Investigate_a_Dataset

March 13, 2022

1 Project: Investigate a Dataset - [TMDB Movies]

1.1 Table of Contents

1.2 Introduction

1.2.1 Dataset Description

The author always had a big interest in watching movies. As most people did, the author also experienced good and bad movies. But what determines if a movie is considered as good or bad? There could be several factors influencig the quality of a movie, as for example the budget, genre, etc. This little project should help the author to improve his data analytics skills and explore some of the success criteria for movies.

1.2.2 Question(s) for Analysis

1. Actors with the most appearances in films
2. Exploring the Movie genres through the years of the dataset
3. Top Movies based on features
4. Average Votes Distribution
5. Correlations

In [47]:
```
#Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# Loading the data and having a look at the first few lines
data = pd.read_csv('Database_TMDb_movie_data/tmdb-movies.csv')
data.head(5)
```

Out[2]:
```
       id    imdb_id  popularity     budget     revenue  \
0  135397  tt0369610   32.985763  150000000  1513528810
1   76341  tt1392190   28.419936  150000000   378436354
2  262500  tt2908446   13.112507  110000000   295238201
3  140607  tt2488496   11.173104  200000000  2068178225
4  168259  tt2820852    9.335014  190000000  1506249360

                original_title  \
0               Jurassic World
1           Mad Max: Fury Road
2                    Insurgent
3  Star Wars: The Force Awakens
4                    Furious 7

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                            homepage          director  \
0                      http://www.jurassicworld.com/   Colin Trevorrow
1                        http://www.madmaxmovie.com/     George Miller
2     http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
4                           http://www.furious7.com/         James Wan

                         tagline      ...       \
0             The park is open.      ...
1             What a Lovely Day.      ...
2       One Choice Can Destroy You      ...
3  Every generation has a story.      ...
4            Vengeance Hits Home      ...

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic ...     124
1  An apocalyptic story set in the furthest reach...     120
2  Beatrice Prior must confront her inner demons ...     119
3  Thirty years after defeating the Galactic Empi...     136
4  Deckard Shaw seeks revenge against Dominic Tor...     137

                                       genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                       Action|Crime|Thriller
```

```
                              production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

In [3]:
```
#Types and look for instances of missing or possibly errant data.
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [4]:
```
#Types and look for instances of missing or possibly errant data.
```

```
data.describe()
```

Out[4]:

	id	popularity	budget	revenue	runtime
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

2 Result

- There are some rows have values separated by (|). They must be cleaned.

1. cast
2. genres
3. production_companies
4. keywords
5. director

- I will clean it later in EDA section.

- There are some columns not important . They must be cleaned.

1. imdb_id
2. homepage
3. overview
4. release_date
5. tagline

- There are some columns have some NAN values. They must be cleaned.

1. cast
2. director
3. genres
4. production_companies

3 Data Cleaning

In [5]:
```python
#To remove not important columns
data = data.drop(['imdb_id','homepage','overview','release_date','tagline'], axis = 1)
```

In [6]:
```python
#To remove rows of NANs acording to cast, genres and director.
data = data[data["cast"].isnull() == False]
data = data[data["genres"].isnull() == False]
data = data[data["director"].isnull() == False]
```

In [7]:
```python
#To check if there are some rows duplicated
data.drop_duplicates(inplace=True)
data.duplicated().sum()
```

Out[7]: 0

In [8]:
```python
#To remove rows where (revenue_adj) and (budget_adj) is equal to zero
data = data[data.budget_adj != 0]
data = data[data.revenue_adj != 0]
```

Now, Data has been prepared. - No duplicated rows. - No rows having NANs in (cast) and (genres) columns. - No not important columns - No rows having zeros in (revenue_adj) and (budget_adj) columns.

In [9]:
```python
print('Dataframe contains {} rows and {} columns'.format(data.shape[0],data.shape[1]))
```

```
Dataframe contains 3849 rows and 16 columns
```

In [10]:
```python
data.head()
```

Out[10]:
```
       id  popularity     budget     revenue                original_title  \
0  135397   32.985763  150000000  1513528810                Jurassic World
1   76341   28.419936  150000000   378436354            Mad Max: Fury Road
2  262500   13.112507  110000000   295238201                     Insurgent
3  140607   11.173104  200000000  2068178225  Star Wars: The Force Awakens
4  168259    9.335014  190000000  1506249360                     Furious 7

                                                cast          director  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...      J.J. Abrams
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...         James Wan

                                            keywords  runtime  \
0  monster|dna|tyrannosaurus rex|velociraptor|island      124
1   future|chase|post-apocalyptic|dystopia|australia      120
2  based on novel|revolution|dystopia|sequel|dyst...      119
```

```
3               android|spaceship|jedi|space opera|3d      136
4                 car race|speed|revenge|suspense|car      137

                                     genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                      Action|Crime|Thriller

                                production_companies  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...        5562
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4  Universal Pictures|Original Film|Media Rights ...        2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09
```

Now, We finished from the cleaning process so, we are ready to the next step (EDA). ## Exploratory Data Analysis

> **Tip**: Now that you've trimmed and cleaned your data, you're ready to move on to exploration. **Compute statistics** and **create visualizations** with the goal of addressing the research questions that you posed in the Introduction section. You should compute the relevant statistics throughout the analysis when an inference is made about the data. Note that at least two or more kinds of plots should be created as part of the exploration, and you must compare and show trends in the varied visualizations.

