Netflix Exploratory Data Analysis

Introduction

In this notebook, I'll give an Exploratory Data Analysis of the Netflix dataset from Kaggle. We will explore the data and hopefully bring some insights.

- We will unveil;
  - the distribution of genres,
  - the distribution of countries,
  - the distribution of countries, and
  - the distribution of duration
- We will see yearly and monthly contents and how many are those.
- We will understand insides of contents by examining content description using WordCloud

For visualizations I used; seaborn, pyplot, plotly, wordCloud and missingno. Some of the visuals interactive, and some of it static. But there's a lot improve. Feedbacks are welcome.

Dataset: https://www.kaggle.com/datasets/shivamb/netflix-shows

The Outline of this notebook is as follows

1. Basic Data Exploration
   - Feature Exploration
   - Summary Statistics
2. Data Cleaning
   - Null Value Analysis
   - Checking Dublicate Values
   - Handling inconsistent or incorrect data
3. Exploratory data analysis (What is the Story Of Data)

Importing Libraries and Loading the Dataset

In [1]:
```
# Import Relevant Packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import missingno as msno
from wordcloud import WordCloud
```

In [2]:
```
# Load Data set
df = pd.read_csv('data_sets/netflix_titles.csv')
```

Basic Data Exploration

1. Feature Exploration
2. Summary Statistics

1. Feature Exploration

First, let us take a look at a quick peek of what the first three rows in the data has in store for us and what features we have

In [3]:
```
# First 3 Data
df.head(3)
```

Out[3]:

	show_id	type	title	director	cast	country	date_added	release_year	rating	duration	list
0	s1	Movie	Dick Johnson Is Dead	Kirsten Johnson	NaN	United States	September 25, 2021	2020	PG-13	90 min	Documen
1	s2	TV Show	Blood & Water	NaN	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...	South Africa	September 24, 2021	2021	TV-MA	2 Seasons	Interna TV Show Drama Mys
2	s3	TV Show	Ganglands	Julien Leclercq	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...	NaN	September 24, 2021	2021	TV-MA	1 Season	Crir S Interna TV Shov

In [4]:
```
df.columns
```

Out[4]:
```
Index(['show_id', 'type', 'title', 'director', 'cast', 'country', 'date_added',
       'release_year', 'rating', 'duration', 'listed_in', 'description'],
      dtype='object')
```

In this dataset we have,

- Type identifier; Movie or Tv Show
- Titles
- Directors
- Actors
- Country where the Movie or Tv Show was produced
- Date it was added on Netflix
- Actual Release year of the Content
- Ratings
- Total Duration - in minutes or number of seasons

Next, let us take a look at how large the data is:

In [5]:
```
df.shape
```

Out[5]:
```
(8807, 12)
```

We have 8807 Entity from 12 Feature

Okay. Lets look What types of data we have

In [6]:
```python
# Data types in columns
df.info()
```

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

We Have:

- 11 Categorical Feature
- 1 Numeric Feature

2. Summary Statistics

Here we can see basic statistics in the data

In [7]:
```python
# Summary statistics for numerical features
numerical_features = df.select_dtypes(include='number')
# We have only 'release_year' as a numeric feature
numerical_features.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
release_year	8807.0	2014.180198	8.819312	1925.0	2013.0	2017.0	2019.0	2021.0

Content release year analysis looks like this;

- We have content that has been the released year 1925 to 2021.
- We have the mean year 2014
- We have a standard deviation of ~ 8.82 and this can show us; we have release_year data spreads from 1925 to 2021, probably we have outliers mostly from 1925 to 2014

In [8]:
```python
# Summary statistics for categorical features
categorical_features = df.select_dtypes(include='object')
categorical_features.describe().T
```

Out[8]:

	count	unique	top	freq
show_id	8807	8807	s1	1

type	8807	2	Movie	6131
title	8807	8807	Dick Johnson Is Dead	1
director	6173	4528	Rajiv Chilaka	19
cast	7982	7692	David Attenborough	19
country	7976	748	United States	2818
date_added	8797	1767	January 1, 2020	109
rating	8803	17	TV-MA	3207
duration	8804	220	1 Season	1793
listed_in	8807	514	Dramas, International Movies	362
description	8807	8775	Paranormal activity at a lush, abandoned prope...	4

We can see in this summary; frequency of data, unique values, and most repeated data

Data Cleaning

1. Null Value Analysis
2. Checking Dublicate Values
3. Handling inconsistent or incorrect data

1. Null Value Analysis

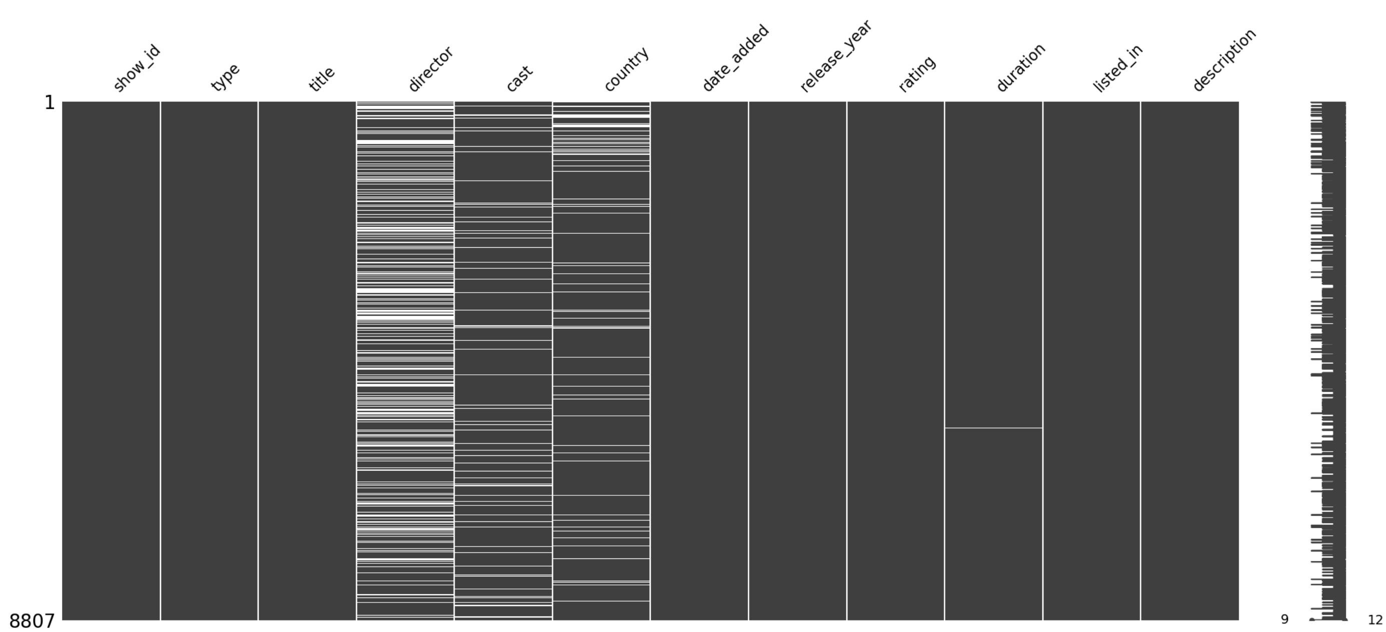
In [9]:
```
# Is there any null value in dataset
df.isnull().values.any()
```

Out[9]:
```
True
```

WE have null values in dataset, but where?

In [10]:
```
# Which features have how much null values?
msno.matrix(df)
```

Out[10]:
```
<Axes: >
```



As we can see, the missing values now become much more apparent and clear when we visualize it. White bands shows us missing data values and dark gray ones are non-missing data.

- We're seeing that dataset a lot of missing director data,
- And we have missing data on cast and country
- We have some missing data on duration

This visualization is really good seeing big picture of missing values. But We need specific number and percentage of missing values.

In [11]:
```
def missing_value_table(df, get_null_columns=False):
    # find columns that only have null values
    null_columns = [col for col in df.columns
                    if df[col].isnull().sum() > 0]

