Investigate_a_Dataset_best_final_version

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1 Project 1: Investigating a Dataset - TMDB dataset

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Introduction
TMDB Movies dataset contains about 10 000 movies collected from the TMDB dataset. It has 21 columns and about 10 800 entries.

- Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|) characters.

1.1 Question(s) for Analysis

1. 20 most popular movies
2. which actor appeared in many movies
3. Is there a correlation between budget and revenue
4. Which movie genre generated the most revenue

```
In [103]: import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          import seaborn as sns
          sns.set_style(style='darkgrid')
          %matplotlib inline
          import warnings
          warnings.filterwarnings('ignore')
```

```
In [ ]: #using google colab notebooks
        #mounting data from the google drive
        from google.colab import drive
        drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
In [ ]: #importing the data set using pandas
        movies_df = pd.read_csv('/content/drive/My Drive/tmdb-movies.csv')
        movies_df.head(2)
```

Out[ ]:
```
       id    imdb_id  popularity     budget     revenue      original_title  \
0  135397  tt0369610   32.985763  150000000  1513528810      Jurassic World
1   76341  tt1392190   28.419936  150000000   378436354  Mad Max: Fury Road

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...

                        homepage          director             tagline  ...  \
0  http://www.jurassicworld.com/  Colin Trevorrow   The park is open.  ...
1    http://www.madmaxmovie.com/    George Miller  What a Lovely Day.  ...

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic ...     124
1  An apocalyptic story set in the furthest reach...     120

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|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

   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 rows x 21 columns]
```

In [ ]:
```
#checking the general information on the data
movies_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
```

Data Wrangling

1.1.1 Data Cleaning

```
In [ ]: #droping columns which are not going to form part of this analysis

        movies_df.drop(['vote_count','tagline','id','budget_adj','revenue_adj',
                        'vote_average',
                        'overview','homepage', 'keywords', 'production_companies',
                        'imdb_id', 'director','release_date',],axis=1,inplace=True)
```

```
In [ ]: #droping every null value
        movies_df.dropna(axis=0, how='any', inplace=True)
```

```
In [ ]: #droping duplicated rows if any
        movies_df.drop_duplicates(keep='first',inplace=True)
```

```
In [ ]: #creating a custom made explode to explode column: cast and genres
        def explode(x, col): return x.assign(**{col:x[col].str.split("|")}).explode(col)

        movies_df = explode(explode(movies_df,'cast' ), 'genres')
```

