investigate_movie_dataset

August 9, 2022

1 Udacity Data Analysis Project: TMDB Movie Data

1.1 Table of Contents

Introduction

```
In [3]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns

        %matplotlib inline
```

Data Wrangling
This is the part where we load our dataset, check it out and make sure it's clean ready for analysis

1.1.1 General Properties

Reading The Data

```
In [5]: df = pd.read_csv('tmdb-movies.csv', sep=',')

        df.head()

Out[5]:        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]
```

Data Shape and Dimensions The Dataset consist of 10,866 Rows and Columns

```
In [6]: df.shape
```

```
Out[6]: (10866, 21)
```

Data Columns Let's check for names of the columns present in the dataset and their properties

```
In [9]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

1.1.2 Data Cleaning

In this process, the data are understood, cleaned, and transformed into a format that allows for analysis. This is done by - Checking for duplicate rows - Checking for null values - Removing non essential columns - formatting data to the right type

In [11]:
```
#Checking for duplicates

df.duplicated().sum()
```

Out[11]:
```
1
```

In [12]:
```
#Checking for null values

df.isna().sum()
```

Out[12]:
```
id                      0
imdb_id                10
popularity              0
budget                  0
revenue                 0
original_title          0
cast                   76
homepage             7930
director               44
tagline              2824
keywords             1493
overview                4
runtime                 0
genres                 23
production_companies 1030
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
revenue_adj             0
dtype: int64
```

In [13]:
```
#dropping Duplicate rows

df.drop_duplicates(inplace=True)
```

Columns to be dropped and reasons 1. The 'imdb_id' has some null values and since we're using the 'id' column as the unique identifier, we have no need for it. 2. The 'homepage' has a lot of missing values, is peculiar to each movie and therefore does not offer any significant info to help in our analysis. 3. The same argument as above could be applied 'tagline', 'keywords', and 'overview'.

In [14]:
```
#dropping non essential columns

df.drop(['imdb_id', 'homepage', 'tagline', 'overview', 'keywords'], axis=1, inplace=Tru
```

In [15]:
```
#parsing date time in 'release_date' column

df['release_date'] = pd.to_datetime(df['release_date'])
type(df.release_date[0])
```

Out[15]:
```
pandas._libs.tslibs.timestamps.Timestamp
```

In [18]:
```
#dropping movies without casts, directors, production_companies and genres

df = df[df['cast'].isnull() == False]
df = df[df['director'].isnull() == False]
df = df[df['production_companies'].isnull() == False]
df = df[df['genres'].isnull() == False]
```

In [19]:
```
#checking data info again to view changes made

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9772 entries, 0 to 10865
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    9772 non-null   int64
 1   popularity            9772 non-null   float64
 2   budget                9772 non-null   int64
 3   revenue               9772 non-null   int64
 4   original_title        9772 non-null   object
 5   cast                  9772 non-null   object
 6   director              9772 non-null   object
 7   runtime               9772 non-null   int64
 8   genres                9772 non-null   object
 9   production_companies  9772 non-null   object
 10  release_date          9772 non-null   datetime64[ns]
 11  vote_count            9772 non-null   int64
 12  vote_average          9772 non-null   float64
 13  release_year          9772 non-null   int64
 14  budget_adj            9772 non-null   float64
 15  revenue_adj           9772 non-null   float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(5)
memory usage: 1.3+ MB
```

Exploratory Data Analysis

1.1.3 Research Question 1 Genres with the most favourable ratings.

Before we start, it will be advisible to write the current updated dataset to a csv file

```
In [23]: df.to_csv('movie_data.csv', index=False)
```

```
In [24]: df = pd.read_csv('movie_data.csv')
         df['release_date'] = pd.to_datetime(df['release_date'])
```

```
In [20]: #investigating the genre column

         df['genres']
```

```
Out[20]: 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
                                    ...
         10861                                  Documentary
         10862                       Action|Adventure|Drama
         10863                               Mystery|Comedy
         10864                                Action|Comedy
         10865                                       Horror
         Name: genres, Length: 9772, dtype: object
```

As we can see the genre column contain several values split by (|), so we need to find a way to parse those