    # Null Value counts
    null_counts = df[null_columns].isnull().sum().sort_values(ascending=True)

    # Null Value Percentage
    null_value_rates = (df[null_columns].isnull().sum() / df.shape[0] * 100).sort_values
    formatted_null_value_rates = null_value_rates.apply(lambda value: f"% {str(np.round(

    # Null Value Table
    null_df = pd.concat([null_counts, formatted_null_value_rates],
                        axis=1, keys=["Null Value Count", "Null Value Rates"])
    print(null_df, end="\n")

    if get_null_columns:
        return null_columns


missing_value_table(df)
```

```
            Null Value Count Null Value Rates
duration                   3           % 0.03
rating                     4           % 0.05
date_added                10           % 0.11
cast                     825           % 9.37
country                  831           % 9.44
director                2634          % 29.91
```

In this table we have more knowledge for missing values

- These features are categorical types, for this reason, so it might be a good idea to eliminate conversion of these values to 'missing' data.

In [12]:
```
# Turn null values to 'missing'
columns_to_fill = missing_value_table(df, get_null_columns=True)
df[columns_to_fill] = df[columns_to_fill].fillna('missing')
```


```
            Null Value Count Null Value Rates
duration                   3           % 0.03
rating                     4           % 0.05
date_added                10           % 0.11
cast                     825           % 9.37
country                  831           % 9.44
director                2634          % 29.91
```


In [13]:
```
# Controlling null values again
df.isnull().sum()
```

Out[13]:
```
show_id          0
```

```
type            0
title           0
director        0
cast            0
country         0
date_added      0
release_year    0
rating          0
duration        0
listed_in       0
description     0
dtype: int64
```

Null Values are elimated

2. Checking Dublicate Values

Checking for duplicating values before EDA always a good idea

In [14]:
```
# Is there any duplicates
duplicated_rows = df[df.duplicated()]
print(f"Dublicates value number in dataset: {duplicated_rows.shape[0]}")
```

```
Dublicates value number in dataset: 0
```

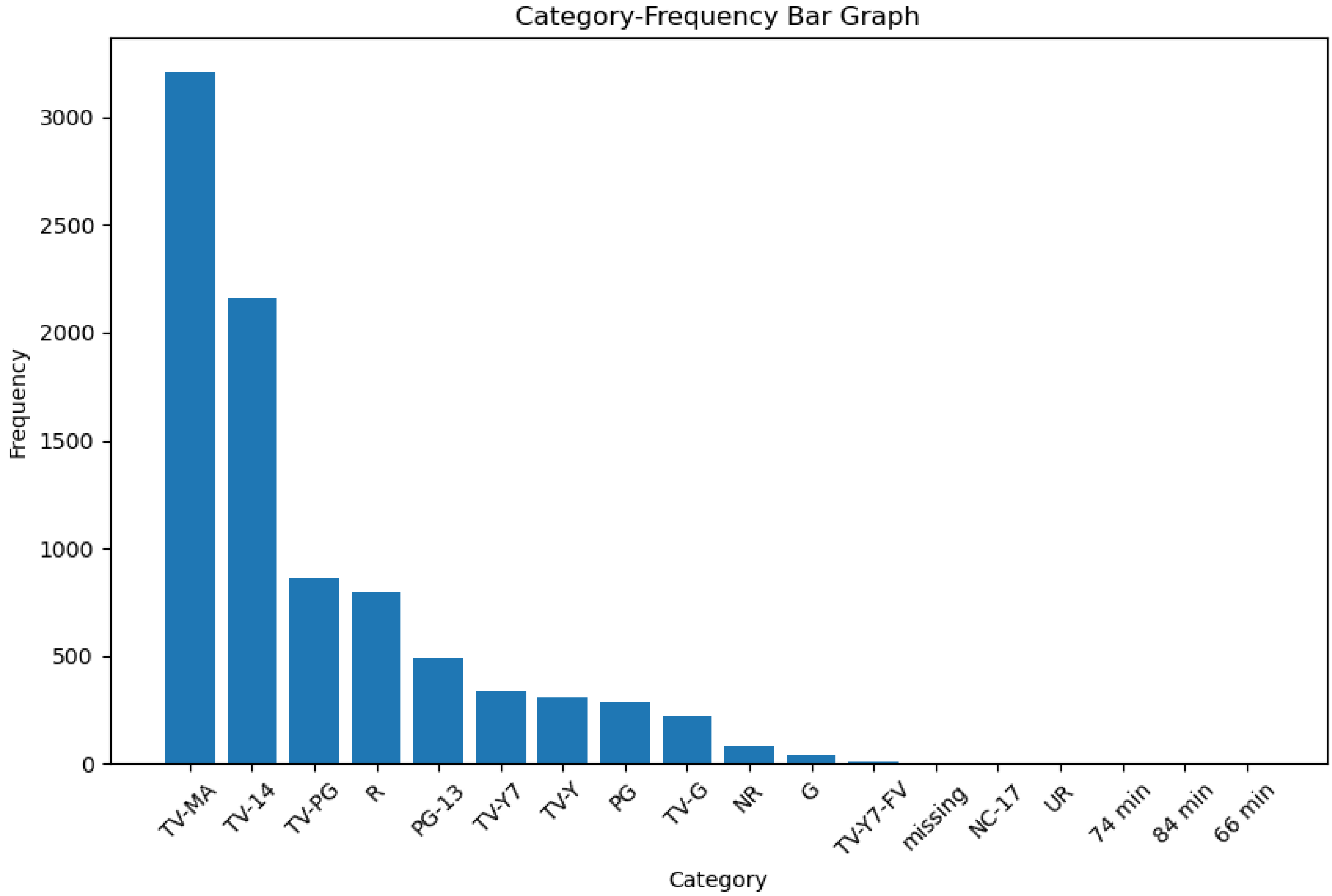
There is no dublicated value in dataset; **Good**

3. Handling inconsistent or incorrect data

We need to look for incorrect data. There's a lot of unique data in dataset, this is normal for movie or tv shows data. But we can look rating data, if it has incorrect data.

In [15]:
```
def plot_categorical_frequency(data, x_label, y_label, title):
    """Show Bar Frequency for categorical Features"""
    frequency_counts = data.value_counts()