3.0.1 Research Question 1 (How many movies in each year?)

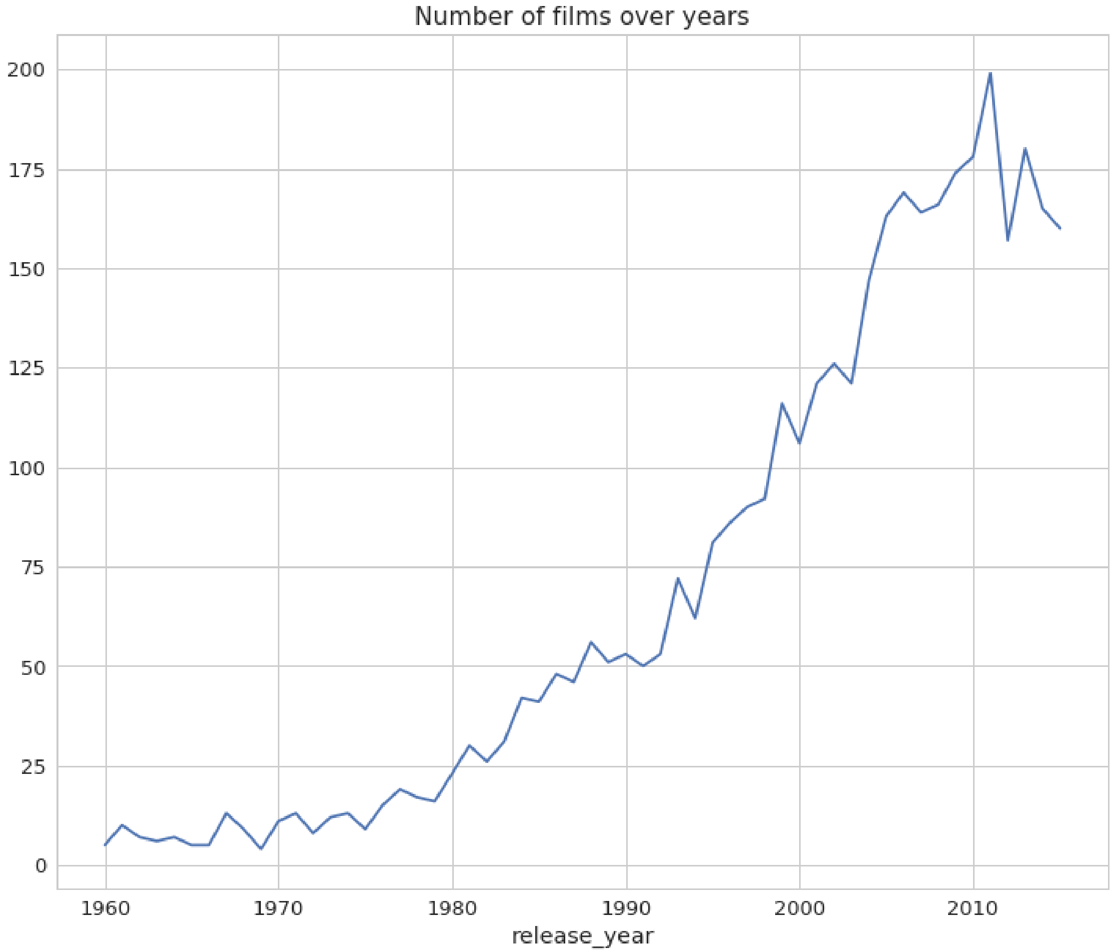
In [11]:
```
#To determine number of movies/year
movies_num_year = data.groupby('release_year').original_title.count()
movies_num_year
```

Out[11]:
```
release_year
1960      5
1961     10
1962      7
1963      6
1964      7
1965      5
1966      5
1967     13
```

1968	9
1969	4
1970	11
1971	13
1972	8
1973	12
1974	13
1975	9
1976	15
1977	19
1978	17
1979	16
1980	23
1981	30
1982	26
1983	31
1984	42
1985	41
1986	48
1987	46
1988	56
1989	51
1990	53
1991	50
1992	53
1993	72
1994	62
1995	81
1996	86
1997	90
1998	92
1999	116
2000	106
2001	121
2002	126
2003	121
2004	147
2005	163
2006	169
2007	164
2008	166
2009	174
2010	178
2011	199
2012	157
2013	180
2014	165
2015	160

```
Name: original_title, dtype: int64
```

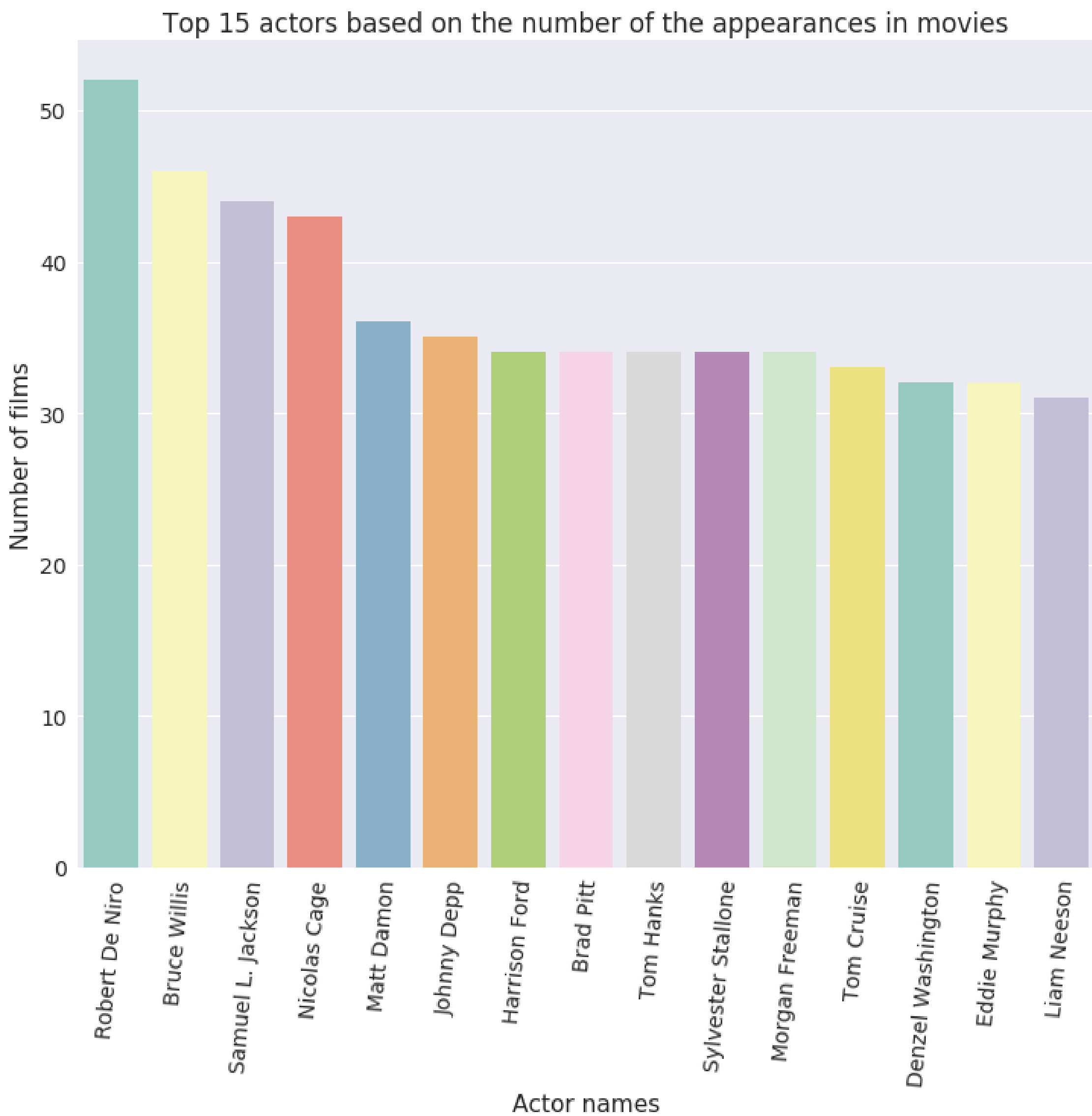
In [50]:
```
#To visualize that
ax = movies_num_year.plot(grid=True,figsize=(12, 10), title='Number of films over years
ax.set_xlabel = 'Year'
ax.set_ylabel = 'Number of films'
```