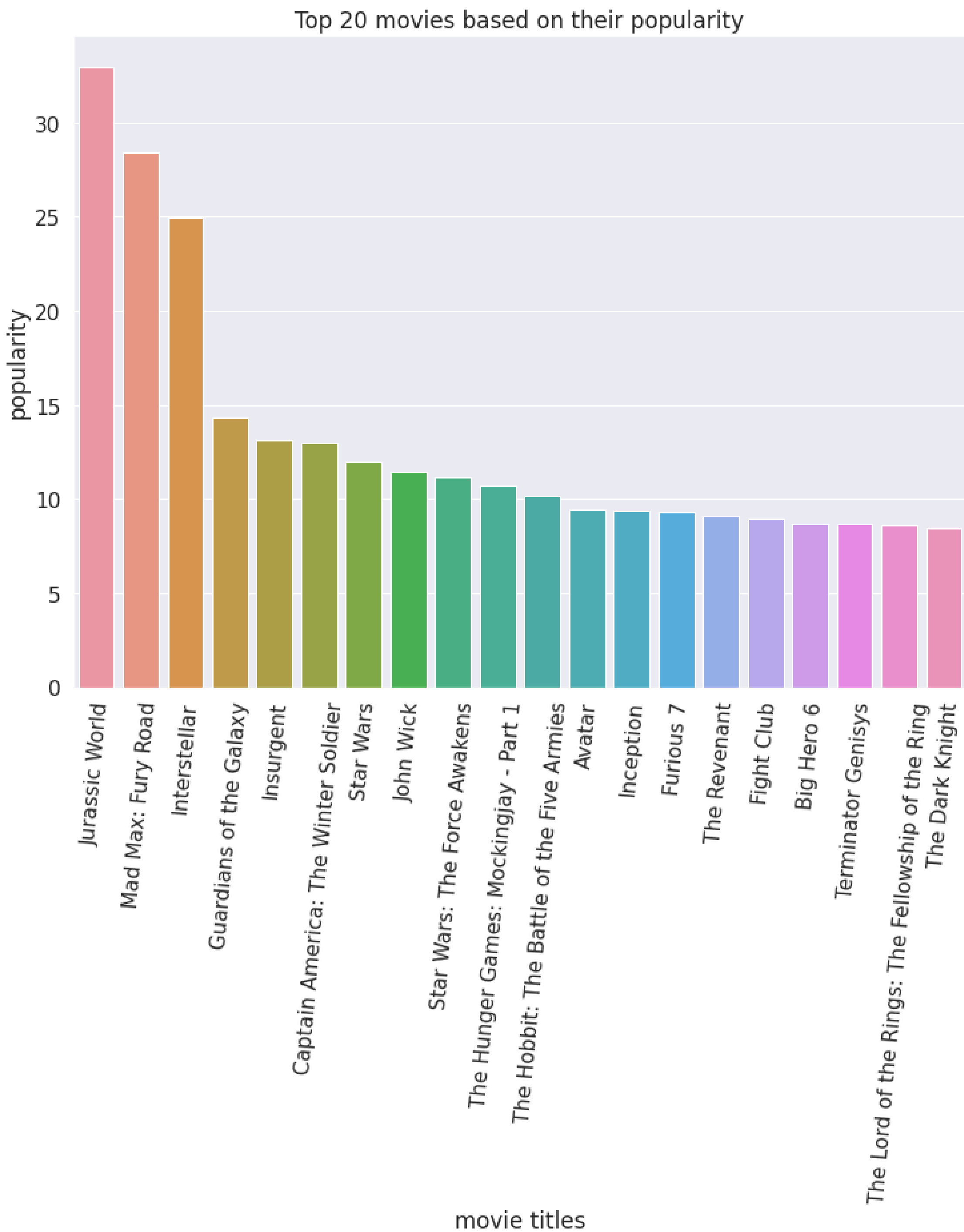
```
In [ ]: #changing columns cast, original_title and genres to be of type string
        movies_df['cast'] = movies_df['cast'].astype("string")
        movies_df['genres'] = movies_df['genres'].astype("string")
        movies_df['original_title'] = movies_df['original_title'].astype("string")
```

Exploratory Data Analysis

1.1.2 Research Question 1 20 most popular movies

```
In [ ]: #creating a dataframe contain columns: popularity and original title of the movie
        df_m = movies_df[['popularity','original_title']]

        # droping the duplicates values from the dataframe
        df_m = df_m.drop_duplicates(keep='first')
```

In [104]:
```python
# 20 popular movies
sns.set(rc={'figure.figsize':(12,9)}, font_scale=1.4)


ax = sns.barplot(
    df_m.sort_values(by="popularity", ascending=False).head(20).original_title,
    df_m.sort_values(by="popularity", ascending=False).head(20).popularity)


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

ax.set(xlabel='movie titles', ylabel='popularity',
       title = 'Top 20 movies based on their popularity')
plt.show();
```



from the bar plot above we can see that *JURASTIC WORLD* was the most popular movie in the dataset.

