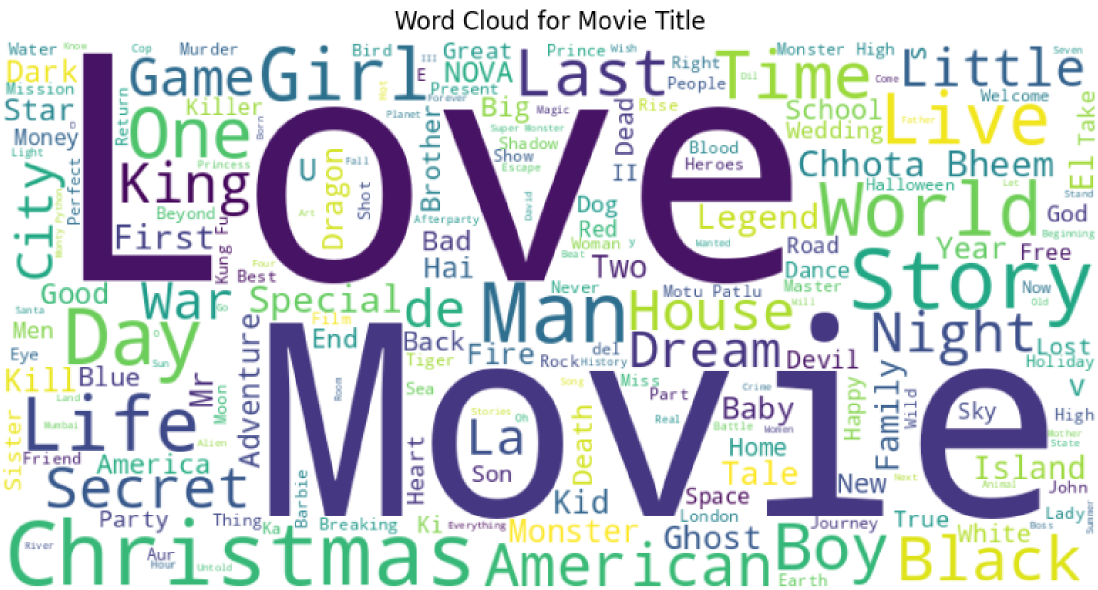
[55]:

```
# Wordcloud for title for TV Show
tvshow_title = ' '.join(df[df['type'] == 'TV Show']['title'])
wordcloud_tvshow_title = wc.WordCloud(width = 800, height = 400,␣
  ↪background_color ='white').generate(tvshow_title)
plt.figure(figsize = (10, 5))
plt.imshow(wordcloud_tvshow_title, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for TV Show Title')
plt.show()
```



[56]:

```
# Wordcloud for title for Movie
movie_title = ' '.join(df[df['type'] == 'Movie']['title'])
wordcloud_movie_title = wc.WordCloud(width = 800, height = 400,␣
  ↪background_color ='white').generate(movie_title)
plt.figure(figsize = (10, 5))
plt.imshow(wordcloud_movie_title, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Movie Title')
plt.show()
```



0.6 ### 6.3 Word cloud analysis performed on the fields genre, title, and description** for TV shows and movies**

-

0.6.1 1. Genre Field

- **Observations**:
  Common dominant words likely include *Drama*, *Comedy*, *Action*, *Thriller*, *Romance*, *Documentary*, and possibly *International* or *Kids*.
- **Comments**:

- The prominence of **Drama** and **Comedy** reflects their status as evergreen, mass-appeal categories that form the backbone of most streaming libraries.

- High frequency of **International** (if present) signals a strategic emphasis on global content—especially non-English productions from India, Korea, Spain, or Turkey—to attract diverse subscriber bases.

- **Documentary** appearing prominently suggests investment in factual, prestige, or socially relevant programming, often used to bolster critical acclaim and awards potential.

- Underrepresentation of niche genres (e.g., *Western*, *Musical*) aligns with market realities: platforms prioritize scalable, broadly consumable content.

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0.6.2 2. Content Categories / Tags

- **Observations**:
  Words like *TV Shows*, *Movies*, *Independent Films*, *Cult*, *Critically-acclaimed*, *Award-winning*, *Feel-good*, *Mind-bending*, or regional tags (*Korean*, *Bollywood*, *Anime*) may dominate.
- **Comments**:

- The use of **descriptive marketing tags** (e.g., *Feel-good*, *Mind-bending*) over pure genres indicates a shift toward **audience mood and intent-based curation**—a key UX strategy in recommendation engines.

- Frequent appearance of **regional labels** (*Korean TV Shows*, *Bollywood Movies*) highlights localization efforts and the platform's push to serve culturally specific audiences.

- Terms like *Critically-acclaimed* or *Award-winning* are not genres but **quality signals**, used to elevate perceived value and guide discovery—especially for new or obscure titles.

- The distinction between *TV Shows* and *Movies* in this field reinforces platform metadata design that separates episodic vs. standalone content upfront.