3.0.2 Research Question 2 (Actors with the most appearances in films?)

In [16]:
```
# After discussing the structure of the data and any problems that need to be cleaned,

#To create a dict for the cast, and how many times each actor casted for movies.

actor_dict = {}

actors = data["cast"]
actors = actors.str.split("|")
actors = np.array(actors)
```

```python
for actorList in actors:
    #check if there is a problematic list which is just a float
    for actor in actorList:
        actor = actor.lstrip() #trim the whitespaces
        if actor not in actor_dict:
            actor_dict[actor] = 1
        else:
            actor_dict[actor] += 1

#To sort this dict in descending sort
sorted_actor_dict = sorted(actor_dict.items(), key=lambda item: item[1],reverse=True)

#To visualize that
x_axis = list()
y_axis = list()

for item in sorted_actor_dict[0:15]:
    x_axis.append(item[0])
    y_axis.append(item[1])

sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)
ax = sns.barplot(x_axis, y_axis, palette="Set3", linewidth=0)

#rotate x-axis' text
for item in ax.get_xticklabels():
    item.set_rotation(85)

ax.set(xlabel='Actor names', ylabel='Number of films', title = 'Top 15 actors based on
plt.show()
```



3.0.3 Research Question 3 (Exploring the Movie genres through the years of the dataset?)

Question #3.1: Most popular movie genre by year Let's see which genre was the most popular over years and the number of movies that belong to this genre.

In [17]:
```
year_set = set()
genre_set = set()
genres_and_year = data[["genres", "release_year"]]

#create a set of unique years of movies
production_year = genres_and_year["release_year"]
production_year = production_year.drop_duplicates()
```

```
for year in production_year:
    if year not in year_set:
        year_set.add(year)


#create a set of unique genres by parsing all the years
for year in year_set:
    genre_dict = {}
    genres_in_year = genres_and_year[genres_and_year.release_year == year]
    genres_in_year = genres_in_year["genres"].values
    for elem in genres_in_year:
        genres_row = elem.split("|")
        for genre in genres_row:
            if genre not in genre_set:
                genre_set.add(genre)


#create a dataframe which contains the sum of movies' genre per year
gerne_count_per_year_df = pd.DataFrame(index = year_set, columns=genre_set)
gerne_count_per_year_df[:] = 0

for year in year_set:
    genre_dict = {}
    genres_in_year = genres_and_year[genres_and_year.release_year == year]
    genres_in_year = genres_in_year["genres"].values
    for elem in genres_in_year:
        genres_row = elem.split("|")
        for genre in genres_row:
            if genre not in genre_dict:
                genre_dict[genre] = 1
            else:
                genre_dict[genre] = genre_dict[genre] + 1

    aux_df = pd.DataFrame(genre_dict, index = [year])
    gerne_count_per_year_df.loc[year, aux_df.columns] = gerne_count_per_year_df.loc[yea



most_popular_genre_by_year = pd.DataFrame([gerne_count_per_year_df.astype('float64').id
                                          gerne_count_per_year_df.apply( max, axis=1 ).
                                          columns = gerne_count_per_year_df.index,
                                         index = ["genre", 'counts'])
most_popular_genre_by_year
```

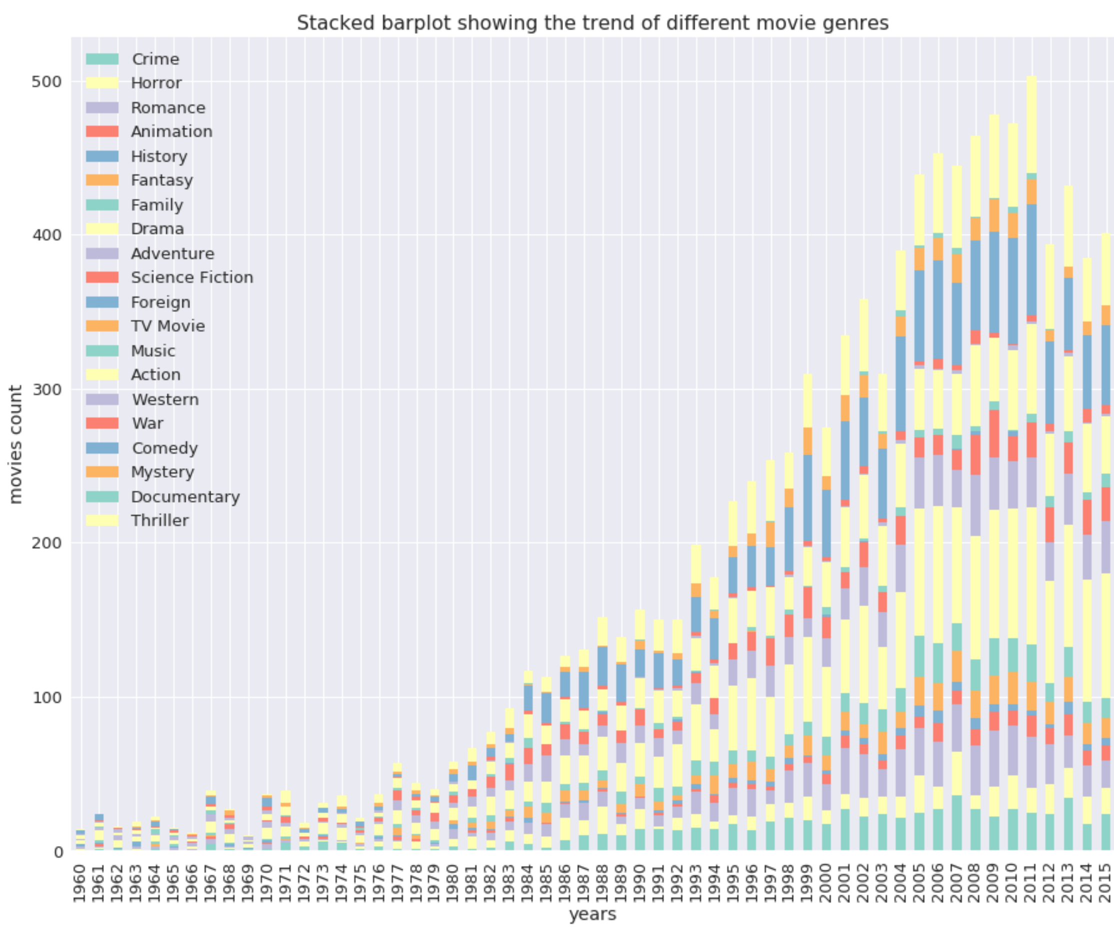
Out[17]:

```
          1960   1961   1962     1963   1964   1965   1966   1967   1968  \
genre    Drama  Drama  Drama  History  Drama  Drama  Drama  Drama  Drama
counts       3      6      5        3      4      3      2      7      6
```

```
          1969   ...    2006   2007   2008   2009   2010   2011   2012   2013  \
genre    Drama   ...   Drama  Drama  Drama  Drama  Drama  Drama  Drama  Drama
counts       2   ...      89     75     80     83     84     89     66     80

          2014   2015
genre    Drama  Drama
counts      79     81

[2 rows x 56 columns]
```

Question #3.2: How much the movie genres changes from year to year Show the flactuations of movie genres from year to year. Bar plot is used to visualize the movie genres' changes/flactuations/trends from year to year.