```
In [37]: #create a copy of genre
         df_genre_copy = df.copy()
```

```
In [38]: #splitting the genre column and converting to an array
         df_genre_copy['genres'] = df_genre_copy.genres.str.split('|')
```

```
In [39]: #verifying array creation
         df_genre_copy.head()
```

```
Out[39]:        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

   runtime                                          genres  \
0      124  [Action, Adventure, Science Fiction, Thriller]
1      120  [Action, Adventure, Science Fiction, Thriller]
2      119          [Adventure, Science Fiction, Thriller]
3      136   [Action, Adventure, Science Fiction, Fantasy]
4      137                        [Action, Crime, Thriller]

                               production_companies release_date  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185
2  Summit Entertainment|Mandeville Films|Red Wago...   2015-03-18        2480
3          Lucasfilm|Truenorth Productions|Bad Robot   2015-12-15        5292
4  Universal Pictures|Original Film|Media Rights ...   2015-04-01        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
```

In [43]:
```
#using the explode function to get each genre on a diffrent row

df_genre_exploded = df_genre_copy.explode('genres')
df_genre_exploded.head(10)
```

Out[43]:
```
       id  popularity     budget     revenue      original_title  \
0  135397   32.985763  150000000  1513528810      Jurassic World
0  135397   32.985763  150000000  1513528810      Jurassic World
0  135397   32.985763  150000000  1513528810      Jurassic World
0  135397   32.985763  150000000  1513528810      Jurassic World
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road
2  262500   13.112507  110000000   295238201           Insurgent
2  262500   13.112507  110000000   295238201           Insurgent

                                                cast          director  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...   Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
```

```
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...     George Miller
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke

   runtime           genres  \
0      124           Action
0      124        Adventure
0      124  Science Fiction
0      124         Thriller
1      120           Action
1      120        Adventure
1      120  Science Fiction
1      120         Thriller
2      119        Adventure
2      119  Science Fiction

                                production_companies release_date  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
0  Universal Studios|Amblin Entertainment|Legenda...   2015-06-09        5562
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185
1  Village Roadshow Pictures|Kennedy Miller Produ...   2015-05-13        6185
2  Summit Entertainment|Mandeville Films|Red Wago...   2015-03-18        2480
2  Summit Entertainment|Mandeville Films|Red Wago...   2015-03-18        2480

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
0           6.5          2015  1.379999e+08  1.392446e+09
0           6.5          2015  1.379999e+08  1.392446e+09
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
1           7.1          2015  1.379999e+08  3.481613e+08
1           7.1          2015  1.379999e+08  3.481613e+08
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
2           6.3          2015  1.012000e+08  2.716190e+08
```

In [44]:
```
#New Dataframe with 'popularity', 'genres' and 'release_year'
df_genre = df_genre_exploded[['popularity', 'genres', 'release_year']]
df_genre.head(10)
```

Out[44]:
```
   popularity           genres  release_year
0   32.985763           Action          2015
0   32.985763        Adventure          2015
0   32.985763  Science Fiction          2015
```

```
0   32.985763         Thriller          2015
1   28.419936           Action          2015
1   28.419936        Adventure          2015
1   28.419936  Science Fiction          2015
1   28.419936         Thriller          2015
2   13.112507        Adventure          2015
2   13.112507  Science Fiction          2015
```

In [46]:
```
#group by genre and popularity

