Investigation_on_5000_movies

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1 Project: Investigation on 5000 movies

1.1 Table of Contents

1. Introduction

> **The selected dataset contains information about 5000 movies collected from 1916 to 2016 from The Movie Database (TMDb). It includes user ratings, revenues, genres, production companies, etc. Certain columns contain multiple dictionaries in one cell for example in genre and production companies. This project will focus on analyzing the popularity and profit of movies based on country of origin, year produced , production companies and genre of the movies, for axample which country produce most polular movies ? Which production company produces the most popular movies, and which one produces the movies that have high profits.**

2. Data Wrangling

> **loading the data, check for cleanliness, trim and clean the dataset for analysis.**

1.1.1 2.1. General Properties

Importing modules

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
import json
from collections import OrderedDict
plt.rcParams['figure.figsize']=(14,8)
```

Loading the data

[2]:
```
# Load your data
movies_df=pd.read_csv('tmdb_5000_movies.csv')
```

Knowing number of samples and features

[3]:
```
#Discovering number of samples and number of features
movies_df.shape
```

[3]:
```
(4803, 20)
```

Structure of dataset

[4]:
```
# Displaying top 5 lines of dataset
movies_df.head()
```

[4]:
```
      budget                                              genres  \
0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
1  300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "…
2  245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
3  250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam…
4  260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…

                                       homepage      id  \
0                   http://www.avatarmovie.com/   19995
1  http://disney.go.com/disneypictures/pirates/     285
2   http://www.sonypictures.com/movies/spectre/  206647
3            http://www.thedarkknightrises.com/   49026
4          http://movies.disney.com/john-carter   49529

                                            keywords original_language  \
0  [{"id": 1463, "name": "culture clash"}, {"id":…               en
1  [{"id": 270, "name": "ocean"}, {"id": 726, "na…               en
2  [{"id": 470, "name": "spy"}, {"id": 818, "name…               en
3  [{"id": 849, "name": "dc comics"}, {"id": 853,…               en
4  [{"id": 818, "name": "based on novel"}, {"id":…               en

                             original_title  \
0                                    Avatar
1  Pirates of the Caribbean: At World's End
2                                   Spectre
3                     The Dark Knight Rises
4                               John Carter

                                            overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di…  150.437577
1  Captain Barbossa, long believed to be dead, ha…  139.082615
2  A cryptic message from Bond's past sends him o…  107.376788
3  Following the death of District Attorney Harve…  112.312950
```

```
4  John Carter is a war-weary, former military ca…   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289…
1  [{"name": "Walt Disney Pictures", "id": 2}, {"…
2  [{"name": "Columbia Pictures", "id": 5}, {"nam…
3  [{"name": "Legendary Pictures", "id": 923}, {"…
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries release_date     revenue  \
0  [{"iso_3166_1": "US", "name": "United States o…   2009-12-10  2787965087
1  [{"iso_3166_1": "US", "name": "United States o…   2007-05-19   961000000
2  [{"iso_3166_1": "GB", "name": "United Kingdom"…   2015-10-26   880674609
3  [{"iso_3166_1": "US", "name": "United States o…   2012-07-16  1084939099
4  [{"iso_3166_1": "US", "name": "United States o…   2012-03-07   284139100

   runtime                                   spoken_languages    status  \
0    162.0  [{"iso_639_1": "en", "name": "English"}, {"iso…  Released
1    169.0           [{"iso_639_1": "en", "name": "English"}]  Released
2    148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},…  Released
3    165.0           [{"iso_639_1": "en", "name": "English"}]  Released
4    132.0           [{"iso_639_1": "en", "name": "English"}]  Released

                                          tagline  \
0                      Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                             A Plan No One Escapes
3                                  The Legend Ends
4            Lost in our world, found in another.

                                      title  vote_average  vote_count
0                                    Avatar           7.2       11800
1  Pirates of the Caribbean: At World's End           6.9        4500
2                                   Spectre           6.3        4466
3                     The Dark Knight Rises           7.6        9106
4                               John Carter           6.1        2124
```

[5]:
```python
# Displaying bottom 5 lines of dataset
movies_df.tail()
```

[5]:
```
      budget                                             genres  \
4798  220000  [{"id": 28, "name": "Action"}, {"id": 80, "nam…
4799    9000  [{"id": 35, "name": "Comedy"}, {"id": 10749, "…
4800       0  [{"id": 35, "name": "Comedy"}, {"id": 18, "nam…
4801       0                                                 []
4802       0                  [{"id": 99, "name": "Documentary"}]
```

```
                                                 homepage      id  \
4798                                                  NaN    9367
4799                                                  NaN   72766
4800  http://www.hallmarkchannel.com/signedsealeddel…  231617
4801                           http://shanghaicalling.com/  126186
4802                                                  NaN   25975

                                                 keywords original_language  \
4798  [{"id": 5616, "name": "united states\u2013mexi…                es
4799                                                   []                en
4800  [{"id": 248, "name": "date"}, {"id": 699, "nam…                en
4801                                                   []                en
4802  [{"id": 1523, "name": "obsession"}, {"id": 224…                en

                original_title  \
4798               El Mariachi
4799                 Newlyweds
4800  Signed, Sealed, Delivered
4801           Shanghai Calling
4802          My Date with Drew

