# Descriptive Statistics on API Data

June 20, 2022

## 1 Final Project - Movie Reviews Analysis

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- Date: 06/20/2022

## 2 Packages

[1]:
```python
import pandas as pd
import numpy as np
import requests
import seaborn as sns
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from requests import TooManyRedirects
import re
import omdb
import time
from collections import Counter, defaultdict
import nltk
#nltk.download('stopwords')
from nltk.corpus import stopwords
from string import punctuation
sw = stopwords.words("english")
```

---

## 3 Loading the Raw Data from API

[2]:
```python
# Read in csv data as pandas data frame
movies_info = pd.read_csv("Raw Movie Data.csv")
# see a random subset of 15 samples
movies_info.shape
```

[2]: (5000, 25)

[3]:
```python
movies_info.sample(10)
```

[3]:

```
                                              title  year  rated  \
351                               One Under the Sun  2017  TV-14
2313                                     Square One  2013    NaN
2518  You Are the One: The Claudine-Raymart Love Story  2006    NaN
4525                              One Day Over L.A.  2014    NaN
38                                The Son of No One  2011      R
3123                           One Sight, One Sound  2009    NaN
4544                       One Day in Perfect Health  1950    NaN
2639                               One Black Coffee  2019    NaN
507    One Damned Day at Dawn… Django Meets Sartana!  1970    NaN
1224           One Direction: What Makes You Beautiful  2011    NaN

         released  runtime                          genre  \
351   14 Mar 2017  101 min          Drama, Mystery, Sci-Fi
2313  15 Aug 2013   15 min                   Short, Comedy
2518  26 Mar 2006      NaN             Documentary, Music
4525          NaN    3 min  Documentary, Short, Adventure
38    09 Jul 2011   90 min            Action, Crime, Drama
3123          NaN   75 min             Documentary, Music
4544          NaN   18 min             Documentary, Short
2639  30 Mar 2019      NaN                          Short
507   25 Jun 1970   90 min                        Western
1224  19 Aug 2011    3 min                   Short, Music

                            director                               writer  \
351   Riyaana Hartley, Vincent Tran     Katherine Tomlinson, Vincent Tran
2313                  Emanuel Parvu                         Emanuel Parvu
2518                            NaN                                   NaN
4525                    Cole Kawana                  Cole Kawana (story)
38                     Dito Montiel                          Dito Montiel
3123                   Josh Pomponio                                  NaN
4544                     John Krish                                   NaN
2639                   Manoj Mathew                          Manoj Mathew
507                  Demofilo Fidani  Demofilo Fidani, Mila Vitelli Valenza
1224                     John Urbano                                  NaN

                                                actors  \
351             Pooja Batra, Gene Farber, Michael Keeley
2313  Dorian Boguta, Dorina Lazar, Emanuel Parvu, Co…
2518  Claudine Barretto, Raymart Santiago, Dennis Pa…
4525                                               NaN
38          Channing Tatum, Al Pacino, Juliette Binoche
3123                                               NaN
4544                                               NaN
2639  Manoj Mathew, Babli Das, Kasturi Banerjee, Tar…
507                 Jack Betts, Fabio Testi, Dino Strano
1224  One Direction, Harry Styles, Louis Tomlinson, …
```

```
                                                   plot  … metascore  \
351   Astronaut Kathryn Voss, sole survivor of a dis…  …       NaN
2313                                                NaN  …       NaN
2518                                                NaN  …       NaN
4525  Harvard-Westlake sophomore Cole Kawana flies h…  …       NaN
38    A young cop is assigned to a precinct in the w…  …      36.0
3123  September-November 2008; three months with the…  …       NaN
4544                                                NaN  …       NaN
2639                                                NaN  …       NaN
507   Framed for a bank robbery, bounty killer Djang…  …       NaN
1224  Official music video for "What Makes You Beaut…  …       NaN

     imdb_rating imdb_votes     imdb_id   type          dvd  box_office  \
351          3.5        612   tt5110386  movie  14 Mar 2018         NaN
2313         6.6          7   tt6479182  movie          NaN         NaN
2518         5.3          5   tt0787250  movie          NaN         NaN
4525         NaN        NaN   tt4540802  movie          NaN         NaN
38           5.1     17,137   tt1535612  movie  21 Feb 2012     $30,680
3123         NaN        NaN   tt1567653  movie          NaN         NaN
4544         NaN        NaN   tt2064890  movie          NaN         NaN
2639         NaN        NaN  tt11062440  movie          NaN         NaN
507          4.9        329   tt0067643  movie          NaN         NaN
1224         7.2         45   tt7318548  movie          NaN         NaN

     production website response
351         NaN     NaN     True
2313        NaN     NaN     True
2518        NaN     NaN     True
4525        NaN     NaN     True
38          NaN     NaN     True
3123        NaN     NaN     True
4544        NaN     NaN     True
2639        NaN     NaN     True
507         NaN     NaN     True
1224        NaN     NaN     True

[10 rows x 25 columns]
```

---

# 4 Exploratory Data Analysis

1. Examine a five-number summary of the numerical and categorical columns
2. Checking for Missing Data
3. Plotting Value Distribtuions
4. Comparing Value Distributions Across Categories

## 4.1 1. Calculating Summary Statistics for Columns

[4]:
```
# Create a new column to look at the length of each plot
movies_info['plot_length'] = movies_info['plot'].str.len()

# 5 number summary of the numerical columns
movies_info.describe().T
```

[4]:
```
              count         mean        std     min     25%     50%     75%  \
year         5000.0  2002.897000  23.082681  1887.0  2002.0  2011.0  2016.0
metascore     115.0    60.026087  18.559747    16.0    47.0    62.0    74.0
imdb_rating  2442.0     6.591155   1.386458     1.0     5.8     6.7     7.5
plot_length  3560.0   159.808989  70.963086    16.0   109.0   170.0   208.0

                max
year         2023.0
metascore      93.0
imdb_rating    10.0
plot_length  1324.0
```

**Interpretation** 1. **Year:** The range of the movies pulled from the API is from the year 1887 to 2023. This may seem plausible, but requires more drilling down in the data to figure out if the first movie ever was actually made in 1887. For movies in the year 2023, this may be upcoming movies that will be released then.