df_genre_grouped  = df_genre_exploded.groupby(['release_year', 'genres']).popularity.me
genre_yearwise = df_genre_grouped.to_frame().groupby(level = 'release_year').popularity
```

In [47]:
```
genre_yearwise.reset_index(level=2,inplace=True)
```

In [48]:
```
genre_yearwise.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 56 entries, (1960, 1960) to (2015, 2015)
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   genres      56 non-null     object
 1   popularity  56 non-null     float64
dtypes: float64(1), object(1)
memory usage: 4.0+ KB
```

In [49]:
```
genre_yearwise.head()
```

Out[49]:

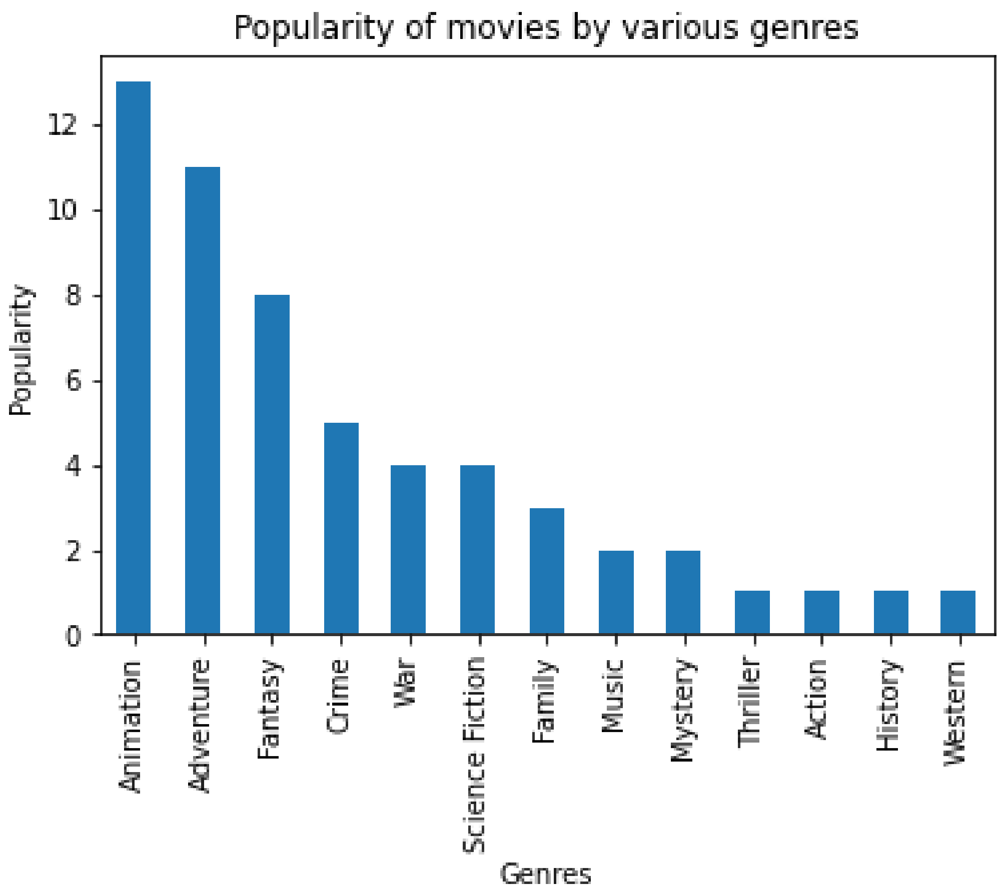
release_year	release_year	genres	popularity
1960	1960	Thriller	0.811910
1961	1961	Animation	2.631987
1962	1962	Adventure	0.942513
1963	1963	Animation	2.180410
1964	1964	War	0.930959

In [50]:
```
genre = genre_yearwise.genres.value_counts()
genre
```

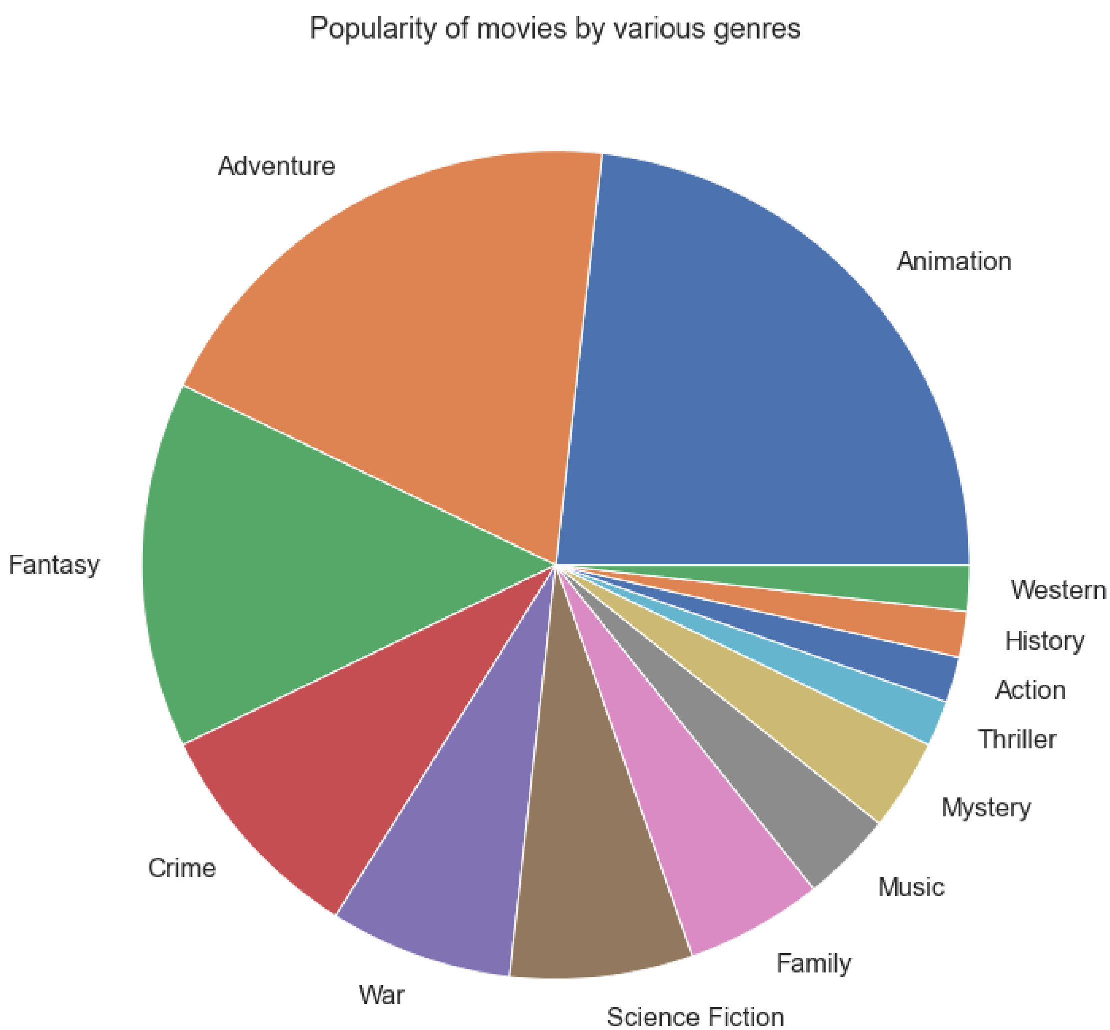
Out[50]:
```
Animation          13
Adventure          11
Fantasy             8
Crime               5
War                 4
Science Fiction     4
Family              3
Music               2
```