                                                 overview  popularity  \
4798  El Mariachi just wants to play his guitar and …   14.269792
4799  A newlywed couple's honeymoon is upended by th…    0.642552
4800  "Signed, Sealed, Delivered" introduces a dedic…    1.444476
4801  When ambitious New York attorney Sam is sent t…    0.857008
4802  Ever since the second grade when he first saw …    1.929883

                                     production_companies  \
4798            [{"name": "Columbia Pictures", "id": 5}]
4799                                                   []
4800  [{"name": "Front Street Pictures", "id": 3958}…
4801                                                   []
4802  [{"name": "rusty bear entertainment", "id": 87…

                                     production_countries release_date  revenue  \
4798  [{"iso_3166_1": "MX", "name": "Mexico"}, {"iso…   1992-09-04  2040920
4799                                                   []   2011-12-26        0
4800  [{"iso_3166_1": "US", "name": "United States o…   2013-10-13        0
4801  [{"iso_3166_1": "US", "name": "United States o…   2012-05-03        0
4802  [{"iso_3166_1": "US", "name": "United States o…   2005-08-05        0

      runtime                               spoken_languages    status  \
4798     81.0  [{"iso_639_1": "es", "name": "Espa\u00f1ol"}]  Released
4799     85.0                                             []  Released
4800    120.0       [{"iso_639_1": "en", "name": "English"}]  Released
4801     98.0       [{"iso_639_1": "en", "name": "English"}]  Released
```

```
4802     90.0       [{"iso_639_1": "en", "name": "English"}]  Released

                                                 tagline  \
4798  He didn't come looking for trouble, but troubl…
4799  A newlywed couple's honeymoon is upended by th…
4800                                                 NaN
4801                             A New Yorker in Shanghai
4802                                                 NaN

                          title  vote_average  vote_count
4798                El Mariachi           6.6         238
4799                  Newlyweds           5.9           5
4800  Signed, Sealed, Delivered           7.0           6
4801           Shanghai Calling           5.7           7
4802          My Date with Drew           6.3          16
```

[6]:
```python
# Getting some sample data
movies_df.sample(5)
```

[6]:
```
         budget                                             genres  \
3493          0                       [{"id": 18, "name": "Drama"}]
4226    1500000  [{"id": 80, "name": "Crime"}, {"id": 18, "name…
4491          0                 [{"id": 99, "name": "Documentary"}]
1255   42000000  [{"id": 53, "name": "Thriller"}, {"id": 18, "n…
170   135000000  [{"id": 12, "name": "Adventure"}, {"id": 28, "…

                                            homepage      id  \
3493                                             NaN   18602
4226                                             NaN   18079
4491              http://www.thehadzalastofthefirst.com/  296943
1255                                             NaN   80278
170   http://www.mgm.com/view/movie/231/The-World-Is…   36643

                                            keywords original_language  \
3493  [{"id": 10183, "name": "independent film"}, {"…                en
4226  [{"id": 612, "name": "hotel"}, {"id": 3202, "n…                es
4491                                              []                en
1255  [{"id": 3434, "name": "thailand"}, {"id": 6941…                en
170   [{"id": 6731, "name": "british"}, {"id": 10364…                en

                  original_title  \
3493              Morvern Callar
4226                Nueve Reinas
4491  The Hadza:  Last of the First
1255                Lo imposible
170         The World Is Not Enough
```

```
                                           overview  popularity  \
3493  Following her boyfriend's suicide, supermarket…    2.507912
4226  An Argentinian crime drama revolving around a …    8.589355
4491  A look at human origins in the very place of o…    0.045648
1255  In December 2004, close-knit family Maria, Hen…   47.559928
170   Greed, revenge, world dominance and high-tech …   39.604363

                                 production_companies  \
3493        [{"name": "Company Pictures", "id": 11842}]
4226  [{"name": "Naya Films S.A.", "id": 4718}, {"na…
4491                                               []
1255  [{"name": "Summit Entertainment", "id": 491}, …
170   [{"name": "Eon Productions", "id": 7576}, {"na…

                                 production_countries release_date  \
3493  [{"iso_3166_1": "GB", "name": "United Kingdom"…   2002-01-01
4226        [{"iso_3166_1": "AR", "name": "Argentina"}]   2000-08-31
4491  [{"iso_3166_1": "US", "name": "United States o…   2014-10-31
1255  [{"iso_3166_1": "US", "name": "United States o…   2012-09-09
170   [{"iso_3166_1": "GB", "name": "United Kingdom"…   1999-11-08

        revenue  runtime                                  spoken_languages  \
3493          0     97.0  [{"iso_639_1": "en", "name": "English"}, {"iso…
4226          0    114.0      [{"iso_639_1": "es", "name": "Espa\u00f1ol"}]
4491          0     70.0           [{"iso_639_1": "en", "name": "English"}]
1255  180274123    113.0  [{"iso_639_1": "en", "name": "English"}, {"iso…
170   361832400    128.0  [{"iso_639_1": "en", "name": "English"}, {"iso…

        status                                          tagline  \
3493  Released                                              NaN
4226  Released                                  Sticky & Square
4491  Released                                              NaN
1255  Released    Nothing is more powerful than the human spirit.
170   Released  As the countdown begins for the new millennium…