2. **Metascore**: The metascore is a weighted average of many reviews coming from reputed critics. The Metacritic team reads the reviews and assigns each a 0–100 score, which is then given a weight, mainly based on the review's quality and source. That means the higher the metascore, the more positive reviews a movie has. In our summary, we can see that the range for our movies in this sample is from 16 as the lowest and 93 as the highest. The average metascore is 60, where as the median is 62. This can be interesting later as we dive into the average metascore over time.

3. **imdb_rating**: IMDB rating allow users to rate films on a scale of 1-10. As expected, the range for this variable is 1 as the lowest and 10 as the highest. However, the average IMDB rating is 6.6 and the median is 6.7.

4. **plot_length**: This column displays the length of each movies' plot. Movies plots length range from 16 words as the lowest to 208 as the highest. On average, a movie plot has the length of 160 words whereas the median is 170. This could also indicate that a longer plot description will provide more information to understanding the movies' genres.

[5]:
```
movies_info[['awards','runtime', 'language', 'country']].describe(include =␣
↪'O').T
```

[5]:
```
         count unique          top  freq
awards     840    177  1 nomination   139
runtime   3826    173        4 min   163
language  4586    233      English  3414
```

```
country   4797    321           USA  1444
```

**Interpretation**

1.**awards** This variable shows that 139 movies out of 5000 were able to receive 1 nomination for an award. However, due to the number of unique values, we may need to consider that awards recorded down for each movie is not consistent since this has a high cardinality. Therefore, this may not be a reliable insight for the awards variable

2. **runtime** This variable also sees a high cardinality, but at a quick glance we can see that there are 163 movies that has a runtime of only 4 minutes.
3. **language** There number of unique languages here is 233, while that may seem plausible it is also expected to see that movies in English was most prevalent.
4. **country** Understandably, the country with the most movies are from the United States of America (USA). Exactly 1444 movies out of 5000 in this API sample are American.

## 4.2 2. Checking for Missing Data

[6]:
```
movies_info.isna().sum()
```

[6]:
```
title              0
year               0
rated           4245
released        1349
runtime         1174
genre            159
director         415
writer          1435
actors           754
plot            1440
language         414
country          203
awards          4160
poster          2180
ratings            0
metascore       4885
imdb_rating     2558
imdb_votes      2446
imdb_id            0
type               0
dvd             4497
box_office      4884
production      4965
website         4996
response           0
plot_length     1440
dtype: int64
```

[7]:
```
# Only working with rows where plot AND genre is not null
movies_info = movies_info[(movies_info['plot'].notnull()) &␣
↪(movies_info['genre'].notnull())]
movies_info.shape
```

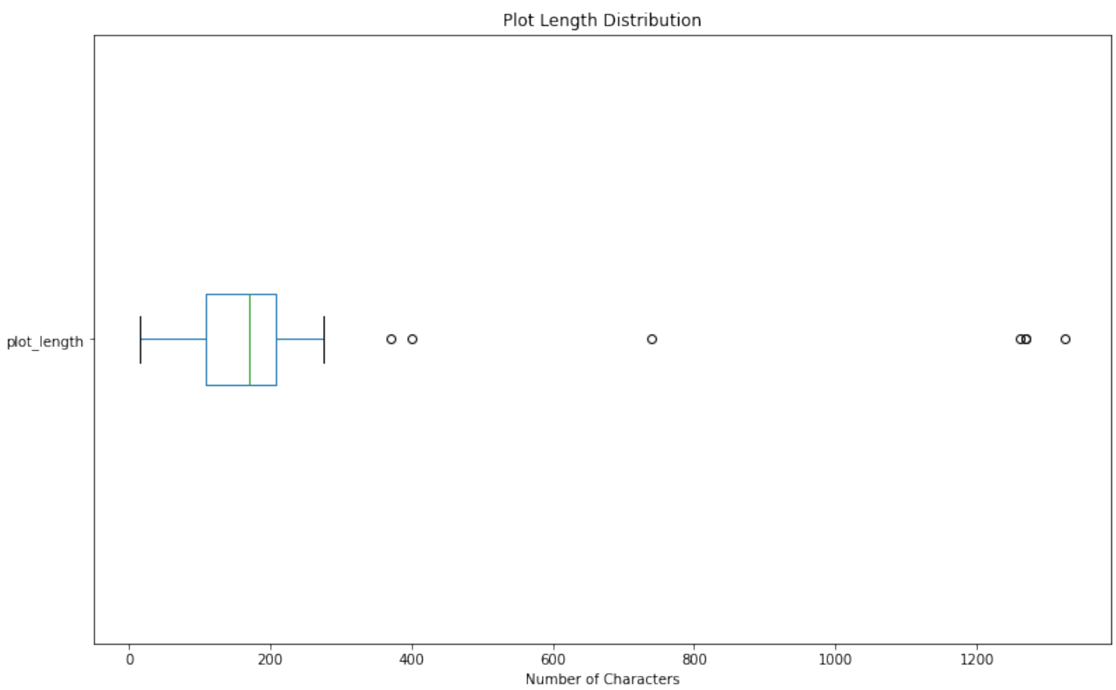
[7]: (3510, 26)

### Interpretation

Since our project is based on classifying the first genre of every movie based on its plot, then we only need to take into consideration the `plot` and `genre` columns to prepare for modeling