```
Mystery             2
Thriller            1
Action              1
History             1
Western             1
Name: genres, dtype: int64
```

In [51]:
```
#plotting popularity by genres

genre.plot.bar(title="Popularity of movies by various genres",xlabel="Genres",ylabel="P
```



In [68]:
```
#genre.plot(kind='pie', figsize=(8,8), title="Popularity of movies by various genres" )

genre.plot.pie(title="Popularity of movies by various genres", ylabel='');
```



According to the plot above, we can see that Animation is the most popular genre, followed by Adventure and Fantasy

1.1.4 Research Question 2 Actors with the most appearance in movies

We have a column for cast with which we can use to find out the actor with the most appearance in all the movies in the dataset

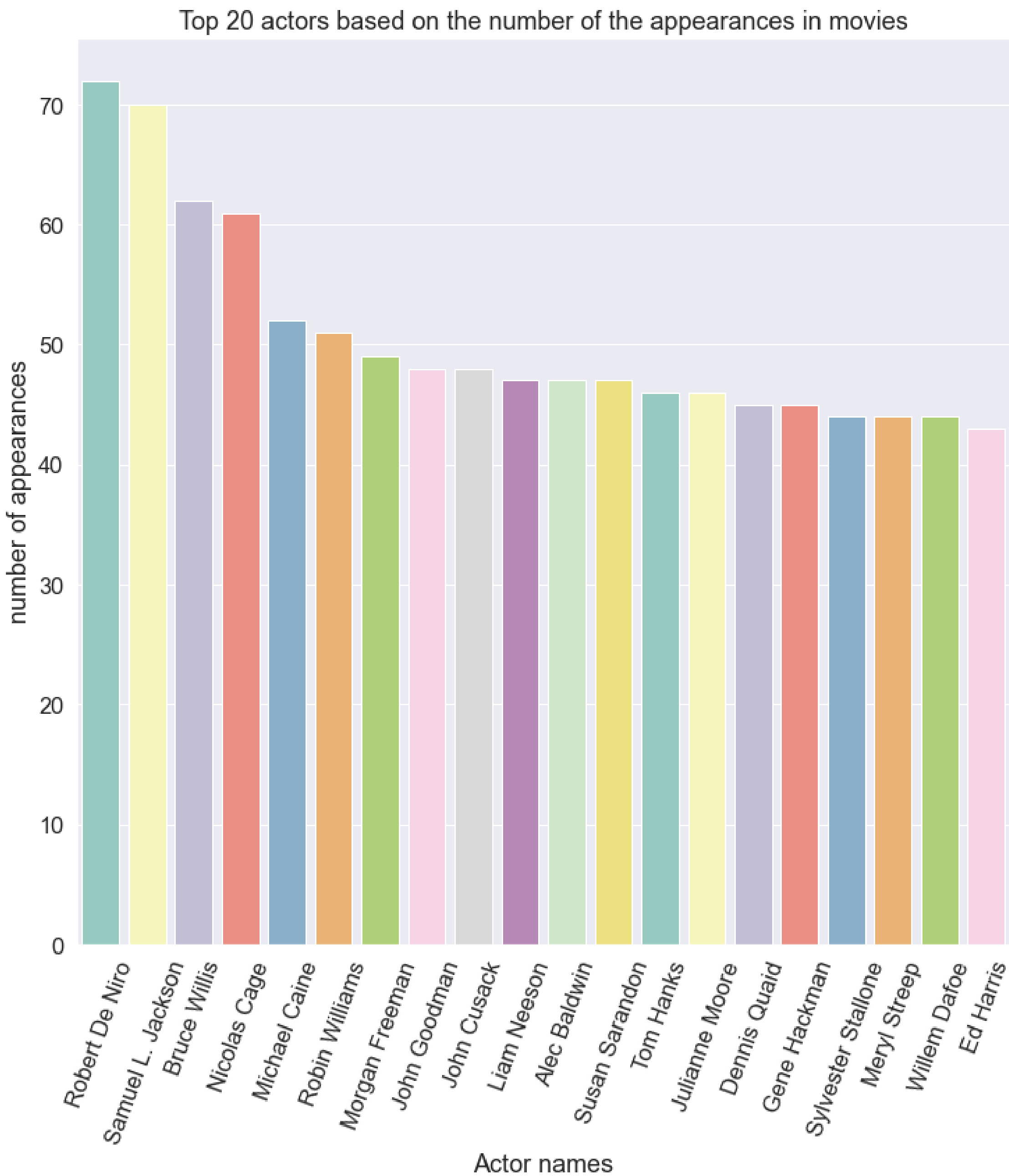
```
In [56]: #create a dict for the cast and number of occurances
         actor_dict = {}

         actors = df['cast']
         #As we saw previously, there are multiple values in the cast columns sepereated by the

         actors = actors.str.split('|')
```

```
actors = np.array(actors)

for actorList in actors:
    for actor in actorList:
        actor = actor.strip() #trim the whitespaces
        if actor not in actor_dict:
            actor_dict[actor] = 1
        else:
            actor_dict[actor] += 1
```

In [58]:
```
import operator
sorted_actor_dict = sorted(actor_dict.items(), key = operator.itemgetter(1), reverse =
```

In [61]:
```
x_axis = list()
y_axis = list()

for item in sorted_actor_dict[0:20]:
    x_axis.append(item[0])
    y_axis.append(item[1])


sns.set(rc={'figure.figsize':(12,12)}, font_scale=1.5)
ax = sns.barplot(x_axis, y_axis, palette="Set3")


#rotate x-axis' text
for item in ax.get_xticklabels():
    item.set_rotation(70)


ax.set(xlabel='Actor names', ylabel='number of appearances', title = 'Top 20 actors bas
plt.show();
```