    plt.figure(figsize=(10, 6))
    plt.bar(frequency_counts.index, frequency_counts.values)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title)
    plt.xticks(rotation=45)
    plt.show()
```

In [16]:
```
# 'rating' Feature
plot_categorical_frequency(df["rating"], "Category", "Frequency", "Category-Frequency Ba
```



with 'rating' frequency analysis we see three unwanted values entered: '74 min', '84 min', '66 min'

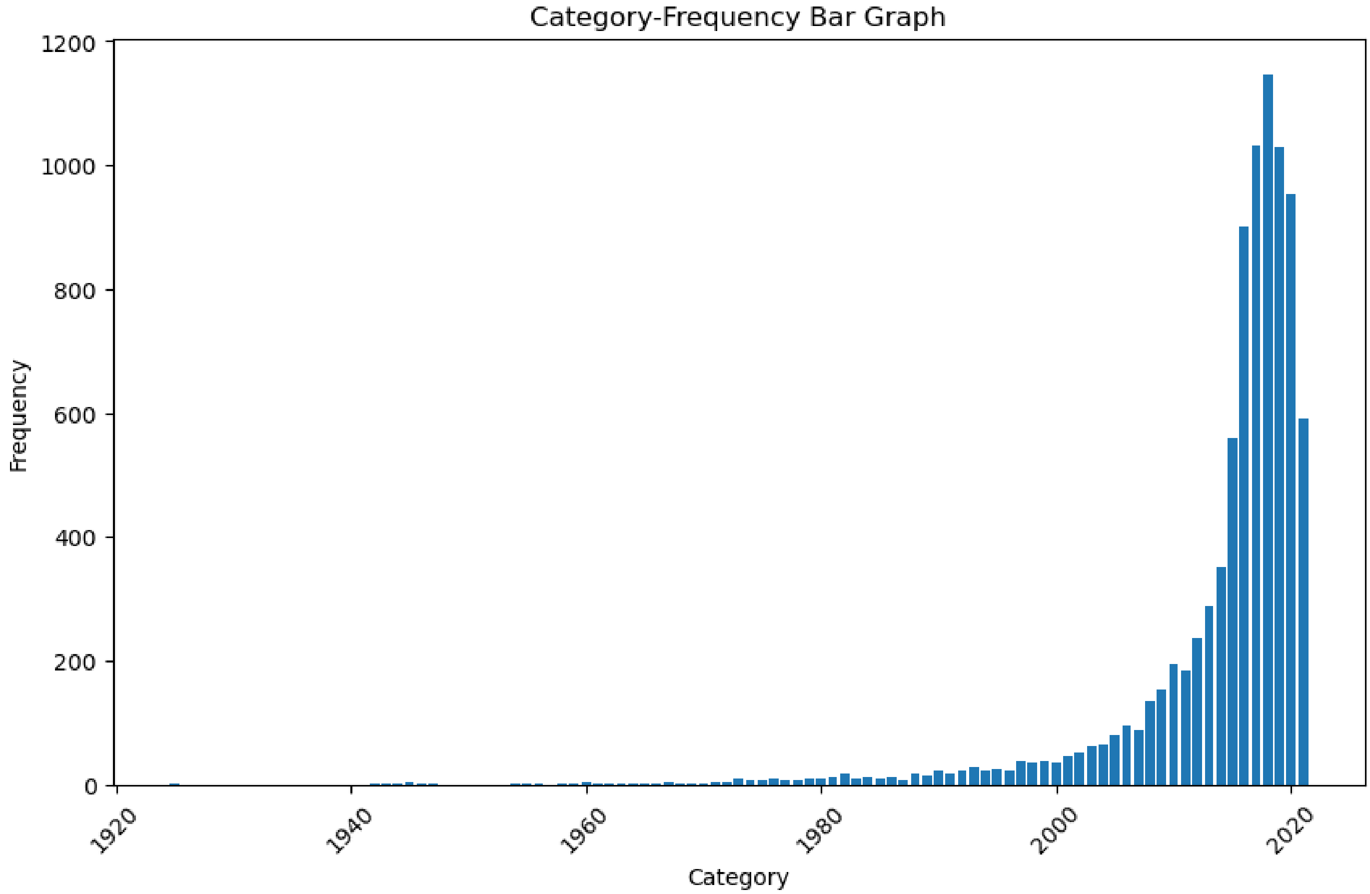
- We can eliminate these with turning values to 'UR'; Because UR means, *Unrated*
- And we can turn 'missing' values to 'UR' as well

In [17]:
```
# Change '74 min', '84 min', '66 min' Values to 'UR'
df['rating'] = np.where(np.isin(df['rating'], ['74 min', '84 min', '66 min', 'missing'])
```

We eliminated sneaky values in ratings.

Is There any sneaky values in release_year?

In [18]:
```
plot_categorical_frequency(df["release_year"], "Category", "Frequency", "Category-Freque
```



Seems like all of the data in release_year correct format

For other columns data we can't see wrong data's with visualizing it. Because unique value count is really high

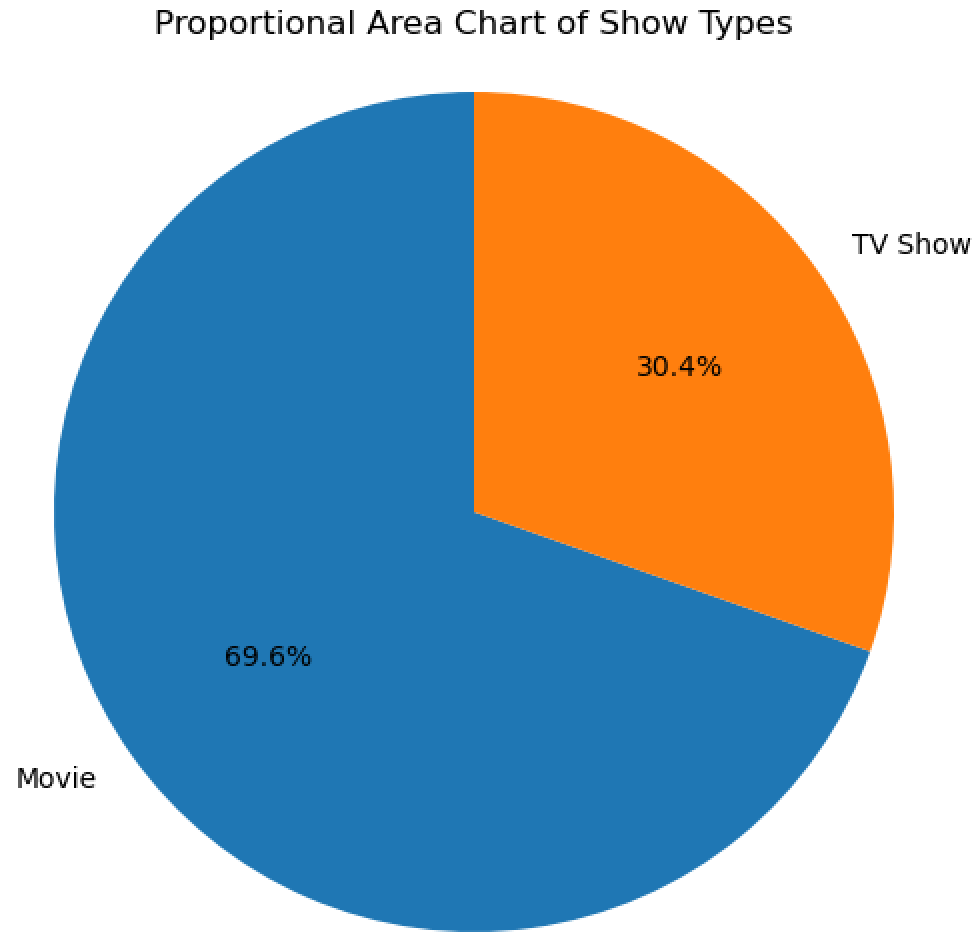
There's other ways to clean data's as well: bu this notebook I did not enter those. Now we can enter the EDA part.

EDA

1. Content Types

1. First, let's look at the percentage of movies and TV shows in the dataset.

In [19]:
```
type_counts = df['type'].value_counts()
total_shows = type_counts.sum()