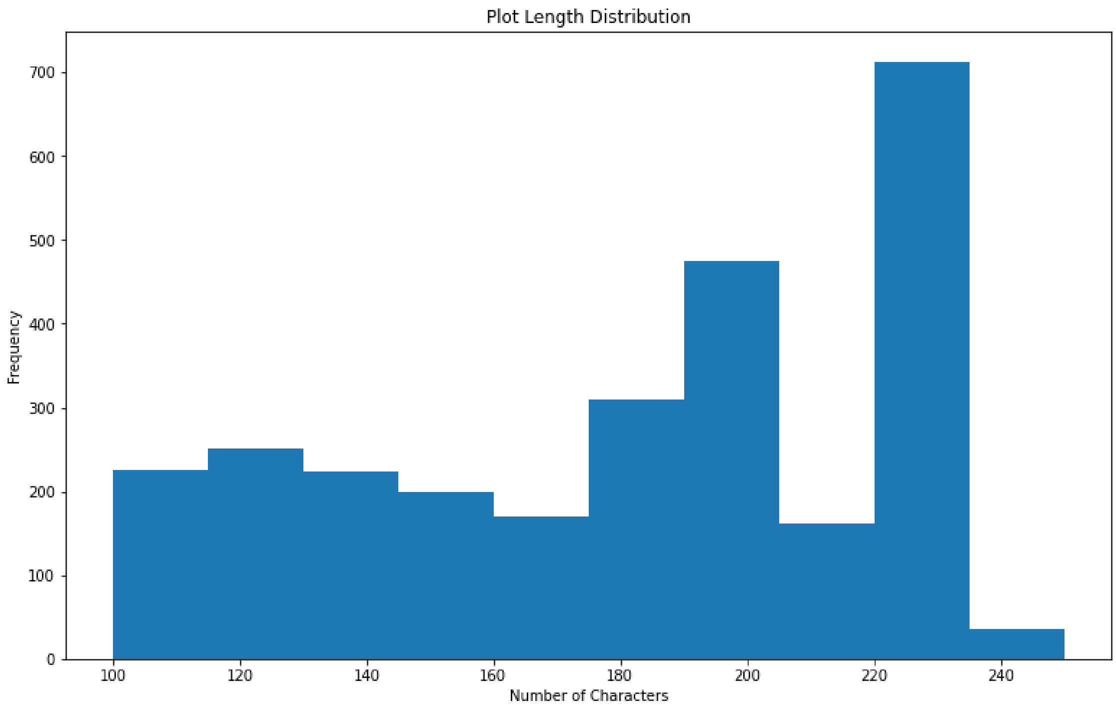
## 4.3 3. Plotting Value Distribtuions

[8]:
```
## Plotting Value Distribtuions
plt.figure(figsize=(13,8))
movies_info['plot_length'].plot(kind='box', vert=False)
plt.xlabel('Number of Characters')
plt.title('Plot Length Distribution')
plt.show()
```




[9]:
```
# Histogram distribution of movie plot lengths
plt.figure(figsize=(13,8))
movies_info['plot_length'].plot(kind = 'hist', range = (100,250))
plt.xlabel('Number of Characters')
```

```
plt.title('Plot Length Distribution')
plt.show()
```




**Interpretation**

After removing the missing values, 50% percent of the plot descriptions have a length between roughly 150 and 230 characters, with the median at about 180 with many outliers to the right. The distribution is obviously left-skewed.

The histogram is showing the bins for the number of characters between the ranges of 100 to 250.

### 4.4 4. Comparing Value Distributions Across Categories

[10]:
```
# top 10 countries with most movie plot descriptions
movies_info['country'].value_counts().nlargest(10)
```

[10]:
```
United States     885
USA               883
UK                174
United Kingdom    155
Canada            139
Japan              81
Australia          78
France             62
India              57
```

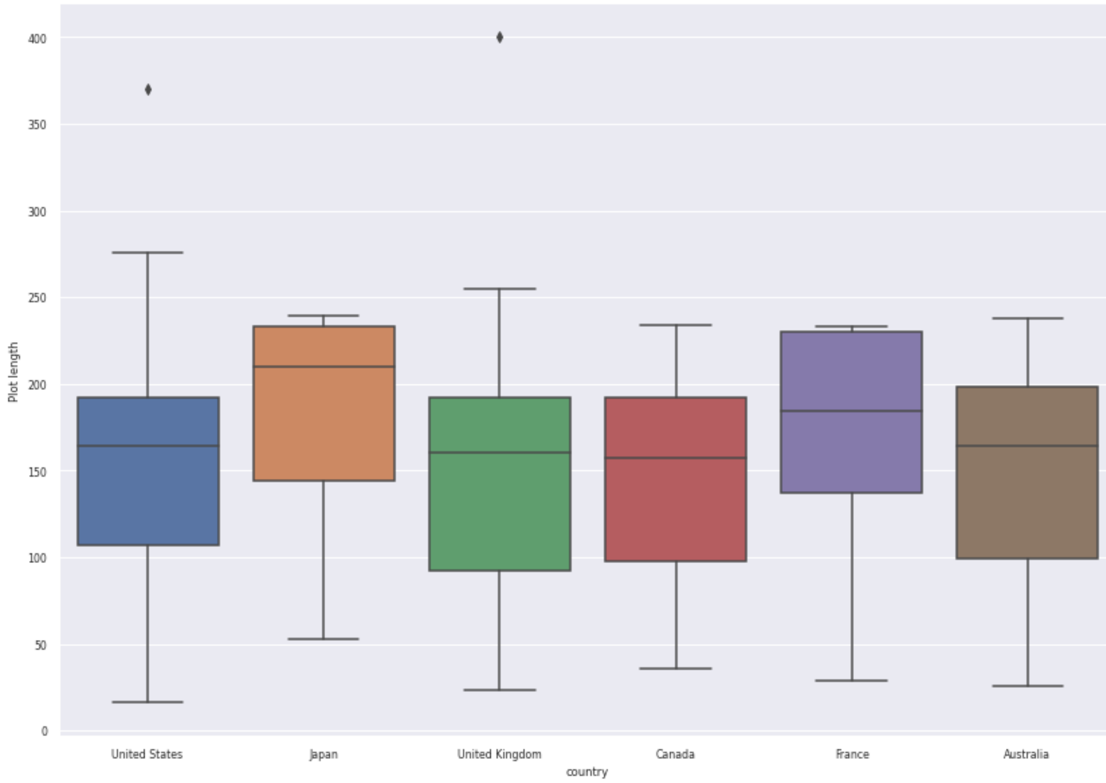
```
Italy               43
Name: country, dtype: int64
```