```
c:\ProgramData\Anaconda3\envs\my_env\lib\site-packages\seaborn\_decorators.py:43: FutureWarning:
  FutureWarning
```



From the above Visuals, we can easily see that Robert De Niro is the top actor followed by Samuel L. Jackson

1.1.5 Research Question 3 Correlation between Movie Budget and Popularity

We're going to investigate if the movies with a higher budget are more popular than those with less budget

```
In [77]: df_new = df[df['budget_adj'] != 0].copy()
         df['budget_adj'].describe()
```

```
df_new['budget_adj'].describe()
```

Out[77]:
```
count    5.021000e+03
mean     3.778790e+07
std      4.220942e+07
min      9.210911e-01
25%      8.890145e+06
50%      2.374361e+07
75%      5.082002e+07
max      4.250000e+08
Name: budget_adj, dtype: float64
```

In [78]:
```
## find quartile,max and min values
min_value = df_new['budget_adj'].min()
first_quantile = df_new['budget_adj'].describe()[4]
second_quantile = df_new['budget_adj'].describe()[5]
third_quantile = df_new['budget_adj'].describe()[6]
max_value = df_new['budget_adj'].max()
## bin edges that will be used to cut data in groups
bin_edges = [min_value,first_quantile,second_quantile,third_quantile,max_value]
## labels for the four budget level groups
bin_names = ['Low','Medium','Moderately High','High']
## Create budget levels column
name = '{}_levels'.format('budget_adj')
df_new['budget_adj_levels'] = pd.cut(df_new['budget_adj'],bin_edges,labels=bin_names,in

df_new['budget_adj_levels']
```

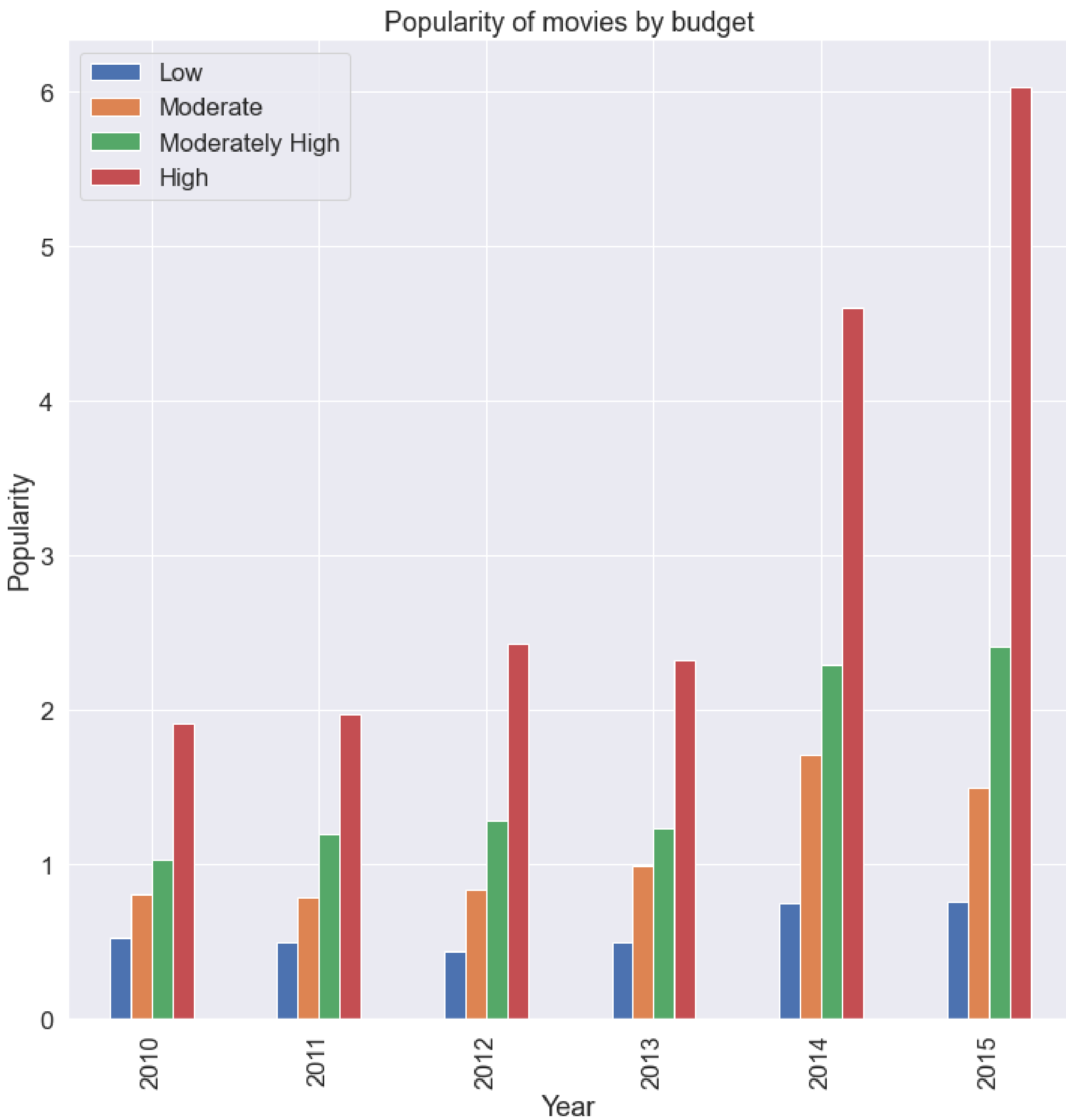
Out[78]:
```
0                  High
1                  High
2                  High
3                  High
4                  High
             ...
9743               High
9749                Low
9755    Moderately High
9761                Low
9771                Low
Name: budget_adj_levels, Length: 5021, dtype: category
Categories (4, object): ['Low' < 'Medium' < 'Moderately High' < 'High']
```

In [79]:
```
df_budget_filtered_data = df_new[df_new['release_year'].isin([2010,2011,2012,2013,2014,