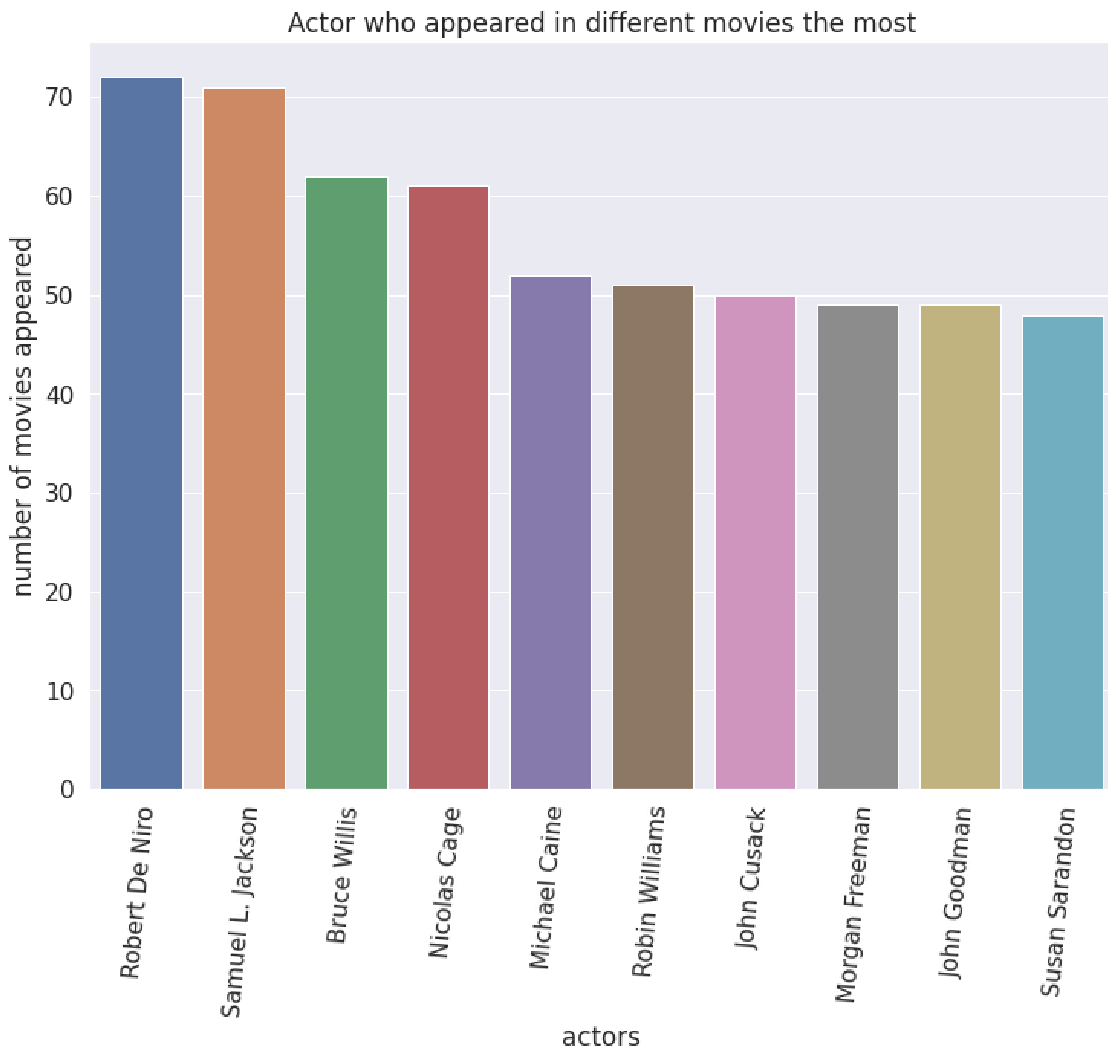
1.1.3 Research Question 2 Which actor appeared in most movies

In [105]:
```
#creating a dataframe containing cast and original_title columns
df_actors = movies_df[['cast', 'original_title'] ]

#removing any duplicates in the dataset
df_actors = df_actors.drop_duplicates(keep='first')

#creating a dataframe that contains value_counts of df_actors dataframe
df_actors = pd.DataFrame(df_actors['cast'].value_counts())
df_actors = df_actors.reset_index()
df_actors.columns = ['actors', 'counts']

#taking only 20 actors from the dataframe for our analysis
df_actors = df_actors.head(20)
df_actors.head()
```

Out[105]:

	actors	counts
0	Robert De Niro	72
1	Samuel L. Jackson	71
2	Bruce Willis	62
3	Nicolas Cage	61
4	Michael Caine	52

In [107]:
```
#ploting a bar chat of the 10 actors that appear in most movies

sns.set(rc={'figure.figsize':(12,9)}, font_scale=1.4)


ax = sns.barplot(
   df_actors.actors.head(10), df_actors.counts.head(10))


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

ax.set(xlabel='actors', ylabel='number of movies appeared',
       title = 'Actor who appeared in different movies the most')
plt.show()
```



From the above we can note that *Robert De Niro* appeared in most movies.