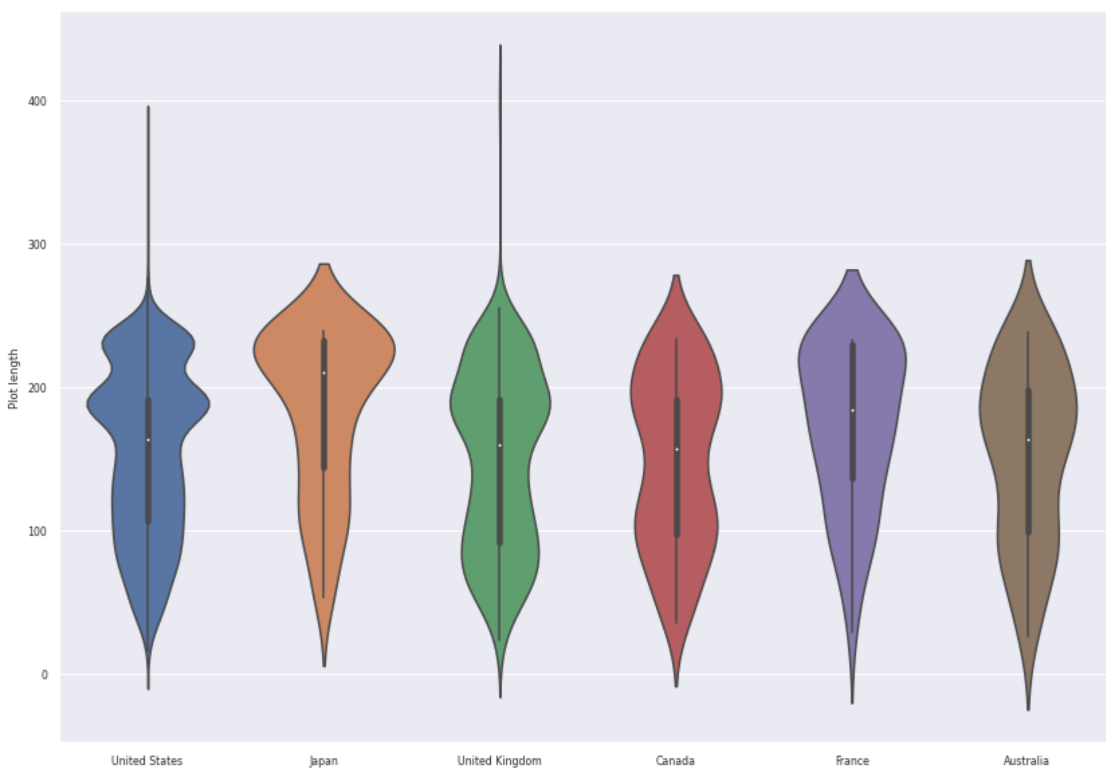
[11]:
```
# Replace United States Values
movies_info['country'] = movies_info['country'].str.replace(r'USA','United␣
↪States', regex=True)

# Replace UK Values
movies_info['country'] = movies_info['country'].str.replace(r'UK', 'United␣
↪Kingdom', regex=True)

# top 10 countries with most movie plot descriptions
movies_info['country'].value_counts().nlargest(10)
```

[11]:
```
United States     1768
United Kingdom     329
Canada             139
Japan               81
Australia           78
France              62
India               57
Italy               43
Germany             37
China               26
Name: country, dtype: int64
```

[12]:
```
# Boxplot and violint plots for movie plot lengths by countries
sns.set(font_scale = 0.7)
where = movies_info['country'].isin(['United States', 'United Kingdom',␣
↪'Canada', 'Japan', 'Australia', 'France'])
sns.catplot(data=movies_info[where], x="country", y="plot_length", kind='box',␣
↪height=8.27, aspect=11.7/8.27)
plt.ylabel("Plot length")
sns.catplot(data=movies_info[where], x="country", y="plot_length",␣
↪kind='violin', height=8.27, aspect=11.7/8.27)
plt.ylabel("Plot length")
```

[12]:
```
Text(2.6970000000000027, 0.5, 'Plot length')
```


400
350
300
250
200
150
100
50
0
Plot length
United States
Japan
United Kingdom
Canada
France
Australia
country