# Calculate proportions
proportions = type_counts / total_shows

# Plotting the proportional area chart
plt.figure(figsize=(8, 6))
plt.pie(proportions, labels=proportions.index, autopct='%1.1f%%', startangle=90)
plt.axis('equal')
plt.title('Proportional Area Chart of Show Types')
plt.show()
```



Observations

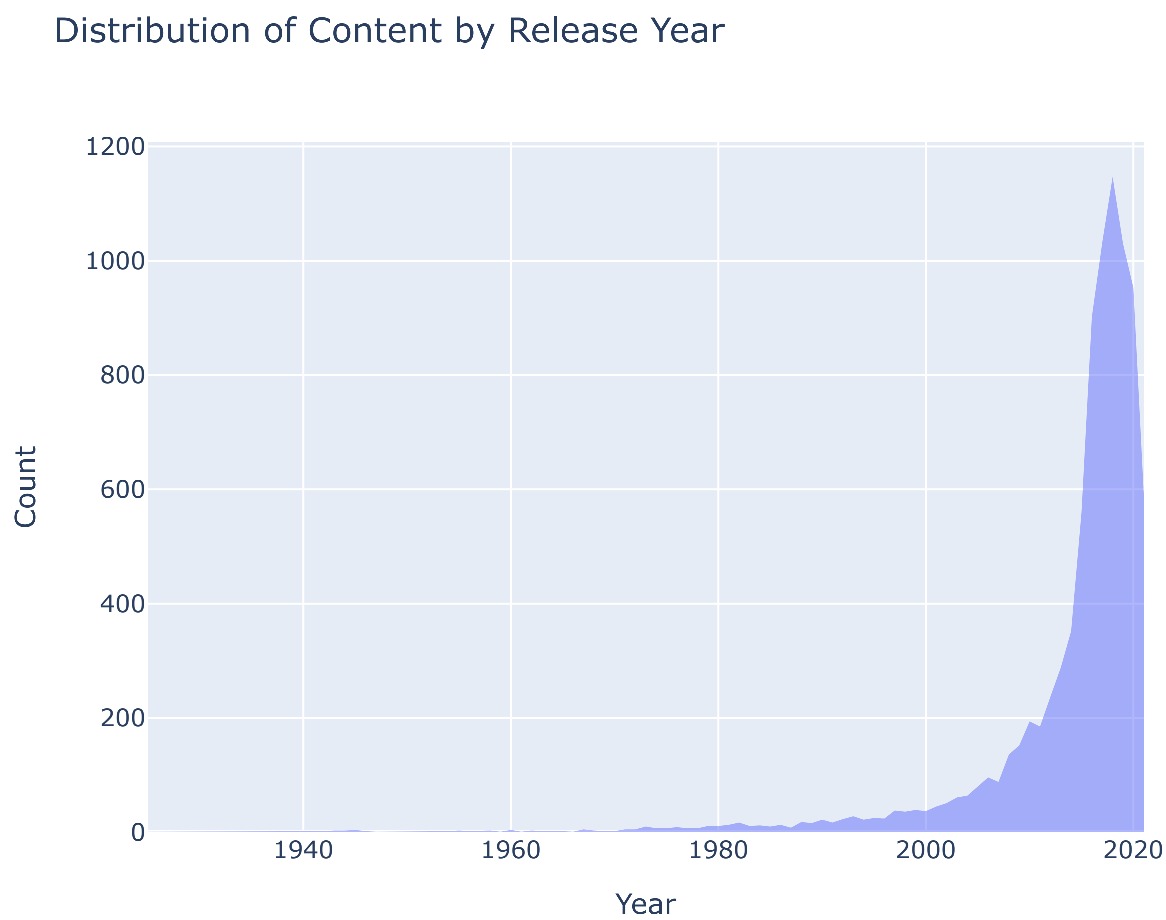
- We can see, Most of the content tends towards movies with 69.6% and others, TV Shows 30.4%.

2. Time Analysis

1. First, let's look at the distribution of content by **released years.**

In [20]:
```
# Count the occurrences of each year
year_counts = df['release_year'].value_counts().sort_index()

# Create a stacked area graph using Plotly
fig = go.Figure()

fig.add_trace(go.Scatter(
    x=year_counts.index,
    y=year_counts.values,
    mode='none',
    fill='tozeroy',
    hovertemplate='Year: %{x}<br>Count: %{y}<extra></extra>',
    name='Count'
))

# Customize the axes labels and title
fig.update_layout(
    xaxis=dict(title='Year'),
    yaxis=dict(title='Count'),
    title='Distribution of Content by Release Year'
)
```

```
# Show the stacked area graph
fig.show()
```



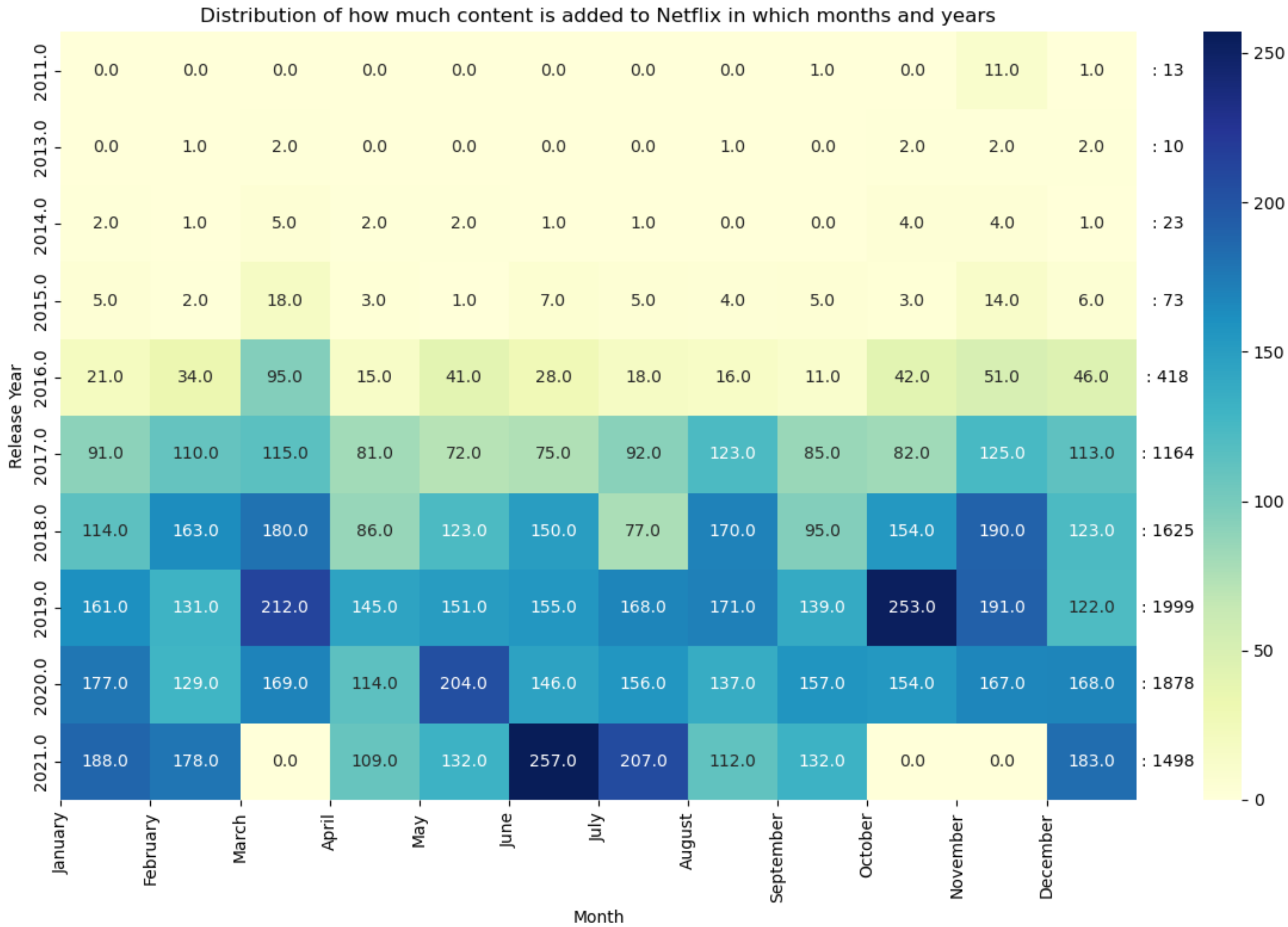
Observations

- Release year of contents are in mostly 2018 (1147), 2017 (1032), 2019 (1030)
- After 2010, we can see that movies or series are more concentrated.

1. We saw release years. But we need to look at another feature 'date_added' for understanding which year and month, and how much content was added to Netflix. Because the release of years of movies or TV Shows is different from the entrance of Netflix.

In [21]:
```
from datetime import datetime