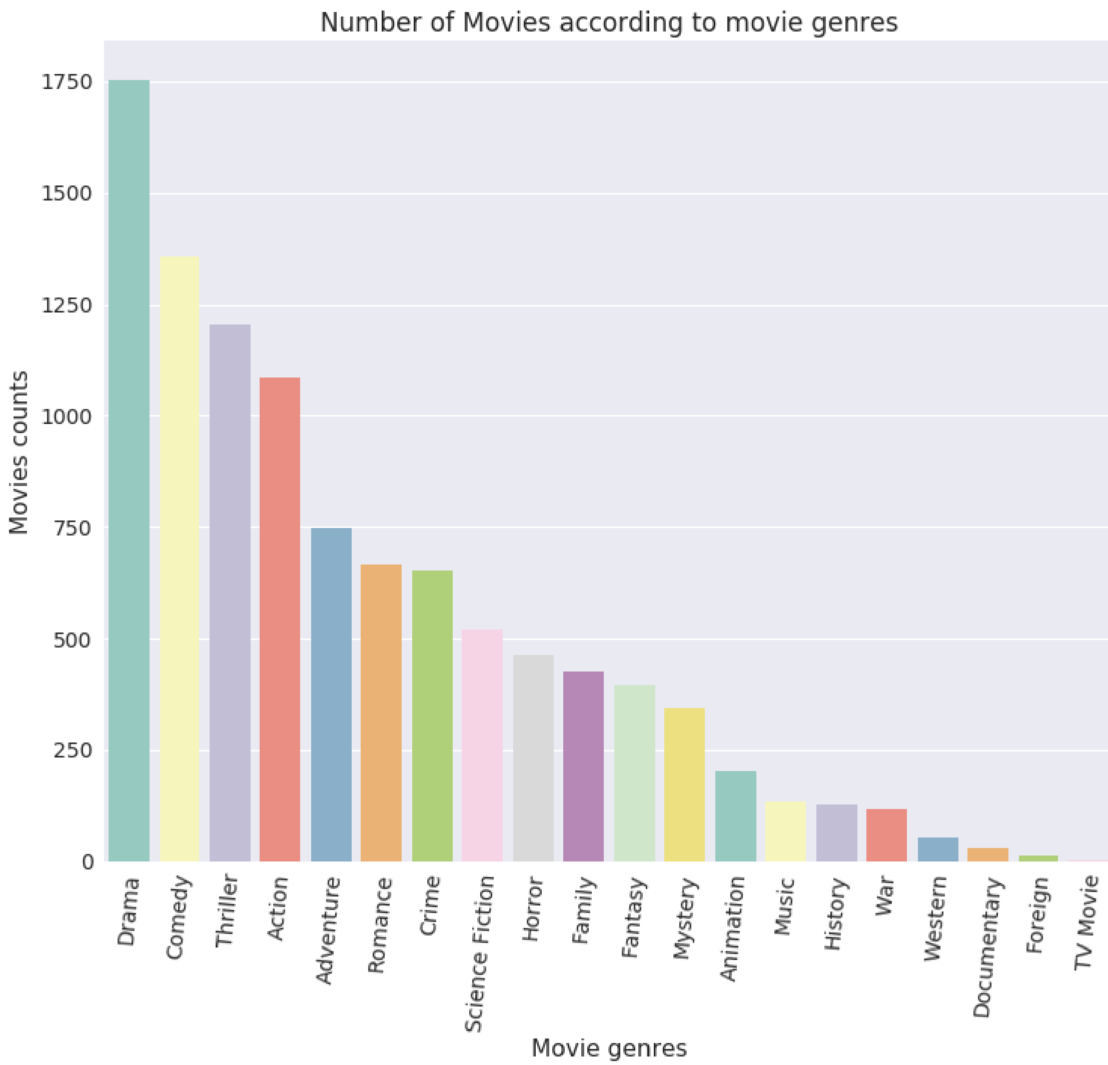
In [18]:
```
#Two visualize that
sns.set(rc={'figure.figsize':(15,12)}, font_scale=1.3)
sns.set_palette(palette="Set3")

ax = gerne_count_per_year_df.plot.bar(stacked=True,linewidth=0);
ax.set(xlabel='years', ylabel='movies count', title = 'Stacked barplot showing the tren
plt.show()
```



In general, the number of movies and the movie genres show an increase in numbers from 1960 to 2015. As we can see the majority of the movie genres show an increasing trend. Drama seems to be the most frequent genre in movies through all these years. Other categories such as Thriller, Comedy and Action movies show a similar pattern.

Question #3.3: How many movies based on their genres were produced Showing the number of movies that produced in 1960 to 2015 according to their respective movie genres.

```
In [19]: #Two visualize that
         genre_count = gerne_count_per_year_df.apply(sum)
         genre_count = genre_count.sort_values(ascending= False)

         sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)
         ax = sns.barplot(genre_count.index, genre_count, palette="Set3", linewidth = 0)


         #rotate x-axis' text
         for item in ax.get_xticklabels():
             item.set_rotation(85)

         ax.set(xlabel='Movie genres', ylabel='Movies counts', title = 'Number of Movies accordi
         plt.show()
```



As we can see, Drama movies are the most frequent movie genre that other genres. In general The top 3 dominant movie genres all over these years (1960 - 2015) are [Drama, Comedy and Thriller].