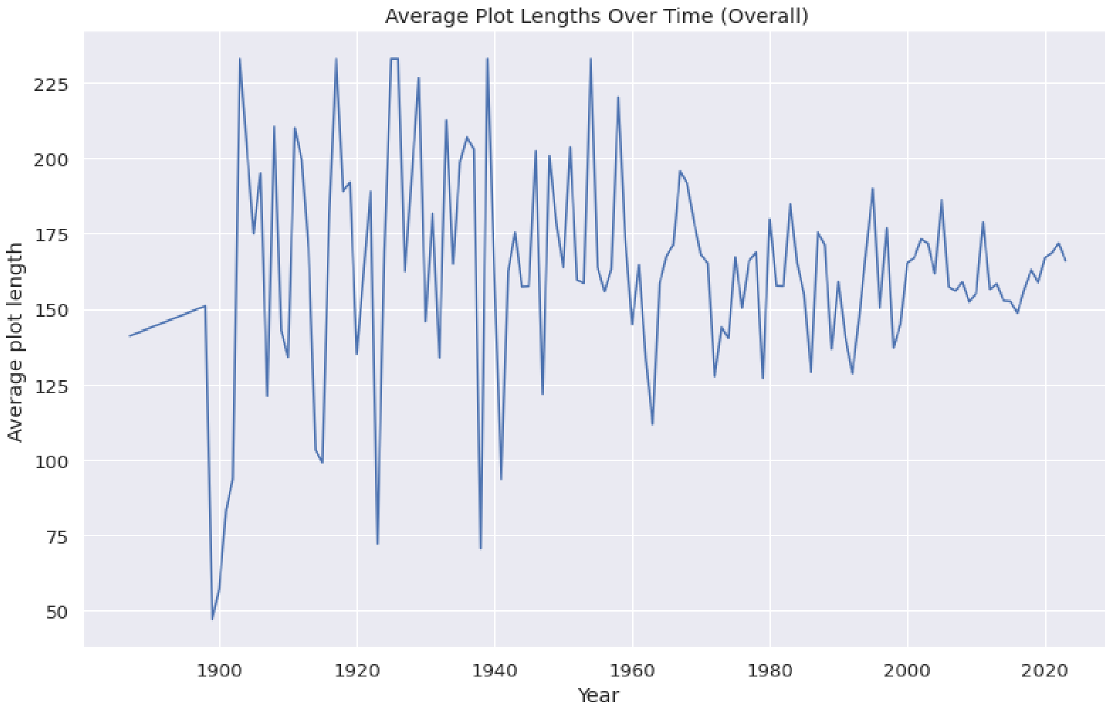

400
300
200
100
0
Plot length
United States
Japan
United Kingdom
Canada
France
Australia
country

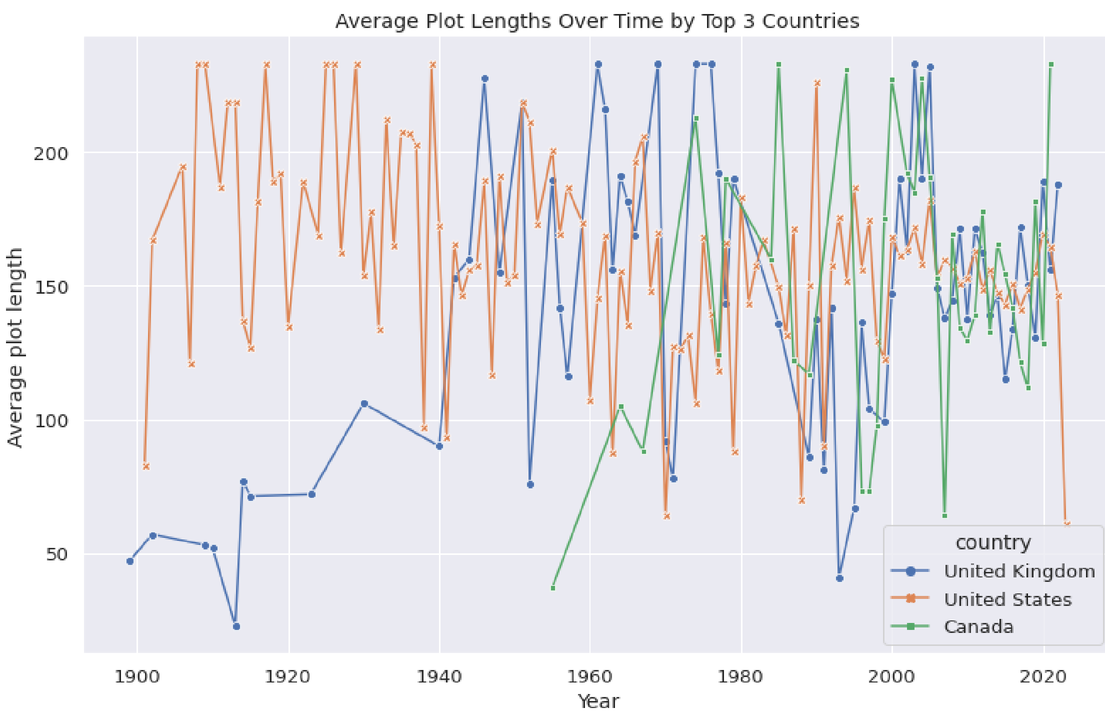
**Interpretation**

Both plots reveal that the lengths of the movie plots, for Japan has a higher median number of characters than the rest, otherwise all other countries seem to be closely distributed around the same length for movie plots.

### 4.5 5. Visualizing Movie Plots Over Time

[13]:
```
# Average plot lengths over
plots_avg = movies_info.groupby(['year'])['plot_length'].mean().reset_index()


# time series plot of average plot length overall
plt.figure(figsize=(13,8))
sns.set(font_scale = 1.2)
sns.lineplot(data=plots_avg, x="year", y="plot_length")
plt.title("Average Plot Lengths Over Time (Overall)")
plt.xlabel("Year")
plt.ylabel("Average plot length")
plt.show()


# Average plot lengths over time by countries
plt.figure(figsize=(13,8))
plots_over_time = movies_info.groupby(['year','country'])['plot_length'].mean().
 ↪reset_index()
where = plots_over_time['country'].isin(['United States', 'United␣
 ↪Kingdom','Canada'])
plots_over_time = plots_over_time[where]

# time series plot of average plot length by countries
sns.lineplot(data=plots_over_time, x="year", y="plot_length", hue="country",␣
 ↪style = "country",
    markers=True, dashes=False)
plt.title("Average Plot Lengths Over Time by Top 3 Countries")
plt.xlabel("Year")
plt.ylabel("Average plot length")
plt.show()
```




### Intepretation

The timeline reflects the number of average movie plot lengths over the years with all the countries, then a second plot aggregating by the top 3 countries with the most movies avaliable in this sample, which is the United States, United Kingdom, and Canada. Overall, movies across all countries in this sample have created shorter movie plot descriptions over time, whereas in the top 3 countries, any real pattern is hard to distinguish as there are a lot of variations.