# Helper function to parse date with varying formats
def parse_date(date_string):
    formats = ["%B %d, %Y", "%B %Y", "%Y"]
    for fmt in formats:
        try:
            return datetime.strptime(date_string, fmt).date()
        except ValueError:
            pass
    return None

# Filter out rows with 'missing' in the 'date_added' column
filtered_df = df[df['date_added'] != 'missing'].copy()

filtered_df['release_date'] = filtered_df['date_added'].apply(parse_date)
```

```python
filtered_df['release_date'] = pd.to_datetime(filtered_df['release_date'])

filtered_df['release_day'] = filtered_df['release_date'].dt.day
filtered_df['release_month'] = filtered_df['release_date'].dt.month_name()
filtered_df['release_year'] = filtered_df['release_date'].dt.year

# Count the occurrences of each release year
year_counts = filtered_df['release_year'].value_counts()

# Select the years with the most movies
top_years = year_counts.head(10).index

# Filter the data for the selected years
filtered_df = filtered_df[filtered_df['release_year'].isin(top_years)].copy()

# Count the occurrences of each release year and month combination
release_counts = filtered_df.groupby(['release_year', 'release_month']).size().unstack()

# Create a heatmap plot
plt.figure(figsize=(12, 8))  # Set the figure size
sns.heatmap(release_counts, cmap='YlGnBu', annot=True, fmt=".1f")

# Add labels and title
plt.xlabel('Month')
plt.ylabel('Release Year')
plt.title('Distribution of how much content is added to Netflix in which months and year

# Customize x-axis tick labels to show month names
month_labels = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
                'August', 'September', 'October', 'November', 'December']
plt.xticks(ticks=range(0, 12), labels=month_labels)

# Add total count annotations for each year below the bars
for i, year in enumerate(release_counts.index):
    plt.text(12.35, i + 0.5, f': {year_counts.loc[year]}', ha='center', va='center')

# Display the plot
plt.tight_layout()
plt.show()
```



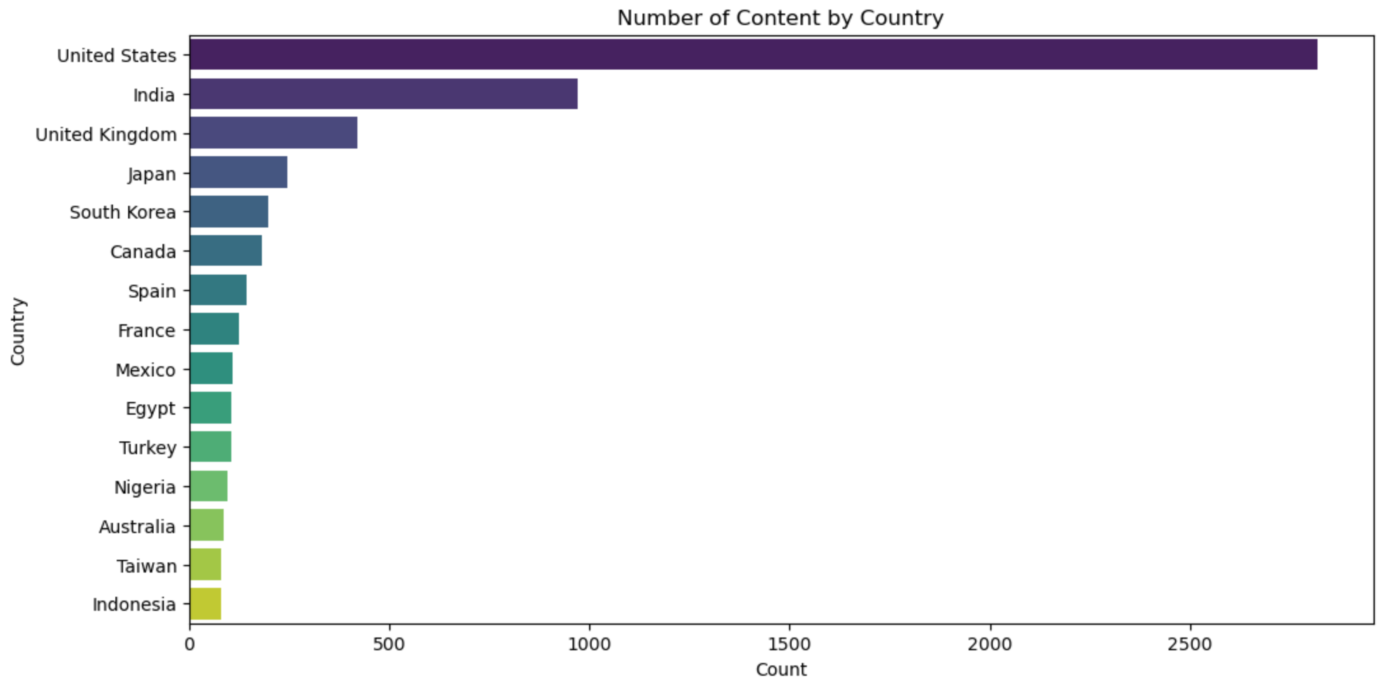
Observations

- There are differences between the release dates of the content and the dates it was added to Netflix. For Example;
  - In 2018, 1147 content was released to the world but Netflix had 1625 content that year
  - In 2015, 560 content was released to the world but Netflix had only 73 content that year
    - We can see that most of the content released in 2016 and before has been incorporated into the following years.
- And the density of content numbers in Netflix, from which we received the data, belongs to the years 2019 and 2020

3. Content Numbers by Country

In [22]:
```
# Filter out rows with 'missing' in the 'country' column
filtered_df = df[df['country'] != 'missing'].copy()