df_popularity_on_budget = df_budget_filtered_data.groupby(['release_year','budget_adj_l
```

In [80]:
```
short_movie_vote = df_popularity_on_budget[df_popularity_on_budget['budget_adj_levels']
medium_movie_vote = df_popularity_on_budget[df_popularity_on_budget['budget_adj_levels'
mod_long_movie_vote = df_popularity_on_budget[df_popularity_on_budget['budget_adj_level
long_movie_vote = df_popularity_on_budget[df_popularity_on_budget['budget_adj_levels']
```

In [85]:
```
release_years = ['2010', '2011', '2012', '2013', '2014', '2015']
```

In [86]:
```
plotdata = pd.DataFrame({
    "Low": short_movie_vote,
    "Moderate": medium_movie_vote,
    "Moderately High": mod_long_movie_vote,
    "High": long_movie_vote
},index=release_years)

plotdata.plot(kind='bar')
plt.title('Popularity of movies by budget')
plt.xlabel("Year")
plt.ylabel("Popularity");
```



Correlation between Budget and Popularity Based on the graph above, we can comfortable deduce that higher budget movies are more popular than the lower cost ones

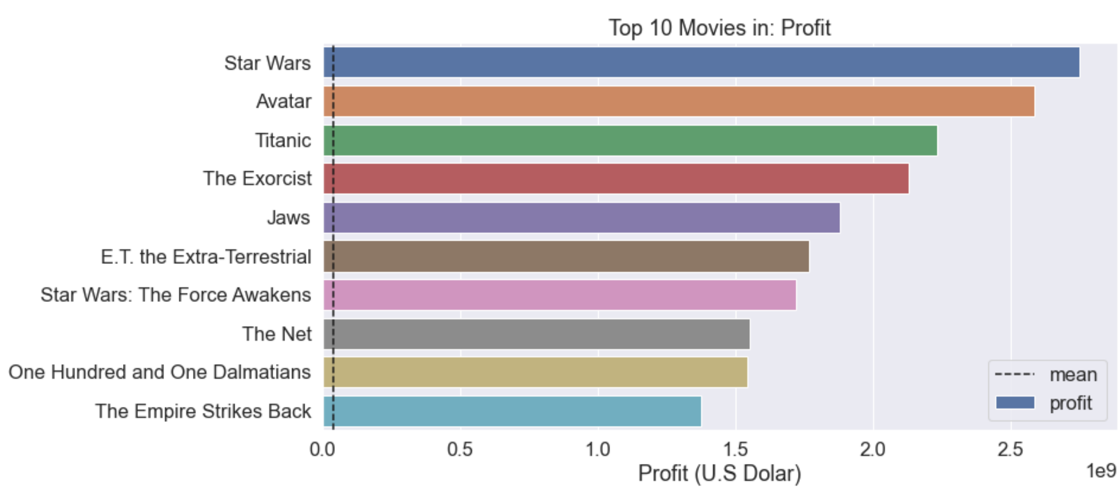
1.1.6 Research Question 4 Top 10 Movies by Profit

We would need to calculate the profit for each movie to get this.

In [87]:
```
df['profit'] = df['revenue_adj']-df['budget_adj']
df['profit'] = df['profit'].apply(np.int64)
df['budget_adj'] = df['budget_adj'].apply(np.int64)
df['revenue_adj'] = df['revenue_adj'].apply(np.int64)
```

In [88]:
```
def top_10(col_name,size=10):
    #find the all times top 10 for a given column
    #sort the given column and select the top 10
    df_sorted = pd.DataFrame(df[col_name].sort_values(ascending=False))[:size]
    df_sorted['original_title'] = df['original_title']
    plt.figure(figsize=(12,6))
    #Calculate the avarage
    avg = np.mean(df[col_name])
    sns.barplot(x=col_name, y='original_title', data=df_sorted, label=col_name)
    plt.axvline(avg, color='k', linestyle='--', label='mean')
    if (col_name == 'profit' or col_name == 'budget' or col_name == 'revenue'):
        plt.xlabel(col_name.capitalize() + ' (U.S Dolar)')
    else:
        plt.xlabel(col_name.capitalize())
    plt.ylabel('')
    plt.title('Top 10 Movies in: ' + col_name.capitalize())
    plt.legend()
```

In [89]:
```
top_10('profit')
```



As we can see above, Star Wars has the most profit when adjusted for inflation
Conclusions