3.0.4 Research Question 4 (Top Movies based on features?)

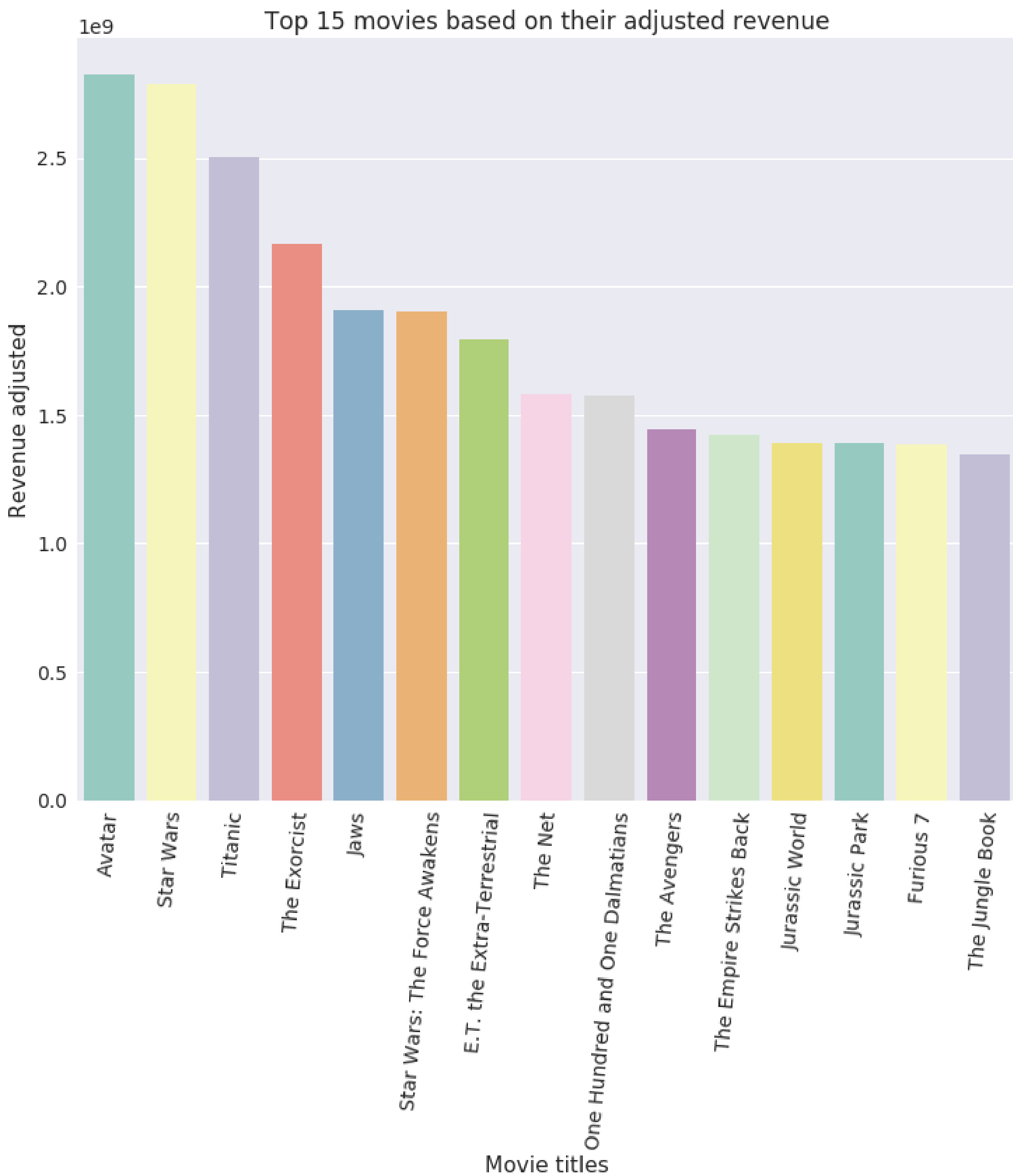
It would be beneficial to find out which movies had the highest (budget), (revenue popularity) and (average votes). So let's find out which are these top 15 movies based on these attributes.

In [20]:
```
#Top 15 Movies based on these features

revenue_dict = {}

#Fetching different columns with 2 different ways of code
movies_and_revenue = data[["original_title", "revenue_adj"]]
movies_and_budget = data[['original_title','budget_adj']]
```

```
movies_and_popularity = data[['original_title','popularity']]
movies_and_votes= data[['original_title','vote_average']]
```

Question #4.1: Top Movies based on their revenue The top 15 movies based on their adjusted revenue.

```
In [21]: #To visualize that
         sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)

         ax = sns.barplot(
             movies_and_revenue.sort_values(by = "revenue_adj", ascending=False).head(15).origin
             movies_and_revenue.sort_values(by = "revenue_adj", ascending=False).head(15).revenu
             linewidth = 0,
             palette="Set3")


         #rotate x-axis' text
         for item in ax.get_xticklabels():
             item.set_rotation(85)


         ax.set(xlabel='Movie titles', ylabel='Revenue adjusted', title = 'Top 15 movies based o
         plt.show()
```

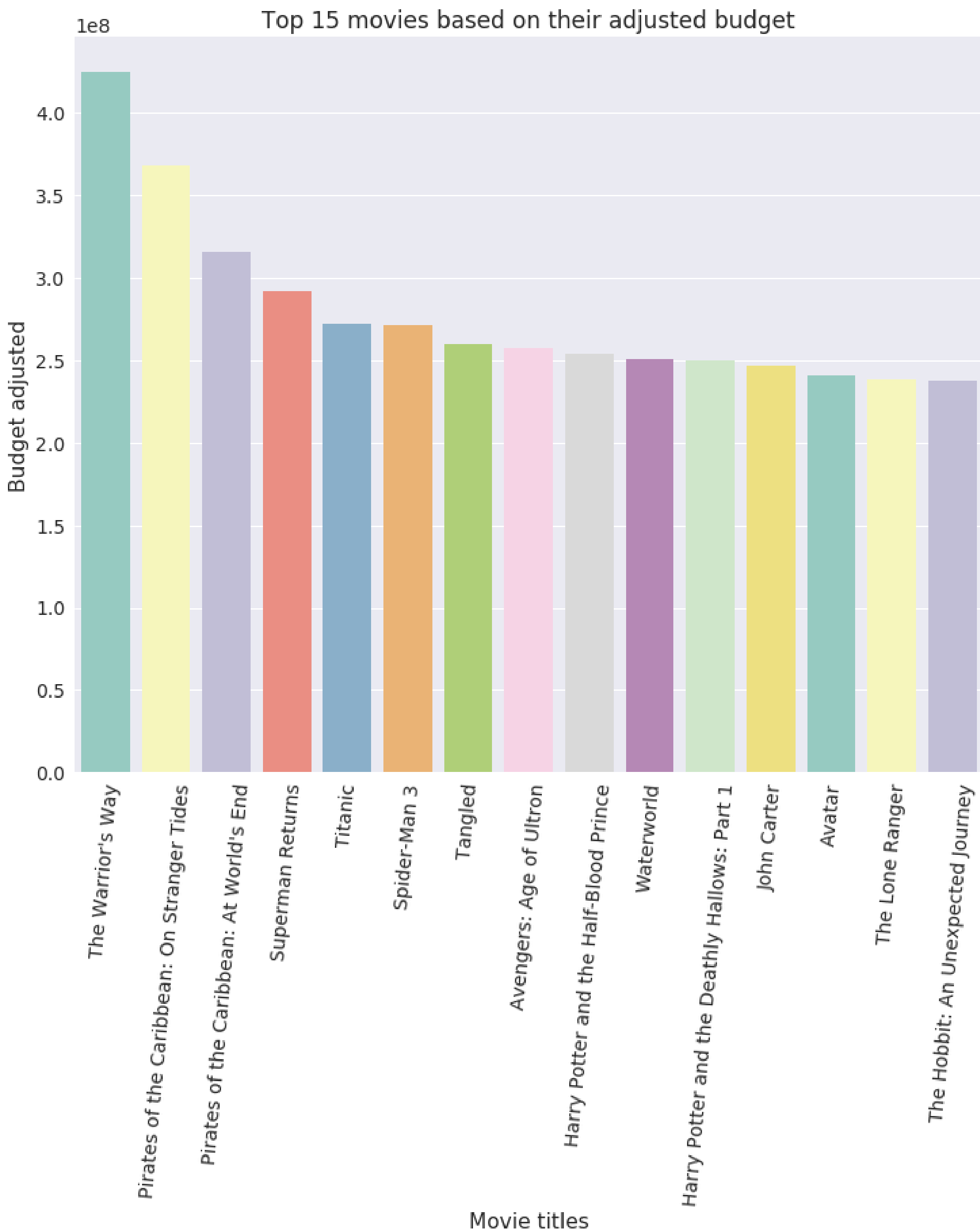


According to the table above, the top 5 movies from the given dataset based on their adjusted revenue are the followings; Avatar, Star Wars, Titanic, The Exorcist and Jaws.