                            title  vote_average  vote_count
3493                Morvern Callar           7.2          34
4226                   Nine Queens           7.4         153
4491  The Hadza:  Last of the First           0.0           0
1255                The Impossible           7.0        2025
170          The World Is Not Enough           6.0         862
```

displaying more information about dataset

[7]:
```
#Displaying information of dataset
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   budget                4803 non-null   int64
 1   genres                4803 non-null   object
 2   homepage              1712 non-null   object
 3   id                    4803 non-null   int64
 4   keywords              4803 non-null   object
 5   original_language     4803 non-null   object
 6   original_title        4803 non-null   object
 7   overview              4800 non-null   object
 8   popularity            4803 non-null   float64
 9   production_companies  4803 non-null   object
 10  production_countries  4803 non-null   object
 11  release_date          4802 non-null   object
 12  revenue               4803 non-null   int64
 13  runtime               4801 non-null   float64
 14  spoken_languages      4803 non-null   object
 15  status                4803 non-null   object
 16  tagline               3959 non-null   object
 17  title                 4803 non-null   object
 18  vote_average          4803 non-null   float64
 19  vote_count            4803 non-null   int64
dtypes: float64(3), int64(4), object(13)
memory usage: 750.6+ KB
```

Displaying Nan Values for every column in dataset

[8]:
```
# Finding Nan values
movies_df.isnull().sum()
```

[8]:
```
budget                     0
genres                     0
homepage                3091
id                         0
keywords                   0
original_language          0
original_title             0
overview                   3
popularity                 0
production_companies       0
production_countries       0
release_date               1
revenue                    0
runtime                    2
spoken_languages           0
status                     0
```

```
tagline                   844
title                       0
vote_average                0
vote_count                  0
dtype: int64
```

[9]:
```
# coverting special character to Nan Values
movies_df[movies_df['production_countries']=='[]']
```

[9]:
```
        budget                                             genres  \
272   90000000  [{"id": 35, "name": "Comedy"}, {"id": 10749, "…
1011         0                     [{"id": 27, "name": "Horror"}]
1360         0                      [{"id": 18, "name": "Drama"}]
1511         0  [{"id": 18, "name": "Drama"}, {"id": 10751, "n…
1898  26000000  [{"id": 35, "name": "Comedy"}, {"id": 10751, "…
…          …                                                …
4780         0  [{"id": 53, "name": "Thriller"}, {"id": 80, "n…
4784         0  [{"id": 18, "name": "Drama"}, {"id": 35, "name…
4787         0  [{"id": 878, "name": "Science Fiction"}, {"id"…
4797         0  [{"id": 10769, "name": "Foreign"}, {"id": 53, …
4799      9000  [{"id": 35, "name": "Comedy"}, {"id": 10749, "…

                             homepage      id  \
272                               NaN   24113
1011                              NaN   53953
1360    http://therebedragonsmovie.com/   45054
1511                              NaN   12920
1898                              NaN   18147
…                                 …       …
4780                              NaN  366967
4784  http://www.thepuffychairmovie.com   24055
4787                              NaN   86304
4797                              NaN   67238
4799                              NaN   72766

                                               keywords original_language  \
272   [{"id": 2301, "name": "architect"}, {"id": 345…                en
1011  [{"id": 10292, "name": "gore"}, {"id": 12339, …                de
1360  [{"id": 5509, "name": "spanish civil war"}, {"…                en
1511  [{"id": 643, "name": "horse race"}, {"id": 267…                en
1898                  [{"id": 65, "name": "holiday"}]                  en
…                                                  …               …
4780                                                []                 en
4784             [{"id": 171993, "name": "mumblecore"}]               en
4787                  [{"id": 9715, "name": "superhero"}]              en
4797                                                []                 en
4799                                                []                 en
```

```
                      original_title  \
272                   Town & Country
1011                  The Tooth Fairy
1360                There Be Dragons
1511  Dreamer: Inspired By a True Story
1898             Unaccompanied Minors
…                                  …
4780                     Dutch Kills
4784                 The Puffy Chair
4787          All Superheroes Must Die
4797                          Cavite
4799                      Newlyweds

                                              overview  popularity  \
272   Porter Stoddard is a well-known New York archi…    1.004579
1011  A woman and her daughter (Nicole Muñoz) encoun…    0.716764
1360  Arising out of the horror of the Spanish Civil…    6.668679
1511  Ben Crane believes that a severely injured rac…    6.048743
1898  Five disparate kids snowed in at the airport o…   10.006282
…                                                 …          …
4780  A desperate ex-con is forced to gather his old…    0.038143
4784  Josh's life is pretty much in the toilet. He's…    1.243955
4787  Masked vigilantes Charge (Jason Trost), Cutthr…    3.545991
4797  Adam, a security guard, travels from Californi…    0.022173
4799  A newlywed couple's honeymoon is upended by th…    0.642552