1.2 Question 3: Is there a correlation between budget and revenue

```
In [ ]: movies_df.head()
```

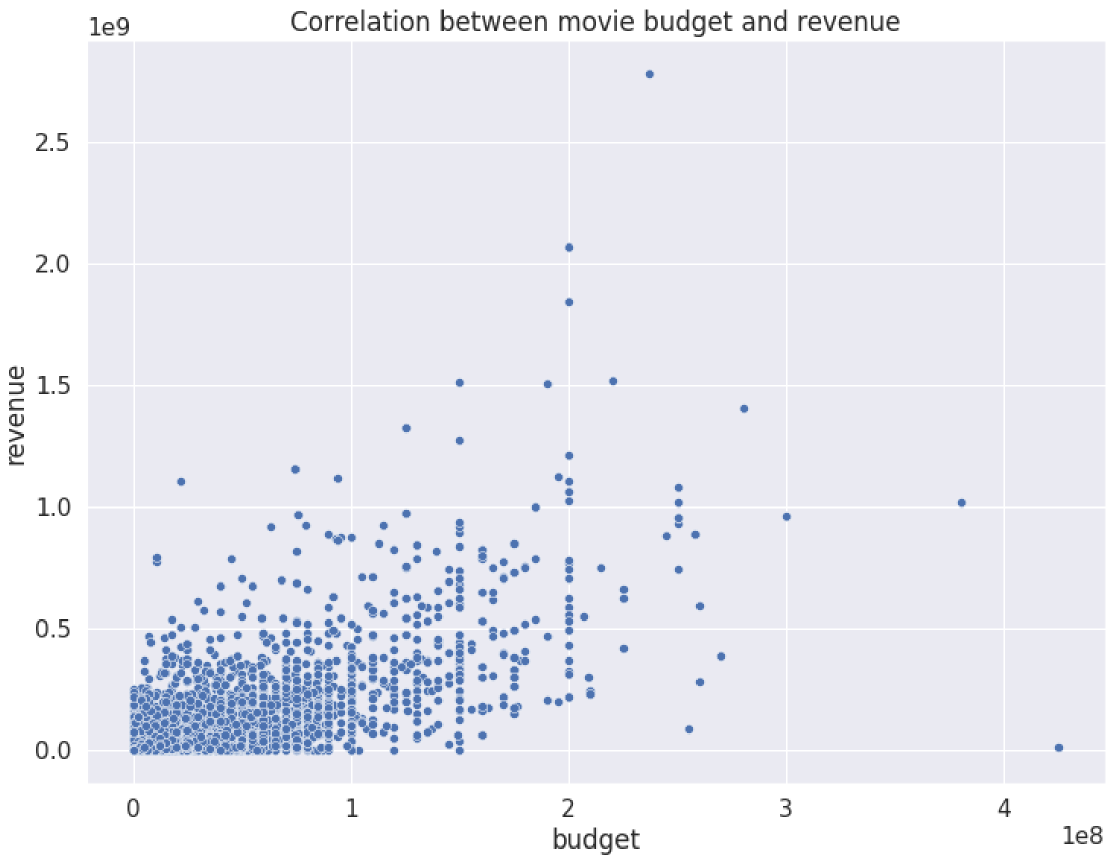
```
Out[ ]:    popularity     budget     revenue  original_title                cast  \
        0   32.985763  150000000  1513528810  Jurassic World         Chris Pratt
        0   32.985763  150000000  1513528810  Jurassic World         Chris Pratt
        0   32.985763  150000000  1513528810  Jurassic World         Chris Pratt
        0   32.985763  150000000  1513528810  Jurassic World         Chris Pratt
        0   32.985763  150000000  1513528810  Jurassic World  Bryce Dallas Howard

           runtime        genres  release_year
        0      124        Action          2015
        0      124     Adventure          2015
```

```
0       124  Science Fiction          2015
0       124         Thriller          2015
0       124           Action          2015
```