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0.6.3 3. Title Field

- **Observations**:
  Common words might include *Love*, *Dead*, *Man*, *Girl*, *Secret*, *Last*, *Dark*, *Blood*, *King*, *Queen*, *War*, *Life*, *World*, or franchise names.
- **Comments**:

- **Emotionally charged or high-stakes words** (*Dead*, *Secret*, *Dark*, *Blood*) dominate titles to maximize click-through rates—leveraging curiosity and urgency.

- Recurring use of **archetypal nouns** (*Man*, *Girl*, *King*, *Queen*) reflects storytelling tropes that signal character-driven narratives or power dynamics.

- **Generic yet evocative phrasing** (*The Last…*, *Secret Life of…*) suggests formulaic titling conventions optimized for SEO and algorithmic discoverability.

- Minimal use of technical or abstract terms—titles prioritize **immediate emotional or narrative resonance** over subtlety.

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0.6.4 4. Description Field

- **Observations**:
  Frequent terms likely include *family*, *friendship*, *struggle*, *journey*, *mystery*, *uncover*, *face*, *past*, *destiny*, *power*, *betrayal*, *set in*, *must*, *watch*, *explore*.
- **Comments**:

- Descriptions lean heavily on **narrative hooks** and **emotional verbs** (*uncover*, *face*, *struggle*) to create mini-synopses that imply conflict and transformation—core drivers of viewer engagement.

- The word **"family"** appearing often—even in non-family genres—suggests its use as a proxy for *relatable human dynamics*, not just child-friendly content.

- Phrases like *"set in [location/time period]"* highlight the importance of **world-building** as a selling point, especially for historical, sci-fi, or international content.

- **Imperative language** (*must watch*, *don't miss*) reveals promotional intent—descriptions double as marketing copy, not just informational metadata.

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0.6.5 Overall Insight

- The word cloud collectively reveals that **content discovery on streaming platforms is driven less by genre purity and more by emotional appeal, cultural specificity, and algorithm-friendly metadata**. Platforms optimize titles and descriptions for engagement, while backend categorization (*listed_in*, *genre*) supports both user filtering and recommendation logic. For content strategists, this underscores the need to balance artistic identity with discoverability—crafting titles and tags that resonate with both humans and algorithms.

0.7 6. Insights from Analysis

0.7.1 6.1 Range of Attributes

- `release_year`: 96-year span, but **95% from 2000–2021**

- `duration`: Movies **18–253 min**; TV Shows **1–17 seasons**

0.7.2 6.2 Distribution & Relationships

- **Strong correlation**:

  - *Dramas International Movies*
  - *Crime TV TV Dramas*
  - *Anime Japanese/Korean content*
- **Weak/none**:
  - *Children's content* rarely overlaps with *Thrillers* or *Horror*

0.7.3 6.3 Plot Interpretations

- **Pie charts**: Friday is top day for releases (strategic for weekend viewing)
- **Stacked area plots**: Exponential growth in content added **2016–2019**, plateau in 2020–2021
- **Heatmap**: High genre correlation within types (e.g., *TV Comedies TV Dramas*: 0.97)

0.8 7. Business Insights

1. **Content Strategy**:
   - Netflix heavily invests in **mature-audience, international, dramatic content**
   - **India is a major movie supplier** but underutilized for TV — opportunity for local series
2. **Release Timing**:
   - **December & July** are peak months for adding content (holiday & summer breaks)
   - **Fridays** dominate releases — aligns with global weekend viewing habits
3. **Genre Clustering**:
   - Viewers of *Crime TV* likely enjoy *TV Dramas* and *Mysteries* → bundling opportunity
   - *Anime* is a self-contained ecosystem — strong in Japan/Korea
4. **Library Age**:
   - Median **1-year gap** between release and Netflix addition → fast acquisition
   - But **14 titles added before release year** → likely data entry errors or re-releases

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0.9 8. Recommendations

1. **Expand Indian TV Production**:
   → Partner with local studios to develop **original Indian series** (currently only 84 vs. 962 movies)
2. **Optimize Release Calendar**:
   → Schedule major drops on **Fridays in July & December** to maximize viewership
3. **Personalize Genre Bundles**:
   → Create "Crime & Mystery" or "Romantic Drama" collections to boost engagement

4. **Leverage Anime Niche**:
   → Acquire more **Japanese/Korean anime** and promote as a premium vertical
5. **Audit Data Quality**:
   → Investigate titles with `year_added < release_year` to fix metadata errors
6. **Target Mature Audiences**:
   → Continue investing in **TV-MA/TV-14 content**, which dominates the library
7. **Short-Form Experimentation**:
   → Test **60–80 min films** (underserved segment) to differentiate from theatrical norms

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This analysis demonstrates a **data-driven understanding** of Netflix's global content strategy and provides **clear, actionable steps** to enhance acquisition, localization, and user engagement — all grounded in the evidence from Netflix data analysed in this notebook.