                                 production_companies production_countries  \
272            [{"name": "New Line Cinema", "id": 12}]                   []
1011                                                []                   []
1360                                                []                   []
1511  [{"name": "DreamWorks SKG", "id": 27}, {"name"…                  []
1898                                                []                   []
…                                                 …                  …
4780                                                []                   []
4784                                                []                   []
4787              [{"name": "Grindfest", "id": 18818}]                   []
4797                                                []                   []
4799                                                []                   []

     release_date   revenue  runtime  \
272    2001-04-27  10372291    104.0
1011   2006-08-08         0      0.0
1360   2011-03-25         0    112.0
1511   2005-09-10         0    106.0
1898   2006-12-08         0     90.0
…             …         …       …
```

```
4780  2015-10-02        0     90.0
4784  2005-01-17        0     85.0
4787  2011-10-26        0     78.0
4797  2005-03-12        0     80.0
4799  2011-12-26        0     85.0

                                       spoken_languages    status  \
272            [{"iso_639_1": "en", "name": "English"}]  Released
1011  [{"iso_639_1": "en", "name": "English"}, {"iso…  Released
1360           [{"iso_639_1": "en", "name": "English"}]  Released
1511           [{"iso_639_1": "en", "name": "English"}]  Released
1898           [{"iso_639_1": "en", "name": "English"}]  Released
…                                                   …       …
4780                                                 []  Released
4784                                                 []  Released
4787           [{"iso_639_1": "en", "name": "English"}]  Released
4797                                                 []  Released
4799                                                 []  Released

                                               tagline  \
272            There's no such thing as a small affair.
1011                                               NaN
1360                                               NaN
1511                                               NaN
1898                  No plane, no parents, no problem!
…                                                   …
4780                                               NaN
4784                                               NaN
4787                               May The Best Man Win
4797                                               NaN
4799  A newlywed couple's honeymoon is upended by th…

                                 title  vote_average  vote_count
272                    Town & Country           3.7          16
1011                   The Tooth Fairy           4.3          13
1360                  There Be Dragons           5.9          27
1511  Dreamer: Inspired By a True Story           6.3          67
1898               Unaccompanied Minors           5.4          66
…                                    …           …           …
4780                       Dutch Kills           0.0           0
4784                   The Puffy Chair           6.2          15
4787          All Superheroes Must Die           4.2          13
4797                            Cavite           7.5           2
4799                         Newlyweds           5.9           5

[174 rows x 20 columns]
```

Since there are other special character in dataset as [] this have to be changed to Nan

values since they contain nothing for my analysis.

1.1.2 2.2. Data Cleaning

Deleting unnecessary columns

[10]:
```
# dropping some column
movies_df.
↪drop(['homepage','id','keywords','overview','tagline','spoken_languages'],axis␣
↪= 1,inplace=True)
# displaying info
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4803 entries, 0 to 4802
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   budget                4803 non-null   int64
 1   genres                4803 non-null   object
 2   original_language     4803 non-null   object
 3   original_title        4803 non-null   object
 4   popularity            4803 non-null   float64
 5   production_companies  4803 non-null   object
 6   production_countries  4803 non-null   object
 7   release_date          4802 non-null   object
 8   revenue               4803 non-null   int64
 9   runtime               4801 non-null   float64
 10  status                4803 non-null   object
 11  title                 4803 non-null   object
 12  vote_average          4803 non-null   float64
 13  vote_count            4803 non-null   int64
dtypes: float64(3), int64(3), object(8)
memory usage: 525.5+ KB
```

The droped columns contais many Nan Values and others will not be used in dataset, I removed them to get a clean dataset

Repacing special character with Nan

[11]:
```
#Replacing [] character with Nan
movies_df.replace('[]', np.nan,inplace=True)

# displaying Nan values for each column
movies_df.isnull().sum()
```

[11]:
```
budget                   0
genres                  28
original_language        0
original_title           0
```

```
popularity                0
production_companies    351
production_countries    174
release_date              1
revenue                   0
runtime                   2
status                    0
title                     0
vote_average              0
vote_count                0
dtype: int64
```

More Nan Values have been found since there was some columns with only [] characters with is repaced by Nan

Droping Nan Values

[12]:
```
# Dropping Nans
movies_df.dropna(inplace=True)

# displaying Nan values for each column
movies_df.isna().sum()
```

[12]:
```
budget                  0
genres                  0
original_language       0
original_title          0
popularity              0
production_companies    0
production_countries    0
release_date            0
revenue                 0
runtime                 0
status                  0
title                   0
vote_average            0
vote_count              0
dtype: int64
```

There is no Nan Values in my dataset

New shape of modified dataset

[13]:
```
# new shape
movies_df.shape
```

[13]:
```
(4429, 14)
```

Getting every production companies for each movie

```
[14]: """
The following loop will extract only production companies for each movie from
dictionaries containing lots of details of every production company for every␣
↪movie

"""
# Initializing a list of production companies name
Campany_names=[]
# looping trough production companies columns
for name in  movies_df['production_companies']:
    # converting object dictionaries into editable dictionaries
    dict_name=json.loads(name)
    #Initializing a list of each
    campany_name=[]
    #appending the names into production names
    Campany_names.append(campany_name)