In [108]:
```
#creating a dataframe of revenue_adj and budjet_adj
df_bud = movies_df[['revenue', 'budget']]
df_bud = df_bud.drop_duplicates(keep='first')

#creating a dataframe of budget columns and popularity columns
df_pop = movies_df[['popularity', 'budget']]
df_pop = df_pop.drop_duplicates(keep='first')
```

In [109]:
```
#creating a function for scatter plot
def scatter_plotting(x_series, y_series, plot_title, x_label, y_label):
  sns.scatterplot(x=x_series, y=y_series)
  plt.title(plot_title)
  plt.xlabel(x_label)
  plt.ylabel(y_label)
  plt.show();
```

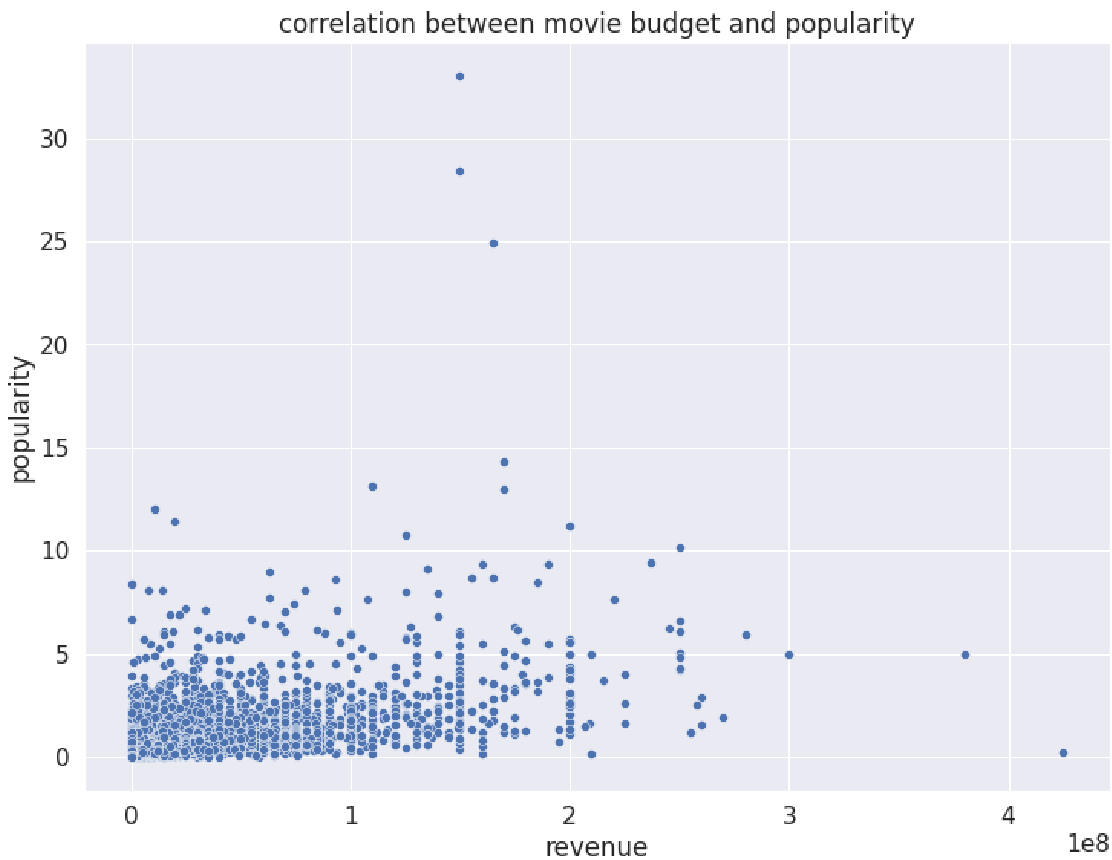
In [110]:
```
#creating a scatter to see if there is a correlation between revenue_adj and budjet_ad
title = 'Correlation between movie budget and revenue'
x_label = 'budget'
y_label = 'revenue'
scatter_plotting(df_bud.budget, df_bud.revenue,title, x_label, y_label)
```



We can note that there is a positive correlation between money spend on the movie(budget) and the revenue that the movie gets.