This dataset contains a wealth of knowledge. The dataset has some restrictions, including some features with null or zero values. The rows that correspond to these zero and null values must be eliminated since they impede the analysis. For instance, examining the top cast actors was stalled by the problem of null values. Zero values also produce erroneous results when calculating the pearson correlation and plotting correlations. As a result, data cleaning must be done before the dataset may be investigated. Robert De Niro is one of the well-known actors who has been in numerous movies over the years.

1. Which Genres recieve more favourable ratings From our Analysis, we deduced that Animation was the most popular movie genre, followed by Adventure and Fantasy. >Limitations: There were some rows who had null values in the genre column so they had to be dropped. There are various genres in every movie. Nevertheless, every movie typically has one core genre and a few smaller ones. For instance, Avatar falls within the Action and Science Fiction categories, according to Google search results. Our analysis, however, revealed that the film also contains Adventure and Fantasy aspects. This classification is therefore ambiguous, and because of this ambiguity, we have classified Avatar as a Adventure, science fiction, action, and Fantasy movie. The same film is counted in each of the four genres.

2. Actors with the most appearances in movies As Evident in the bar chart, Robert De Niro has the most appearances with over 70 movie appearances, followeed closely by Samuel L. Jackson. We can also see that there's not much difference between the top actors with the exception of the Top 4. >Limitations: Some of the rows had the cast missing so also had to be dropped, this made our top actor not inclusive of all movies

3. Correlation between Movie budget and Popularity Higher budget movies usually had more popularity as compared to lower budget movies. >Limitations: 50% of the budget and revenue values are both zero. Due to this, only about 50% of the rows could be used for income and budget analysis, and we were unable to provide information for the remaining 50%.

4. Top 10 Movies by Profit (adjusted for inflation) We can identify the following movies as the top 10 Movies - Star Wars - Avatar - Titanic - The Exorcist - Jaws - E.T The Extra Terrestial - Star Wars: The Force Awakens - The Net - One Hundred and One Dalmatians - The Empire Strikes Back >Limitations: Although each movie's revenue and budget were known, there was no information on its profit, so I computed it.

```
In [ ]:
```