According to the table above, the top 5 movies based on their adjusted budget are the followings; 1. Avatar 2. Star Wars 3. Titanic 4. The Exorcist 5. Jaws.

Question #4.2: Top Movies based on their budget The top 15 movies based on their adjusted budget.

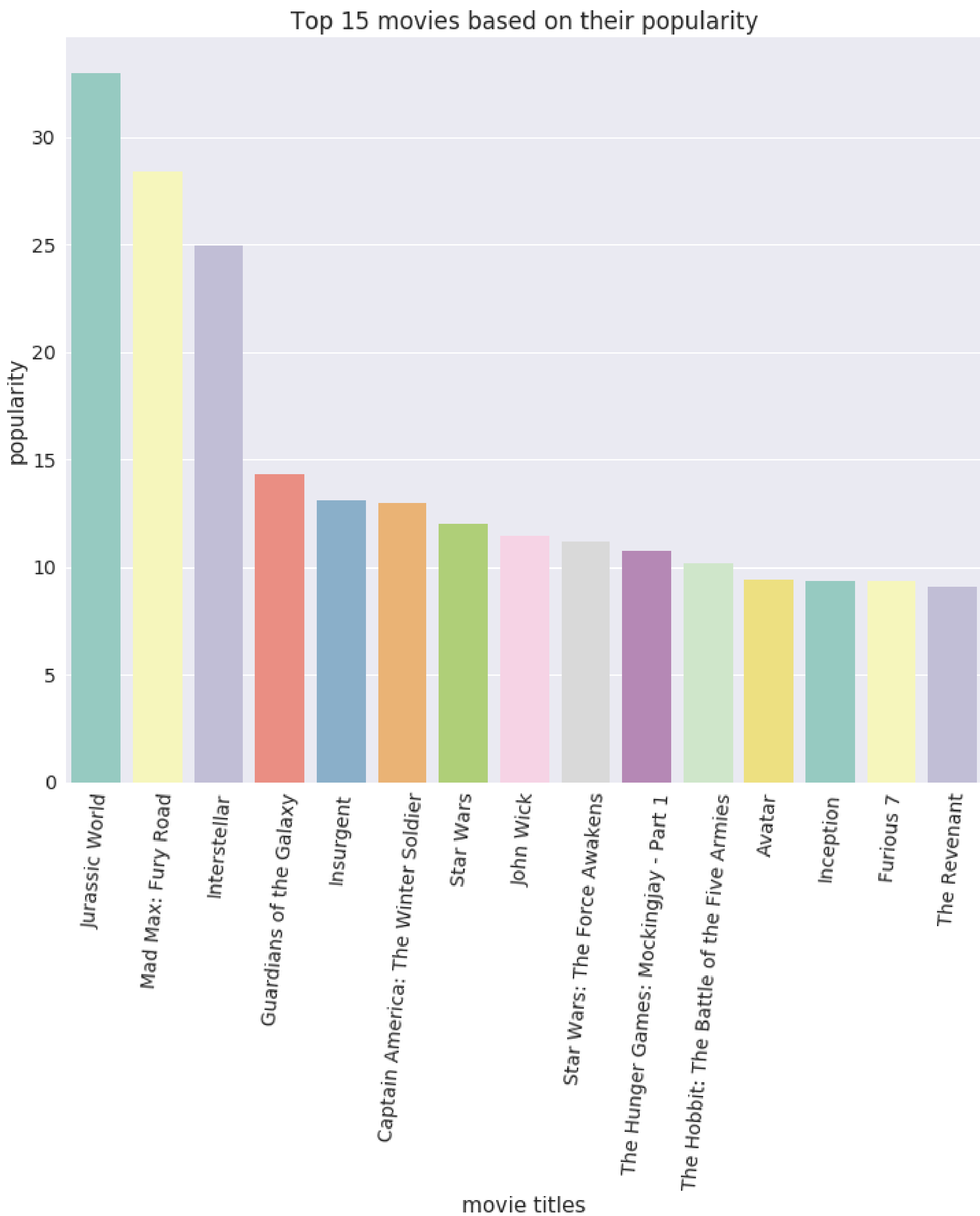
In [22]:
```
#To visualize that
sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)


ax = sns.barplot(
    movies_and_budget.sort_values(by="budget_adj", ascending=False).head(15).original_t
    movies_and_budget.sort_values(by="budget_adj", ascending=False).head(15).budget_adj
    linewidth = 0,
    palette="Set3")

#rotate x-axis' text
for item in ax.get_xticklabels():
    item.set_rotation(85)

ax.set(xlabel='Movie titles', ylabel='Budget adjusted', title = 'Top 15 movies based on
plt.show()
```



According to the table above, the top 5 movies based on their adjusted budget are the followings; 1. The Warrior's Way 2. Pirates of the Caribbean: On Strange Tides 3. Pirates of the Caribbean 4. At World's Ends, Superman Returns 5. Titanic.

Question #4.3: Top Movies based on their popularity The top 15 movies based on their adjusted popularity.