1.2.1 Question 3 part 2 correlation between revenue and popularity

In [111]:
```
# scatter plot between budget and popularity of the moves
title = 'correlation between movie budget and popularity'
x_label = 'revenue'
y_label = 'popularity'
scatter_plotting(df_pop.budget, df_pop.popularity, title, x_label, y_label)
```



we constat that there isn't really not correlation between revenue of the movies and how popular the movie is. So we can safely say the amount of money that the movies invest isn't correlated to how the movie will be popular

1.3 Question 4: Which movie genre produced the most revenue

In [112]:
```
#creating a dataframe of movie genre and revenue
df_gen = movies_df[['revenue', 'genres']]
df_gen = df_gen.drop_duplicates()
```

```
In [113]: df_gen.revenue.values.reshape(-1, 1)
```

```
Out[113]: array([[1513528810],
                 [1513528810],
                 [1513528810],
                 ...,
                 [   6000000],
                 [  20000000],
                 [  12000000]])
```

```
In [114]: #collecting all movie genres
          genres = np.array(df_gen['genres'].unique())
          for genre in genres:
            genre = genre.strip()

          genres
```

```
Out[114]: array(['Action', 'Adventure', 'Science Fiction', 'Thriller', 'Fantasy',
                 'Crime', 'Western', 'Drama', 'Family', 'Animation', 'Comedy',
                 'Mystery', 'Romance', 'War', 'History', 'Music', 'Horror',
                 'Documentary', 'TV Movie', 'Foreign'], dtype=object)
```

```
In [115]: #scaling data
          from sklearn import preprocessing

          def vectorized_array(df):
            #vectorized operation across numpy array
            float_array = df.values.astype(float).reshape(-1, 1)
            min_max_scaler = preprocessing.MinMaxScaler()
            scaled_array = min_max_scaler.fit_transform(float_array)
            return scaled_array
```

```
In [116]: #returning scaled data to revenue column
          df_gen.revenue = vectorized_array(df_gen.revenue)
          df_gen.head()
```