    #Looping through each dictionary for every production company
    for i in dict_name:
        # appending each production film in its list
        campany_name.append(list(i.values())[0])
```

Getting every country of origin for each movie

```
[15]: """
The loop will extract only the original country of the movie from
a details dictionary with original country with other detail.
"""
# Initializing the original country list
country_original=[]

#Looping through production countries columns
for country in movies_df['production_countries']:
    # extracting only country of original in the dictionary object
    country_original.append(country.split('"')[7])
```

Getting every country of origin for each movie

```
[16]: """
The following loop will extract only genre for each movie from
dictionaries containing lots of details of every genre company for every movie

"""
# creating a genre list
genre_names=[]
```

```python
#Looping the genres column
for genre in  movies_df['genres']:
    # converting object dictionaries into editable dictionaries
    dict_name_genre=json.loads(genre)

    #Initializing a list of each genre
    names=[]
    #appending the genre into genre list
    genre_names.append(names)
    #Looping through each dictionary for every genre
    for k in dict_name_genre:
        # extracting only genre the dictionary
        names.append(list(k.values())[1])
```

Creating a profit column

[17]:
```python
# creating a profit column from revenue and budget
movies_df['profit']=movies_df['revenue']-movies_df['budget']
```

Creating profit or loss status column

[18]:
```python
"""
The loop will create a profit or loss status based on the profite or loss made
"""

# Initializing list of profit/ loss status
Loss_profit_status=[]

#looping through profit column
for profit in movies_df['profit']:

    # definning the profit
    if profit>=0:
        Loss_profit_status.append('Profit')
    # definning the loss
    else:
        Loss_profit_status.append('Loss')
```

[19]:
```python
# creating profit/loss status for every data
movies_df['P/L status']=Loss_profit_status
```

Creating cleaned columns

[20]:
```python
# creating cleaned genre column
movies_df['genre_names']=genre_names
#creating cleaned production company column
```

```
movies_df['production_company']=Campany_names
#creating country of origin column
movies_df['country_original']=country_original
```

[21]:
```
#Chwcking for the new added column
movies_df.head()
```

[21]:
```
      budget                                             genres  \
0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
1  300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "…
2  245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…
3  250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam…
4  260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam…

  original_language                            original_title  popularity  \
0                en                                    Avatar  150.437577
1                en  Pirates of the Caribbean: At World's End  139.082615
2                en                                   Spectre  107.376788
3                en                     The Dark Knight Rises  112.312950
4                en                               John Carter   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289…
1  [{"name": "Walt Disney Pictures", "id": 2}, {"…
2  [{"name": "Columbia Pictures", "id": 5}, {"nam…
3  [{"name": "Legendary Pictures", "id": 923}, {"…
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries release_date     revenue  \
0  [{"iso_3166_1": "US", "name": "United States o…   2009-12-10  2787965087
1  [{"iso_3166_1": "US", "name": "United States o…   2007-05-19   961000000
2  [{"iso_3166_1": "GB", "name": "United Kingdom"…   2015-10-26   880674609
3  [{"iso_3166_1": "US", "name": "United States o…   2012-07-16  1084939099
4  [{"iso_3166_1": "US", "name": "United States o…   2012-03-07   284139100

   runtime    status                                     title  vote_average  \
0    162.0  Released                                    Avatar           7.2
1    169.0  Released  Pirates of the Caribbean: At World's End           6.9
2    148.0  Released                                   Spectre           6.3
3    165.0  Released                     The Dark Knight Rises           7.6
4    132.0  Released                               John Carter           6.1

   vote_count      profit P/L status  \
0       11800  2550965087     Profit
1        4500   661000000     Profit
2        4466   635674609     Profit
3        9106   834939099     Profit
```

```
4        2124     24139100     Profit

                                   genre_names  \
0  [Action, Adventure, Fantasy, Science Fiction]
1                  [Adventure, Fantasy, Action]
2                    [Action, Adventure, Crime]
3              [Action, Crime, Drama, Thriller]
4          [Action, Adventure, Science Fiction]

                                  production_company          country_original
0  [Ingenious Film Partners, Twentieth Century Fo…  United States of America
1  [Walt Disney Pictures, Jerry Bruckheimer Films…  United States of America
2                  [Columbia Pictures, Danjaq, B24]            United Kingdom
3  [Legendary Pictures, Warner Bros., DC Entertai…  United States of America
4                            [Walt Disney Pictures]  United States of America
```

[22]:

```
# dropping old uncleaned columns
movies_df.drop(['genres','production_countries','production_companies'],axis =␣
 ↪1,inplace=True)
```

[23]:

```
# Converting date into datetime for easy manipulation
movies_df['release_date']=pd.to_datetime(movies_df['release_date'])
```

[24]:

```
#Checking for information for new cleaned data
movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4429 entries, 0 to 4802
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   budget              4429 non-null   int64
 1   original_language   4429 non-null   object
 2   original_title      4429 non-null   object
 3   popularity          4429 non-null   float64
 4   release_date        4429 non-null   datetime64[ns]
 5   revenue             4429 non-null   int64
 6   runtime             4429 non-null   float64
 7   status              4429 non-null   object
 8   title               4429 non-null   object
 9   vote_average        4429 non-null   float64
 10  vote_count          4429 non-null   int64
 11  profit              4429 non-null   int64
 12  P/L status          4429 non-null   object
 13  genre_names         4429 non-null   object
 14  production_company  4429 non-null   object
 15  country_original    4429 non-null   object
dtypes: datetime64[ns](1), float64(3), int64(4), object(8)
```

```
memory usage: 588.2+ KB
```

Checking unique Values in Movie status

[25]:
```python
# checking the status unique values
movies_df['status'].unique()
```

[25]:
```
array(['Released', 'Rumored'], dtype=object)
```

Removing outliers

[26]:
```python
# selecting released movies
movies_df=movies_df[movies_df['status']=='Released']
```

I removed the rumored movies in my dataset because it is not logical to know the revenue of the unrealised movies. Therefore I remained with only released movies

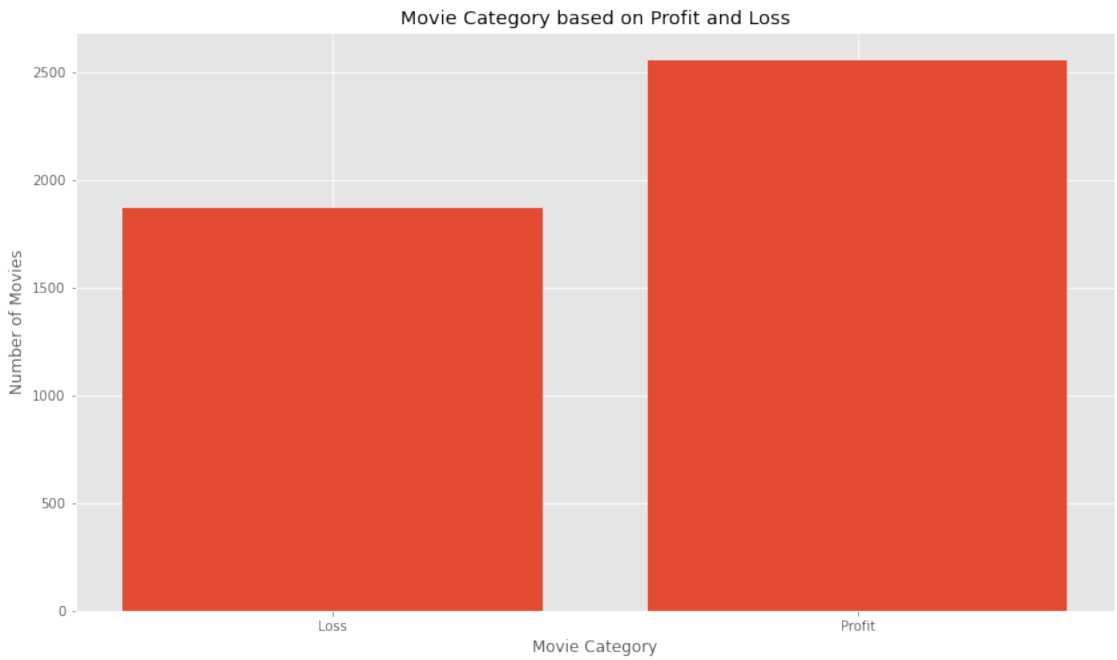
Exploratory Data Analysis

Stastical analysis

[27]:
```python
# stastical analysis of data
movies_df.describe()
```

[27]:
```
             budget   popularity       revenue      runtime  vote_average  \
count  4.427000e+03  4427.000000  4.427000e+03  4427.000000   4427.000000
mean   3.139422e+07    23.184470  8.918173e+07   108.246216      6.178993
std    4.154151e+07    32.577603  1.678161e+08    20.929225      1.024830
min    0.000000e+00     0.001586  0.000000e+00     0.000000      0.000000
25%    2.500000e+06     6.236937  6.000000e+00    94.000000      5.700000
50%    1.700000e+07    14.730796  2.560502e+07   105.000000      6.300000
75%    4.183885e+07    29.986632  1.015800e+08   118.000000      6.800000
max    3.800000e+08   875.581305  2.787965e+09   338.000000     10.000000