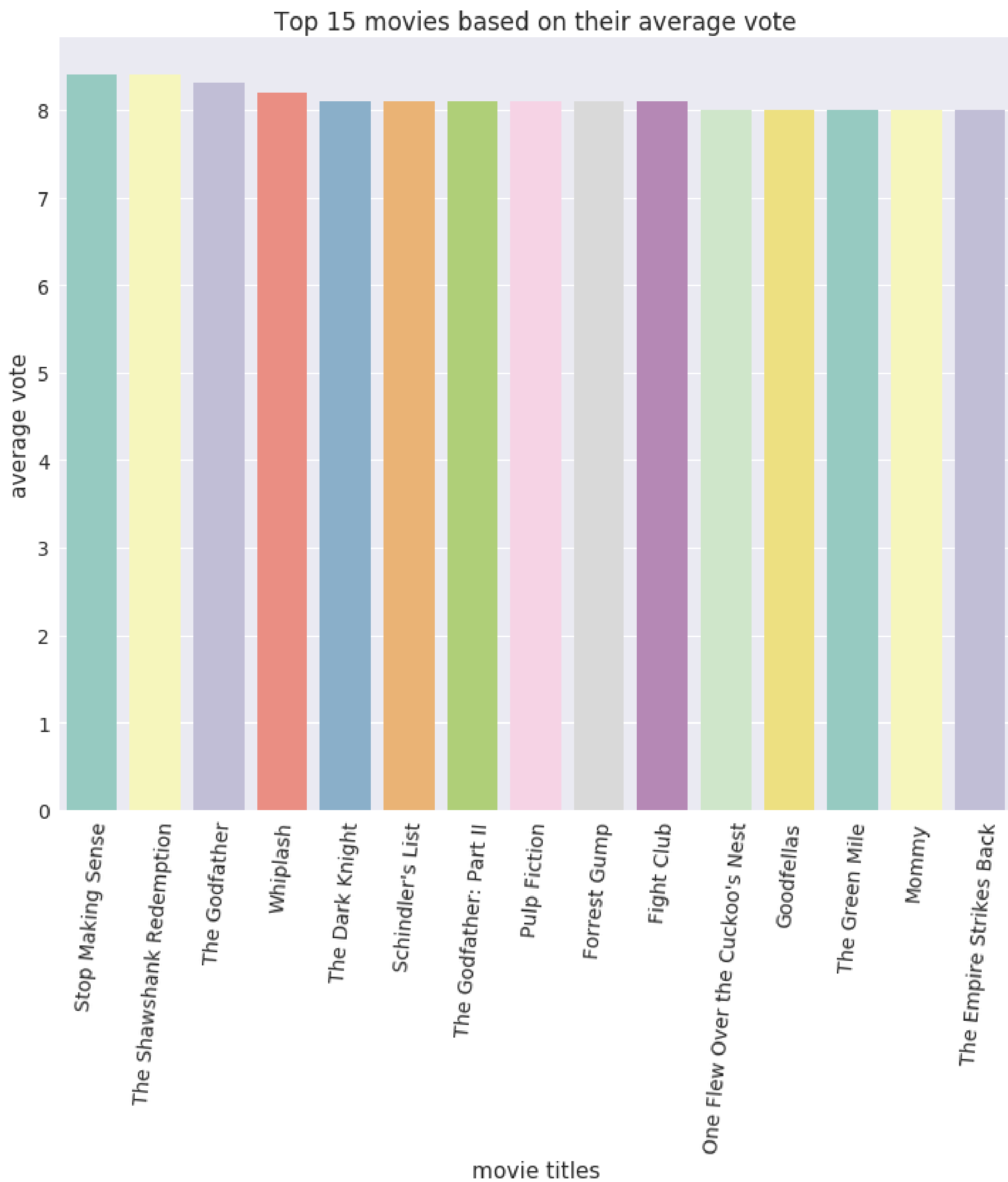
In [23]:
```
#To visualize that
sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)


ax = sns.barplot(
    movies_and_popularity.sort_values(by="popularity", ascending=False).head(15).origin
    movies_and_popularity.sort_values(by="popularity", ascending=False).head(15).popula
    linewidth = 0,
    palette="Set3")


#rotate x-axis' text
for item in ax.get_xticklabels():
    item.set_rotation(85)

ax.set(xlabel='movie titles', ylabel='popularity', title = 'Top 15 movies based on thei
plt.show()
```



According to the table above, the top 5 movies based on their adjusted budget are the followings; 1. Jurassic World 2. Mad Max: Fury Road 3. Interstellar 4. Guardians of the Galaxy 5. Insurgent.

Question #4.4: Top Movies based on their average vote The top 15 movies based on their adjusted average vote.

In [24]:
```
#To visualize that
sns.set(rc={'figure.figsize':(12,10)}, font_scale=1.4)


ax = sns.barplot(
    movies_and_votes.sort_values(by="vote_average", ascending=False).head(15).original_
    movies_and_votes.sort_values(by="vote_average", ascending=False).head(15).vote_aver
    linewidth = 0,
    palette="Set3")


#rotate x-axis' text
for item in ax.get_xticklabels():
    item.set_rotation(85)

ax.set(xlabel='movie titles', ylabel='average vote', title = 'Top 15 movies based on th
plt.show()
```