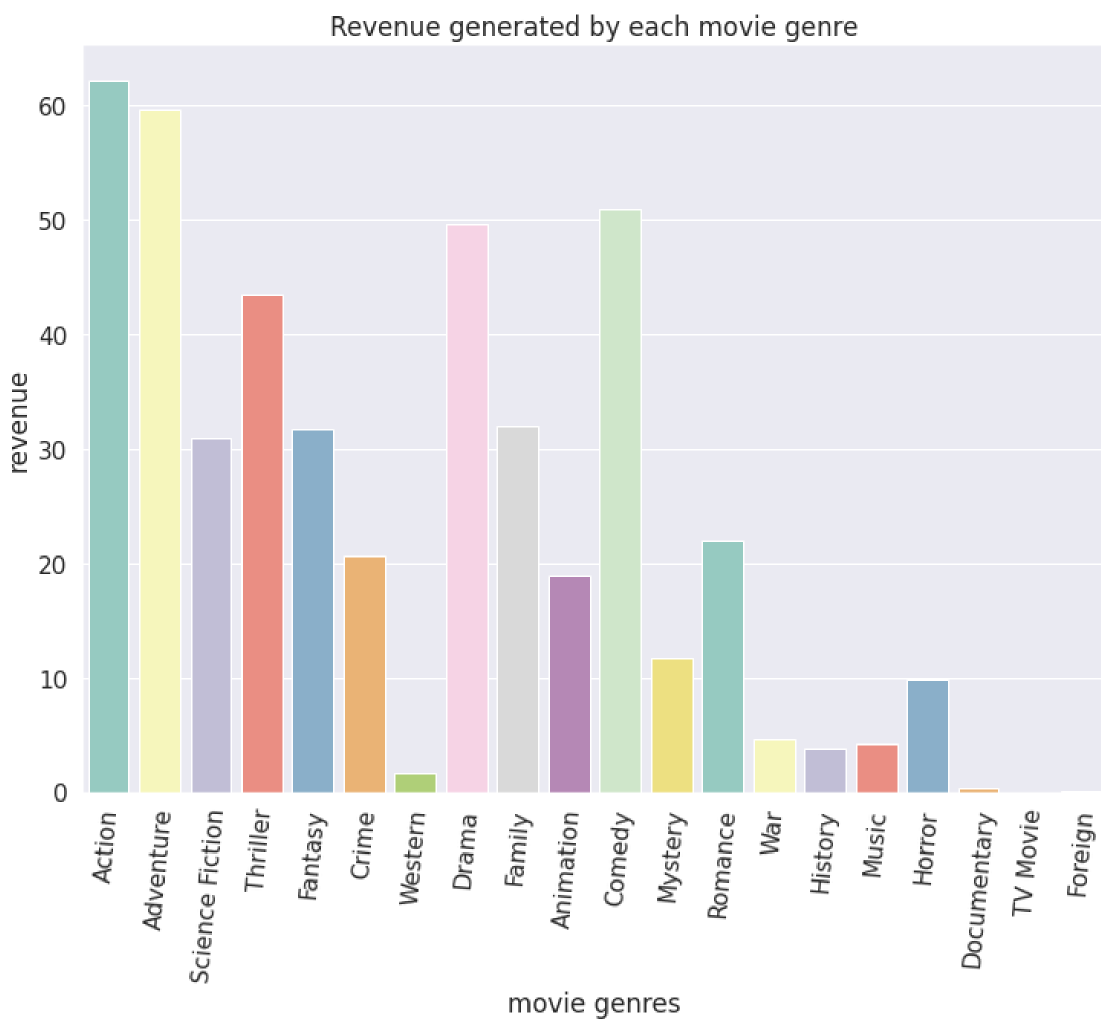
Out[116]:

	revenue	genres
0	0.544140	Action
0	0.544140	Adventure
0	0.544140	Science Fiction
0	0.544140	Thriller
1	0.136054	Action

```
In [118]: #creating a dictionary to hold total revenue for each movie genre

          def apply_ensure_sum(genre,df_gen):
            genre = str(genre)
            #sum of each genre
            sum_value = np.sum( np.array(df_gen[ df_gen['genres'] == genre ].revenue) )
            return sum_value
```

In [119]:
```
gen_values = []
for genre in genres:
  sum_genre = apply_ensure_sum(genre, df_gen)
  gen_values.append(sum_genre)
```

In [120]:
```
#creating a bar plot for revenue and movie genre
sns.set(rc={'figure.figsize':(12,9)}, font_scale=1.4)
ax = sns.barplot(genres, gen_values, palette="Set3")

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

ax.set(xlabel='movie genres', ylabel='revenue',
       title = 'Revenue generated by each movie genre')
plt.show();
```



We can note that Action movies generated more movies that any other movie genre, followed by Adventure movies and then Science Fiction.

Conclusion

The TMDB movie data was quiet clean that there wasn't much effort need to work on it. They were null values which i had to remove for my analysis know that they werent going to affect my analysis too much.

I had to work more the two columns genres and cast which had a pipe after every genre or cast. I had to seperate the cast so that I can be able to answer my question which is which actor appeared in my movies along the course.

From this data I was able to find which actor featured in a lot of movies, I was able to find if there is a correlation between the movie budget and its return. I noticed that there was no correlation. I also used this data to find which was the most popular movie and if popularity was equated with the revenue the movie was earning but I found that there was no correlation between these two.

Limitations

The challenges I faced working with this data was It was difficult to know the meaning of each columns. For example the column popularity what was the values there meaning. Did they mean the popularity of the movies for a day accumulated to a year or they meant something.

Had the data included a file that explains the meaning of each column it would have been helpful.