# Count the occurrences of each country
country_counts = filtered_df['country'].value_counts()

# Select the top 10 countries with the most content
top_countries = country_counts.head(15)

# Create a bar plot
plt.figure(figsize=(12, 6))   # Set the figure size
sns.barplot(x=top_countries.values, y=top_countries.index, palette='viridis')

# Add labels and title
plt.xlabel('Count')
plt.ylabel('Country')
```

```
plt.title('Number of Content by Country')

# Display the plot
plt.show()
```

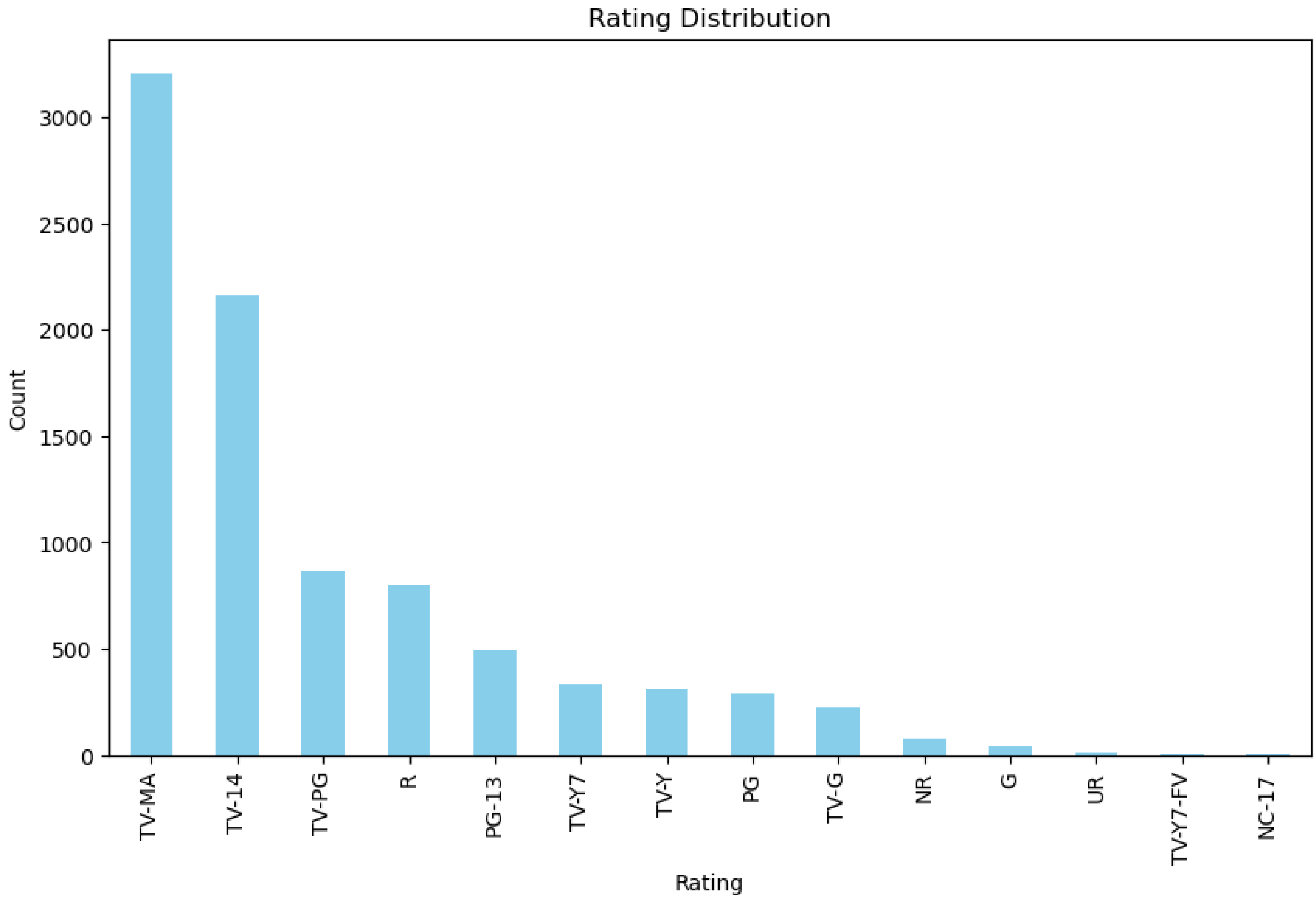


Observations

- We are seeing here, top 15 countries producing the most content
    - US, India, UK, Japan and South Korea on top

4. Rating analysis

In [23]:
```
# Filter out rows with 'missing' in the 'rating' column
filtered_df = df[df['rating'] != 'missing'].copy()