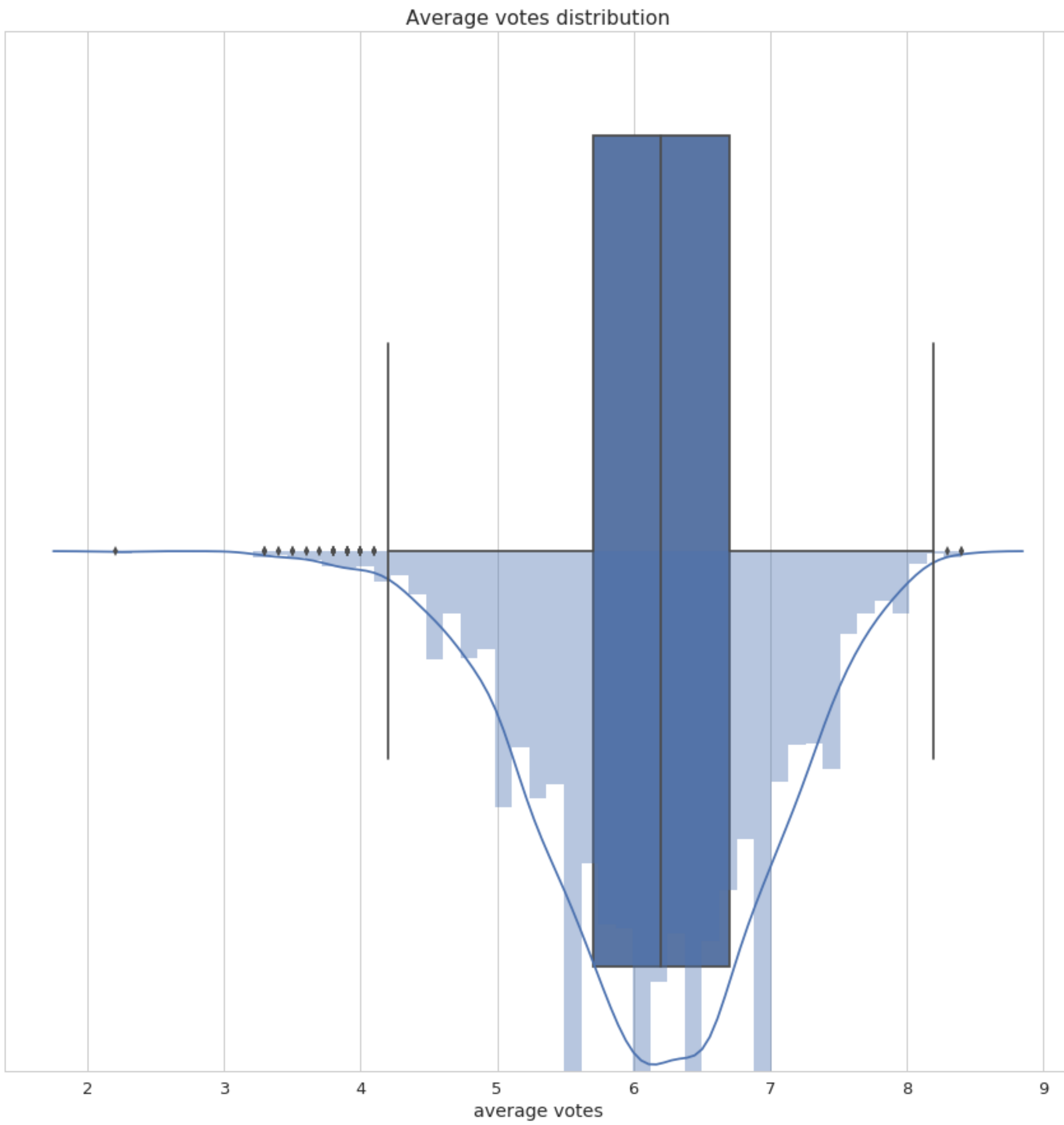


According to the table above, the top 5 movies based on their adjusted budget are the followings; 1. The Shawshank Redemption 2. Stop Making Sense 3. The Godfather 4. Whiplash 5. Pulp Fiction.

3.0.5 Research Question 5 (Average Votes Distribution?)

Let's move to somewhere else. There is some curiosity about the movies' average votes. Lets see their distribution. Let's create a boxplot which illustrates their mean which is about 6. Also two plots were created; 1. One with the distribution of the ratings from 1960 to 2015 2. Another with the ratings distribution from by year.

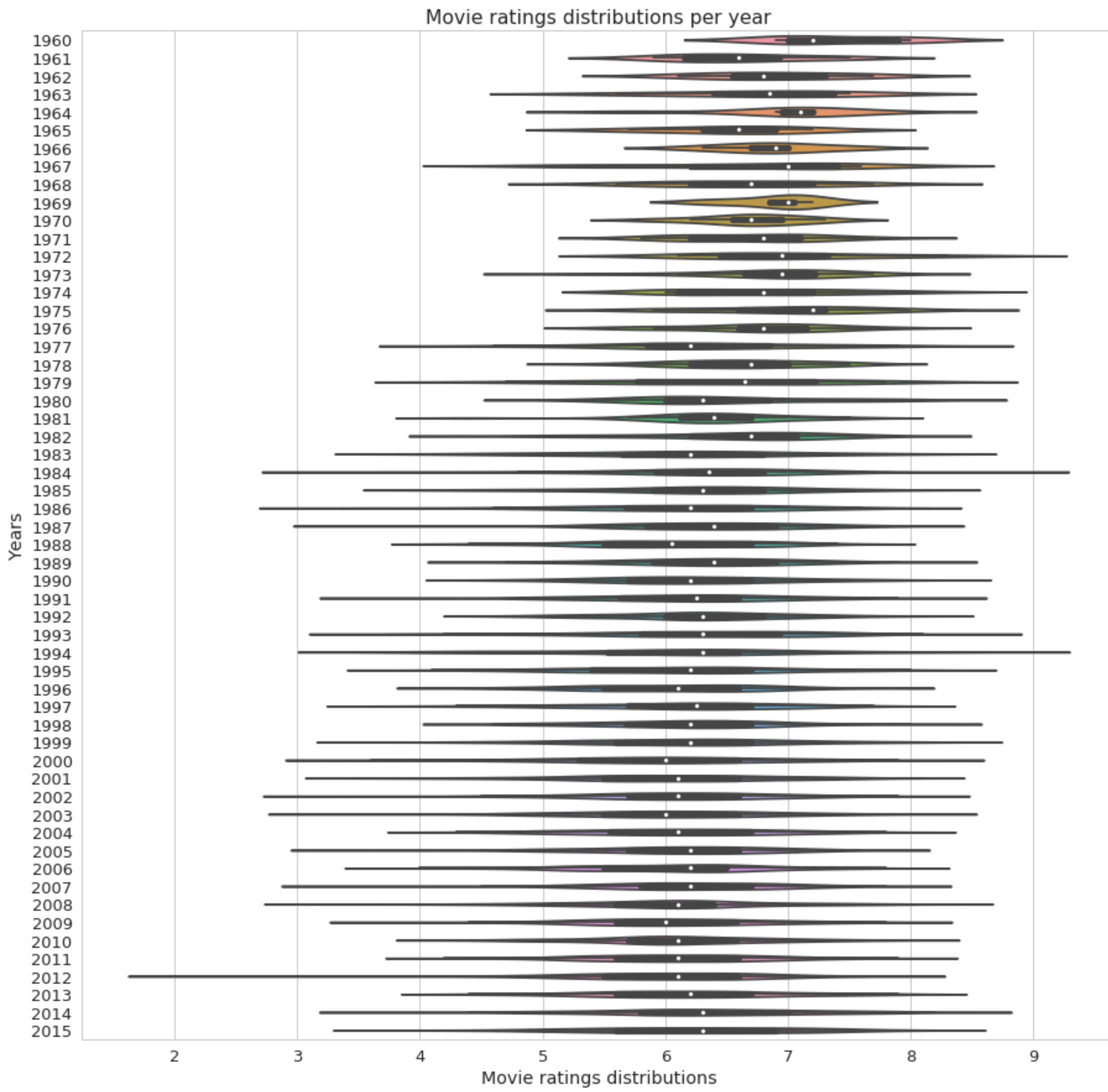
```
In [25]: # Movie ratings' distribution all over the years
         sns.set(rc={'figure.figsize':(15,15)}, font_scale=1.3)

         temp_df = data[["vote_average"]]


         sns.set_style("whitegrid")
         ax = sns.distplot(temp_df.vote_average)

         ax = sns.boxplot(x = temp_df.vote_average)

         ax.set(xlabel='average votes', title = 'Average votes distribution')
         plt.show()
```



Question 5.1: Ratings Distribution by Year The previous question shows that the mean of the ratings all over these years (1960 - 2015) are almost 6. What about the ratings at a specific year. The following snippet code creates a plot showing the ratings distributions per year.

```
In [26]: # Movie ratings' distributions per year
         sns.set(rc={'figure.figsize':(15,15)}, font_scale=1.3)

         temp_df = data[["release_year", "vote_average"]]

         sns.set_style("whitegrid")
         ax = sns.violinplot(x = temp_df.vote_average, y = temp_df.release_year, orient ="h")
```

```
ax.set(xlabel='Movie ratings distributions', ylabel='Years', title = 'Movie ratings dis
plt.show()
```



- The previous figure illustrates that all the years have mean ratings about 6 to 6.5.
- However some exclusions such as the year 1974 has mean ratings around 7. It seems that during that time great movies with high impact on the crowd were produced.