# 5 Preparing Texual Data for Statistics and Modeling

- Remove Punctuation
- Remove extra white space
- Tokenize on white space pattern
- Fold to lowercase
- Remove stopwords

[14]:
```
punctuation = set(punctuation)
# Text cleaning function
def clean_text_data(column):
    new_description = []
    for description in column:
        update_desc = description
        # Remove the punctuation from each description
        for i in description:
            if i in punctuation:
                update_desc = update_desc.replace(i, "")
        # Remove extra white space
        update_desc = re.sub(r'\s+', ' ', update_desc)
        # Split on whitespace
        update_desc = update_desc.split()
        # Fold to lowercase
        for i in range(len(update_desc)):
            update_desc[i] = update_desc[i].lower()
        # Remove stopwords
        update_desc = [i for i in update_desc if i not in sw]
        new_description.append(update_desc)
    return new_description
```

[15]:
```
#Remove empty lists from cleaned_genre
movies_info = movies_info[movies_info['genre'] != ' ']

# Clean the plot description and genre text
movies_info['cleaned_plot'] = clean_text_data(movies_info['plot'])
movies_info['cleaned_genre'] = clean_text_data(movies_info['genre'])

# Keep only the first word in the cleaned genre lists
movies_info['first_genre'] = [i[0] for i in movies_info['cleaned_genre']]

# Create new df with only the first_genre and cleaned_plot columns
```

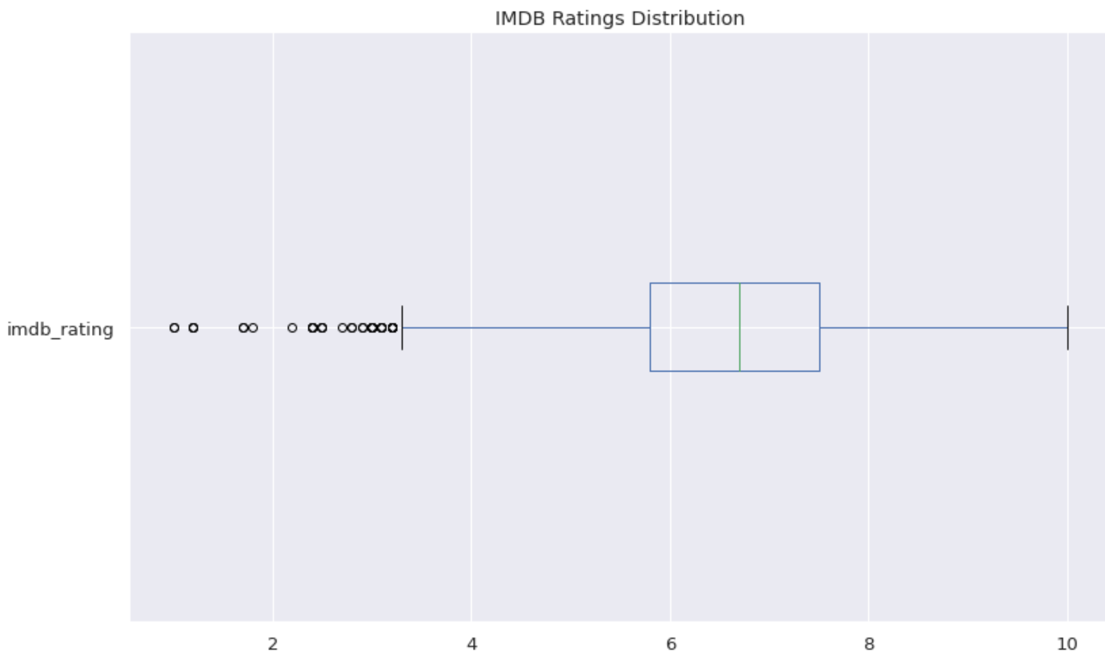
```
cleaned_df = movies_info[['title', 'first_genre', 'cleaned_plot',␣
↪'imdb_rating']]
cleaned_df.sample(15)
```

[15]:

```
                                title  first_genre  \
4856              And Then There Was One        short
494            One Day You'll Understand        drama
436                   One in a Thousand        drama
1787           Fifty People One Question  documentary
4293                      One Year Later        short
4318                  One Pillow One Soul       family
2998                   I Am the Other One  documentary
3758              One Minute to Midnight        short
488      Sam Smith: I'm Not the Only One        short
1540                      One Small Step        short
3961             Laal Vaali (The Red One)        short
1435              I'm Your Number One Fan  documentary
4114                One Heart: One Spirit  documentary
2330  One Hot Rotting, Zombie Love Song        short
4246                    One and the Same        short

                                          cleaned_plot  imdb_rating
4856  [woman, discovers, shes, pregnant, finds, husb…          NaN
494   [man, endeavors, collect, memories, grandparen…          5.7
436   [iris, expelled, school, spends, days, cousins…          6.3
1787  [one, town, 50, different, people, one, diffic…          5.8
4293  [one, year, later, spooky, halloween, fairytal…          NaN
4318  [story, tomb, removal, story, conflict, family…          NaN
2998  [luca, longs, lost, love, thalles, name, chang…          NaN
3758  [friendship, two, teenage, boys, imminent, nuc…          NaN
488    [music, video, sam, smiths, song, know, im, one]          8.2
1540  [dasani, 9, attempts, juggle, responsibilities…          8.8
3961  [comedy, errors, situation, arises, lata, find…          NaN
1435  [professor, paul, mullen, looks, way, admirati…          7.2
4114  [aboriginal, australian, native, american, doc…          NaN
2330  [jonas, kindhearted, zombie, sick, tired, kill…          5.4
4246  [still, photographer, sound, recordist, indepe…          NaN
```

[16]:

```
# Plotting Value Distribtuions
plt.figure(figsize=(13,8))
sns.set(font_scale = 1.2)
cleaned_df['imdb_rating'].plot(kind='box', vert=False)
plt.title('IMDB Ratings Distribution')
plt.show()
```




[17]:
```
# Count instances of each genre
cleaned_df['first_genre'].value_counts()
```