         vote_count        profit
count   4427.000000  4.427000e+03
mean     747.501694  5.778751e+07
std     1269.530348  1.406690e+08
min        0.000000 -1.657101e+08
25%       79.000000 -1.298568e+06
50%      284.000000  6.154592e+06
75%      824.500000  6.305509e+07
max    13752.000000  2.550965e+09
```

[28]:
```python
loss=movies_df[movies_df['profit']<=0]
loss_profit= {'Loss':len(loss),'Profit':len(movies_df)-len(loss)}
plt.bar(loss_profit.keys(),loss_profit.values())
plt.title('Movie Category based on Profit and Loss')
plt.xlabel('Movie Category')
plt.ylabel('Number of Movies')
plt.show()
```

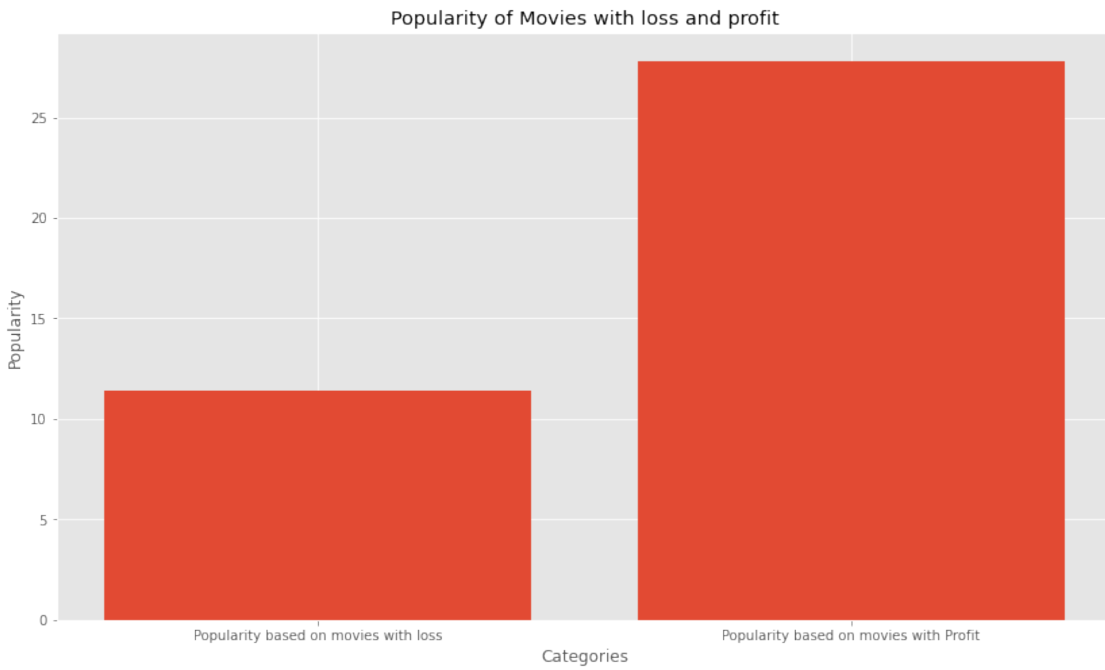


Popularity based on Loss and profit

[29]:
```
# Average popularity of movies which have loss
pop_mean_loss=movies_df.groupby('P/L status').get_group('Loss').
 ↪mean()['popularity']

# Average popularity of movies which have profit
pop_mean_prof = movies_df.groupby('P/L status').get_group('Profit').
 ↪mean()['popularity']
```

[30]:
```
# Popularity of profit and loss movies dictionary
loss_profit_popularity={'Popularity based on movies with loss':pop_mean_loss,
                        'Popularity based on movies with Profit':pop_mean_prof}
```

[31]:
```
#ploting the graph
plt.bar(loss_profit_popularity.keys(),loss_profit_popularity.values())
plt.title('Popularity of Movies with loss and profit')
plt.xlabel('Categories')
plt.ylabel('Popularity')
plt.show()
```



1.1.3 Research Question 1 : How countries are ranked in producing popular movies ?

Selecting countries with at least 10 movies in dataset

[32]:
```
# Selecting countries with at least 10 movies in dataset
country_original=pd.DataFrame(movies_df['country_original'].explode().
 ↪value_counts())['country_original'].head(22)