# Count the occurrences of each rating
rating_counts = filtered_df['rating'].value_counts()

# Create a bar plot
plt.figure(figsize=(10, 6))
rating_counts.plot(kind='bar', color='skyblue')

# Add labels and title
plt.xlabel('Rating')
plt.ylabel('Count')
plt.title('Rating Distribution')

# Display the plot
plt.show()
```



Observations

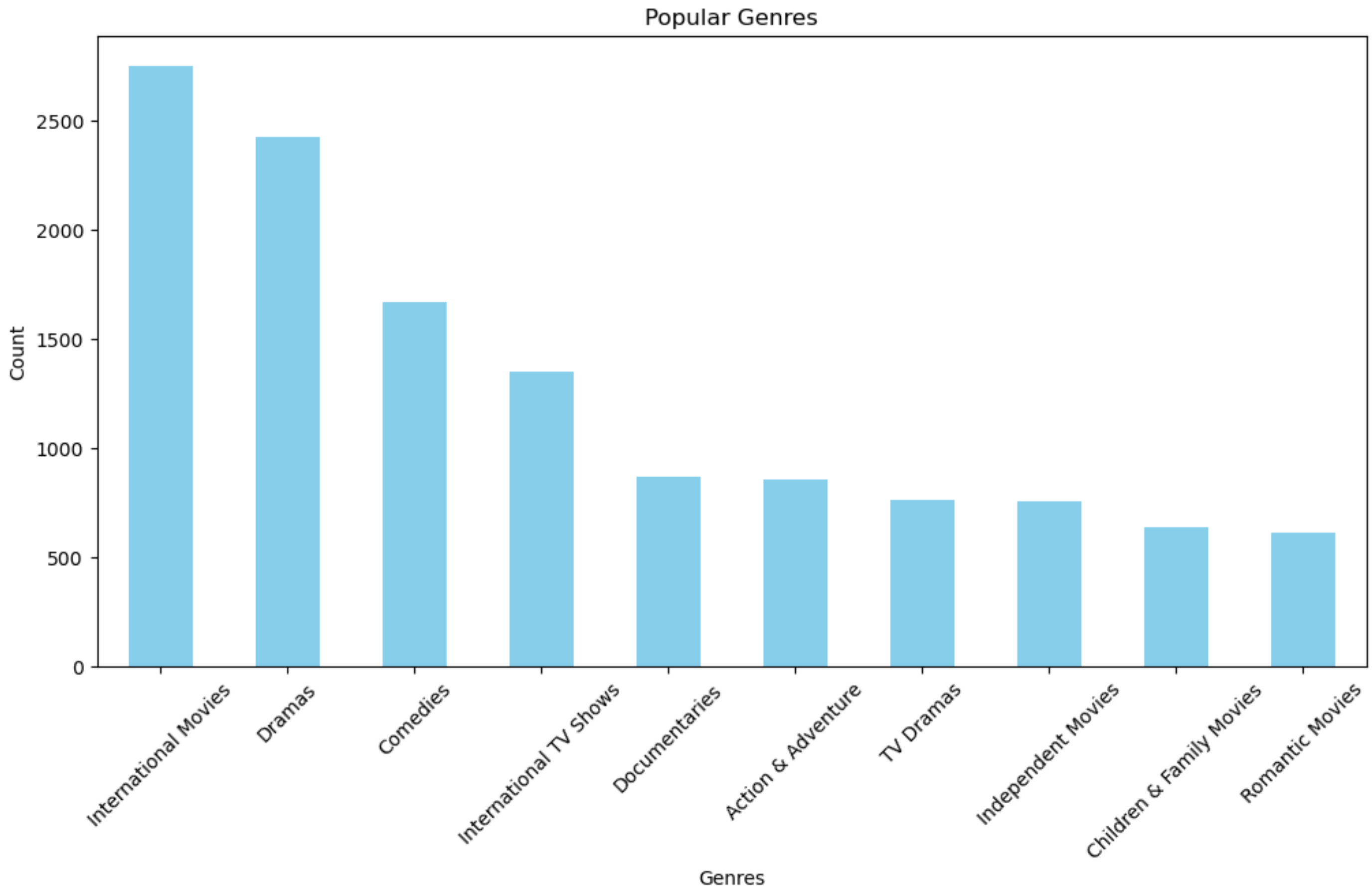
- Most used ratings TV-MA, TV-14, TV-PG is used in tv shows;
    - That means Tv shows mostly for Mature or 14+
- R rating in fourth place used in Movies;
    - That means Movies in Netflix mostly for Mature
- We can say Netflix better place for adult, and mature content

5. Popular Genres

In [24]:

```
# Extract the genres
genres = df['listed_in'].str.split(', ').explode()

# Count the occurrences of each genre
genre_counts = genres.value_counts()

# Select the top 10 popular genres
top_genres = genre_counts.head(10)

# Create a bar plot
plt.figure(figsize=(12, 6))
top_genres.plot(kind='bar', color='skyblue')

# Add labels and title
plt.xlabel('Genres')
plt.ylabel('Count')
plt.title('Popular Genres')

# Rotate x-axis labels for better visibility
plt.xticks(rotation=45)
```

```
# Display the plot
plt.show()
```



Observations

- Most Content in Netflix;
  - International Movies, Dramas and Comedies
- There is international Movies and Tv shows in top five, and I think this is good for Netflix. We can say, Netflix has users around the world.
- If we look just regular genres; Drama is first. Because drama mostly related almost every other genre. There's not a lot movies or TV Shows pure Drama.
- Other Coming genre is Comedies, and this is I think Obvious, because reel world losing funniness. We need to laugh more.

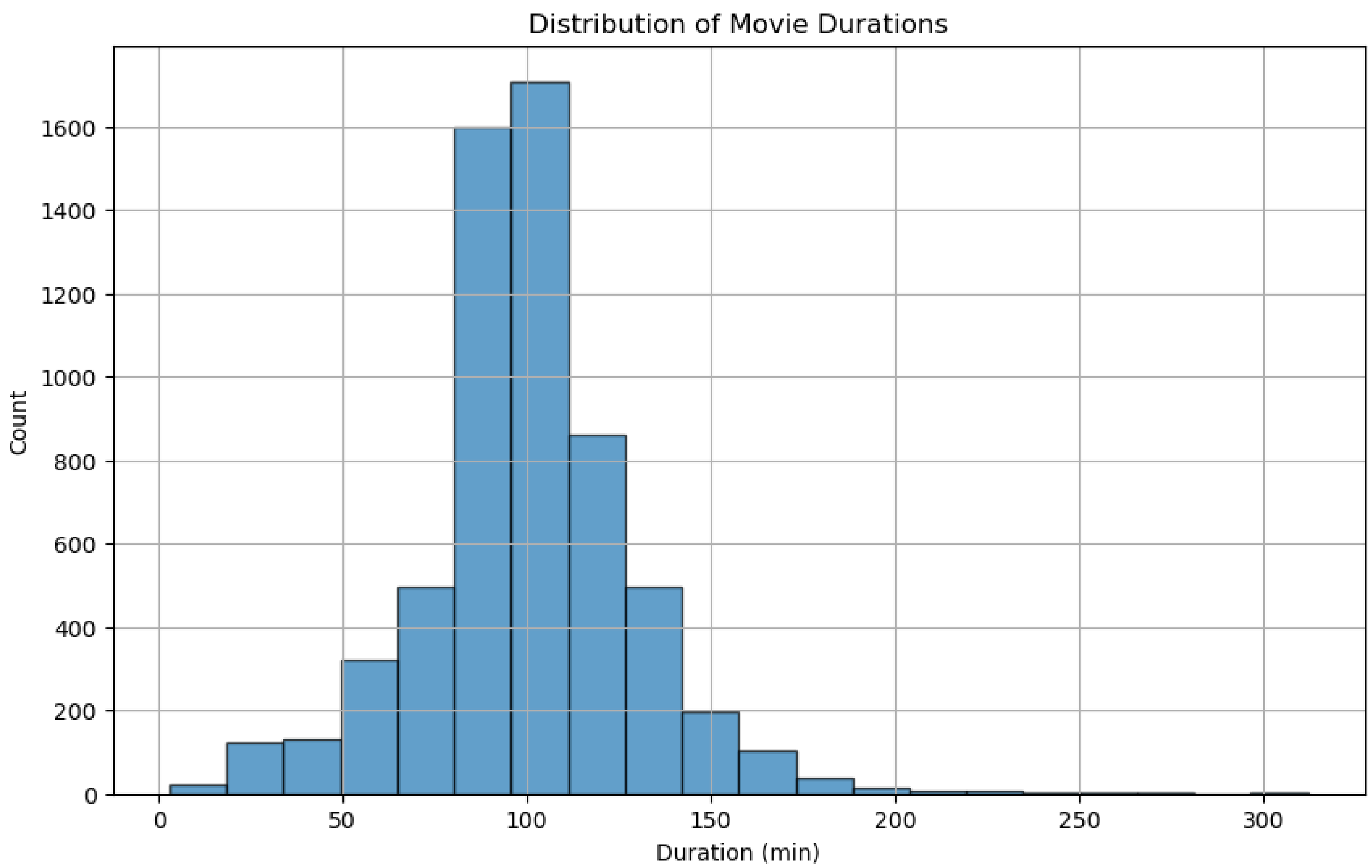
6. Duration Analysis

1. How do movies length change on netflix? Let's look.

In [25]:
```
# Extract the movie durations without 'missing' values
movie_durations = df[(df['type'] == 'Movie') & (df['duration'] != 'missing')]['duration'