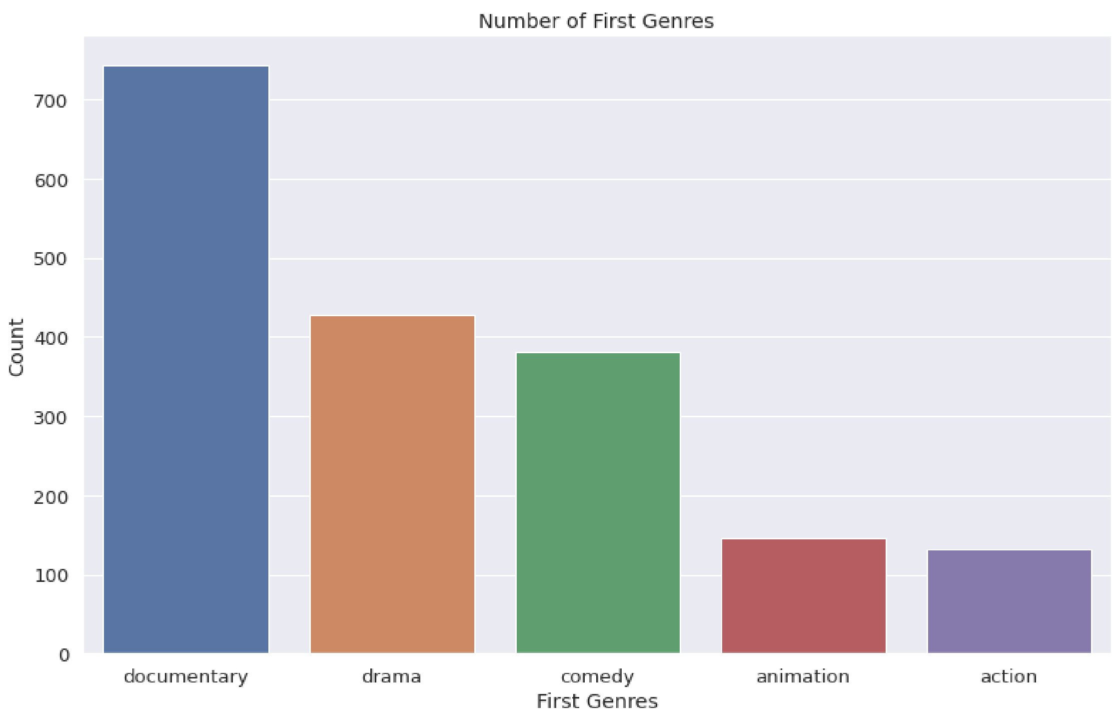
[17]:
```
short          1342
documentary     743
drama           428
comedy          380
animation       145
action          132
crime            71
horror           40
adventure        35
thriller         32
music            32
biography        20
family           19
western          17
romance          15
scifi            15
sport             9
fantasy           9
mystery           9
musical           5
history           5
realitytv         3
talkshow          3
```

```
news                  1
Name: first_genre, dtype: int64
```

### 5.1 Only use top 5 first genres

- Include descriptive statistics on final clean data set
- Frequency Diagram
- Word cloud

[18]:
```python
# Include only the top 5 genres, excluding shorts and na
cleaned_df = cleaned_df.loc[cleaned_df['first_genre'].isin(['documentary',␣
 ↪'drama', 'comedy', 'animation', 'action'])]

# plot top 5 genres
plt.figure(figsize=(13,8))
sns.set(font_scale = 1.2)
sns.countplot(x="first_genre", data=cleaned_df,
order = cleaned_df['first_genre'].value_counts().index)
plt.title("Number of First Genres")
plt.xlabel("First Genres")
plt.ylabel("Count")
plt.show()
```



### 5.2 Descriptive Statistics

[19]:
```
def descriptive_stats(tokens, common_tokens = 5, verbose=True) :
    """
        Given a list of tokens, print number of tokens, number of unique␣
 ↪tokens,
        number of characters, lexical diversity (https://en.wikipedia.org/wiki/
 ↪Lexical_diversity),
        and num_tokens most common tokens. Return a list with the number of␣
 ↪tokens, number
        of unique tokens, lexical diversity, and number of characters.

    """

    # Fill in the correct values here.
    num_tokens = len(tokens)
    num_unique_tokens = len(set(tokens))
    lexical_diversity = num_unique_tokens/num_tokens
    num_characters = sum([len(i) for i in tokens])

    if verbose :
        print(f"There are {num_tokens} tokens in the data.")
        print(f"There are {num_unique_tokens} unique tokens in the data.")
        print(f"There are {num_characters} characters in the data.")
        print(f"The lexical diversity is {lexical_diversity:.3f} in the data.")

        # print the five most common tokens
        counter = Counter(tokens)
        counter_list = counter.most_common(common_tokens)
        print(f"Most {common_tokens} common words: {counter_list}\n")
```

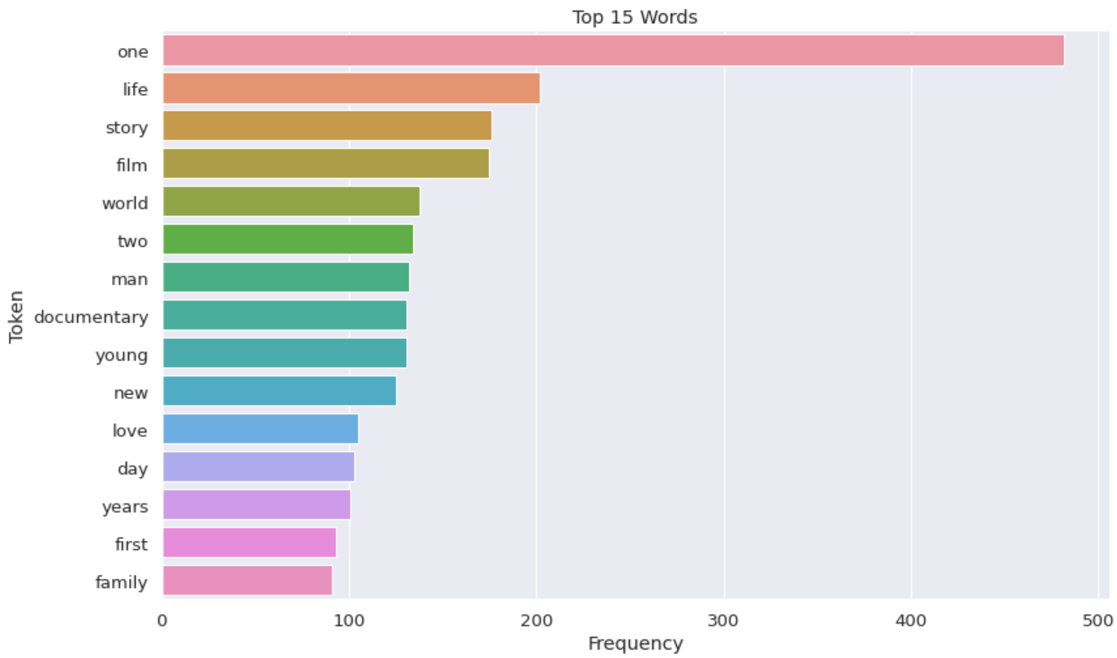
[20]:
```
movie_plot_tokens = cleaned_df.apply(lambda x: pd.
 ↪Series(x['cleaned_plot']),axis=1).stack().reset_index(level=1, drop=True).
 ↪tolist()
print("\t Movies Plot Descriptions:")
descriptive_stats(movie_plot_tokens)
```

```
         Movies Plot Descriptions:
There are 31048 tokens in the data.
There are 9494 unique tokens in the data.
There are 191378 characters in the data.
The lexical diversity is 0.306 in the data.
Most 5 common words: [('one', 482), ('life', 202), ('story', 176), ('film',
175), ('world', 138)]
```

### 5.3 Creating a Frequency Diagram

[21]:
```
def count_words(cleaned_df, column='cleaned_plot', preprocess=None, min_freq=2):
    # process tokens and update counter
    def update(doc):
        tokens = doc if preprocess is None else preprocess(doc)
        counter.update(tokens)

    # create counter and run through all data
    counter = Counter()
    cleaned_df[column].map(update)

    # transform counter into a DataFrame
    freq_df = pd.DataFrame.from_dict(counter, orient='index', columns=['freq'])
    freq_df = freq_df.query('freq >= @min_freq')
    freq_df.index.name = 'token'

    return freq_df.sort_values('freq', ascending=False)


freq_df = count_words(cleaned_df).reset_index()
```

[22]:
```
# Plot Frequency Diagram
plt.figure(figsize=(13,8))
sns.set(font_scale = 1.2)
sns.barplot(x="freq", y="token", data=freq_df.head(15), orient = "h")
#ax.invert_yaxis()
plt.title("Top 15 Words")
plt.xlabel("Frequency")
plt.ylabel("Token")
plt.show()
```



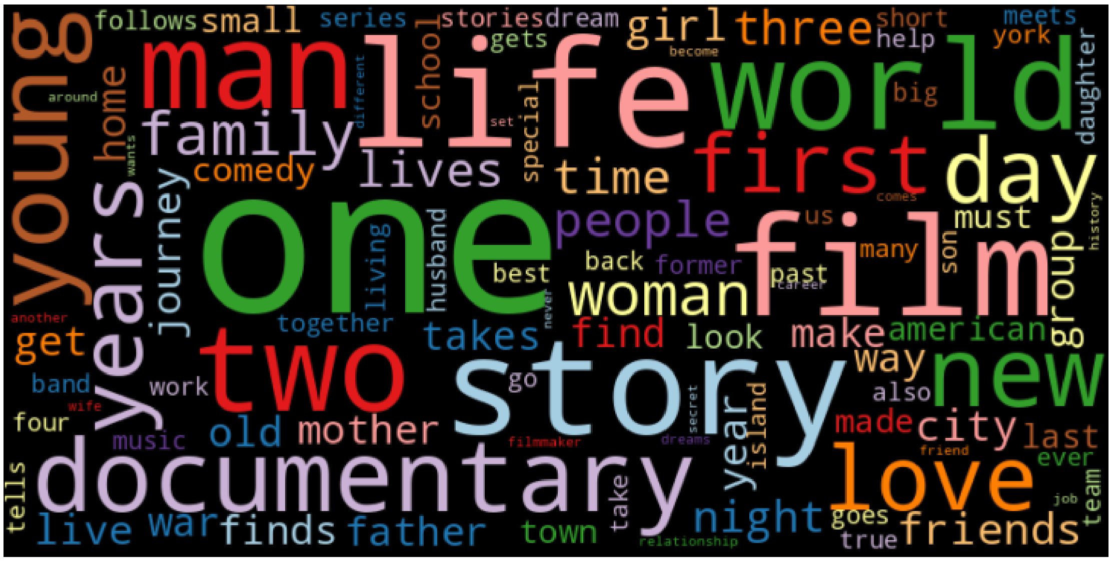

### 5.4 Word Cloud

[23]:
```
def wordcloud(word_freq, title=None, max_words=200, stopwords=None):
    # Create word cloud
    wc = WordCloud(width=800, height=400,
        background_color= "black", colormap="Paired",
        max_font_size=150, max_words=max_words)

    # convert DataFrame into dict
    if type(word_freq) == pd.Series:
        counter = Counter(word_freq.fillna(0).to_dict())
    else:
        counter = word_freq
    # filter stop words in frequency counter
    if stopwords is not None:
        counter = {token:freq for (token, freq) in counter.items() if token not␣
 ↪in stopwords}

    wc.generate_from_frequencies(counter)
    plt.title(title)
    plt.imshow(wc, interpolation='bilinear')
    plt.axis("off")
```

[24]:
```
# Plot Word Cloud
plt.figure(figsize=(13,8))
```

```python
freq_df = count_words(cleaned_df)
wordcloud(freq_df['freq'], max_words=100)
plt.title("Top 100 Words")
plt.show()
```

Top 100 Words




## 5.5 Export Final Clean Dataset

[25]:
```python
# Write to a csv
cleaned_df.to_csv('Cleaned Plot Data.csv', index = False)
```

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