# Convert the durations to numeric values (remove 'min' suffix)
movie_durations = movie_durations.str.replace(' min', '').astype(int)

# Calculate summary statistics
min_duration = movie_durations.min()
max_duration = movie_durations.max()
mean_duration = movie_durations.mean()
median_duration = movie_durations.median()

# Print the summary statistics
```

```
print("Duration Summary Statistics:")
print("Minimum duration: {} min".format(min_duration))
print("Maximum duration: {} min".format(max_duration))
print("Mean duration: {:.2f} min".format(mean_duration))
print("Median duration: {:.2f} min".format(median_duration))

# Create a histogram of movie durations
plt.figure(figsize=(10, 6))  # Set the figure size
plt.hist(movie_durations, bins=20, edgecolor='black', alpha=0.7)
plt.xlabel('Duration (min)')
plt.ylabel('Count')
plt.title('Distribution of Movie Durations')
plt.grid(True)
plt.show()
```

```
Duration Summary Statistics:
Minimum duration: 3 min
Maximum duration: 312 min
Mean duration: 99.58 min
Median duration: 98.00 min
```



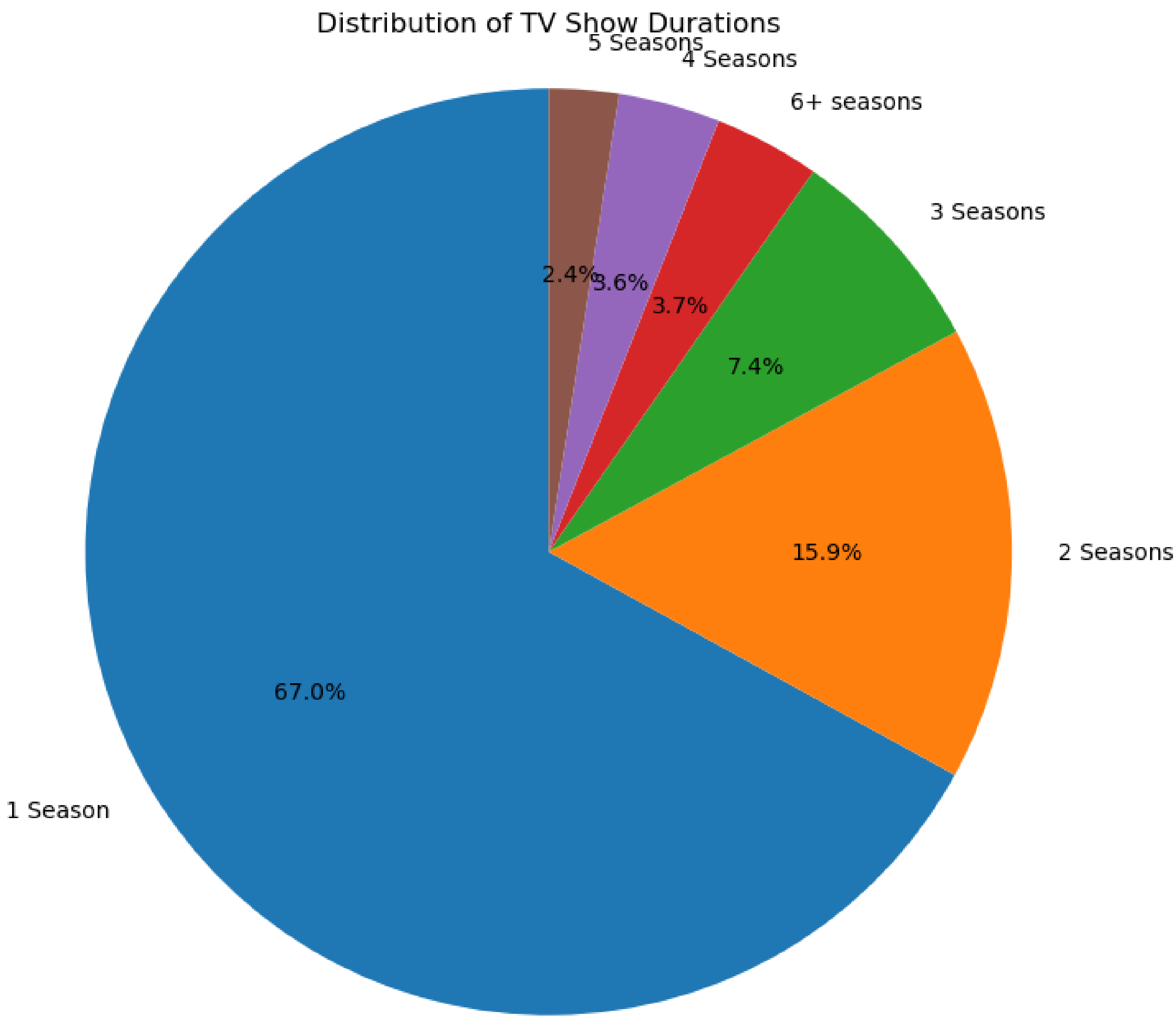
Observations

- The average movie length is around 100 minutes.
- And median is 98 minutes.
- Density of duration not really variant, we can see this from median and mean values, they are close to each other. We can say, around 100 min. ideal for audience.

1. What about TV Shows? Which season more on demand?

In [26]:
```
# Filter TV show durations without 'missing' values
tv_show_durations = df[(df['type'] == 'TV Show') & (df['duration'] != 'missing')]['durat

# Combine durations after 6 seasons into a single category
tv_show_durations = tv_show_durations.apply(lambda x: '6+ seasons' if int(x.split(' ')[0
```

```
# Count the occurrences of each duration
duration_counts = tv_show_durations.value_counts()

# Create a pie chart
plt.figure(figsize=(8, 8))
plt.pie(duration_counts, labels=duration_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Distribution of TV Show Durations')

# Equal aspect ratio ensures that pie is drawn as a circle
plt.axis('equal')

# Display the chart
plt.show()
```



Observations

- 67% of tv shows are 1 season, short and sweet.
- 2 seasons tv shows are 15.9% and 3 seasons tv shows are 7.4% and keeps decreasing. That's normal because, sometimes I want to sit and binge a TV Show. This is imposable if I want to watch Dexter again.

7. Word Cloud From Content Descriptions

By looking at the descriptions of the content of movies or TV series, we can say how the content is consumed more. There is always a supply and demand relation.

In [27]:
```
# Filter out missing description values
description_data = df[df['description'] != 'missing']['description']

# Join all the cast names into a single string
description_text = ' '.join(description_data)

# Generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(descript

# Create a figure and axes
fig, ax = plt.subplots(figsize=(15, 10))

# Display the word cloud
ax.imshow(wordcloud, interpolation='bilinear')
ax.set_title('Description Analysis - Word Cloud')
ax.axis('off')

# Show the plot
plt.show()
```

Description Analysis - Word Cloud

Observations

- We can see most used words in here. And we can say in here, which sides more important for us in life.
  - Of course ***Life*** is itself more important than everything,
  - Maybe ***find***ing ***love*** and creating a great ***family*** with good ***friend***s
  - With these comes a ***new world*** for us.
  - In ***year***s ***man become*** a ***father*** and ***woman become*** a ***mother***.
  - To ***discover life must*** first ***fall***
  - ***Make***ing a good ***home*** needs a ***battle***