country_original
```

[32]:
```
United States of America    2965
United Kingdom               360
Canada                       211
Germany                      196
France                       166
Australia                     86
China                         37
India                         35
Japan                         34
Spain                         33
Italy                         24
Ireland                       22
Hong Kong                     22
New Zealand                   21
Mexico                        21
```

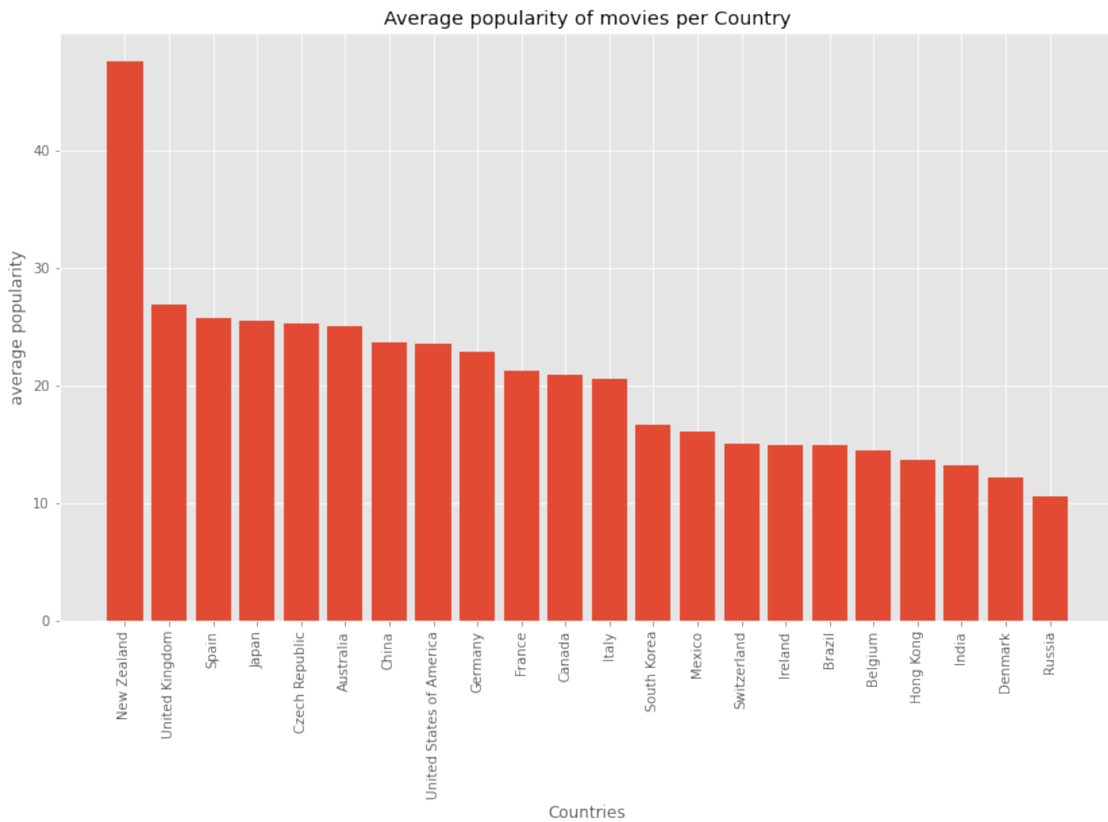
```
Belgium                       17
Czech Republic                17
Denmark                       14
South Korea                   13
Brazil                        12
Russia                        11
Switzerland                   10
Name: country_original, dtype: int64
```

There are 22 countries with more than 10 movies in the dataset. with United State of America ranking the first and United Kingdom the second.

Popularity mean for each country with more than 10 movies

[33]:
```
'''
The loop below will calculate the mean popularity by country
'''
mean_popularity=[]
for i in country_original.index:
    mean_popularity.
 ↪append(movies_df[movies_df['country_original']==i]['popularity'].mean())

# creating average popularity by country dictionary
means_by_country=dict(zip(country_original.index,mean_popularity))
#Sorting the means from big to small
means_by_country = OrderedDict(sorted(means_by_country.items(), key=lambda x:␣
 ↪x[1],reverse=True))
```

[34]:
```
plt.bar(means_by_country.keys(),means_by_country.values())
plt.xticks(rotation=90);
plt.title('Average popularity of movies per Country')
plt.xlabel('Countries')
plt.ylabel('average popularity')
plt.show()
```



From the graph above, movies from New Zeland are most popular and are much ahead than others around 50 of popularity index, the second is United Kingdom with around 27, followed by Spain and Japan. The united State of America occupy the 8th position while Denmark and Russia movies occupy the 21st and 22nd places respectively. Another insight is that despite having a lot of movies in the dataset, United State of America movies are not popular as expect, therefore the popularity index do not deppends on how much movies are produced in your country.

1.1.4 Research Question 2 : which period in which popular movies were produced?

Sorting movies based on release date

[35]:
```
movies_df=movies_df.sort_values('release_date')
movies_df
```

[35]:
```
          budget original_language          original_title  popularity  \
4592    385907                en            Intolerance    3.232447
4661    245000                en          The Big Parade    0.785744
2638  92620000                de              Metropolis   32.351527
4457         0                de  Die Büchse der Pandora    1.824184
4594    379000                en     The Broadway Melody    0.968865
…          …                 …                     …           …
```

```
2273  20000000                en         Hands of Stone    7.444189
4036  35000000                en              Antibirth    3.674294
4720   8500000                en   The Birth of a Nation    9.452808
3249         0                en                  Kicks    3.467923
3302   8000000                en             Mr. Church    7.828459

     release_date   revenue  runtime    status                  title  \
4592   1916-09-04   8394751    197.0  Released            Intolerance
4661   1925-11-05  22000000    151.0  Released          The Big Parade
2638   1927-01-10    650422    153.0  Released             Metropolis
4457   1929-01-30         0    109.0  Released           Pandora's Box
4594   1929-02-08   4358000    100.0  Released     The Broadway Melody
…             …         …        …         …                       …
2273   2016-08-26         0    105.0  Released          Hands of Stone
4036   2016-09-02         0     94.0  Released               Antibirth
4720   2016-09-09  15861566    120.0  Released   The Birth of a Nation
3249   2016-09-09         0     80.0  Released                   Kicks
3302   2016-09-16         0    104.0  Released              Mr. Church

      vote_average  vote_count    profit P/L status  \
4592           7.4          60   8008844     Profit
4661           7.0          21  21755000     Profit
2638           8.0         657 -91969578       Loss
4457           7.6          45         0     Profit
4594           5.0          19   3979000     Profit
…                …           …         …          …
2273           6.1         109 -20000000       Loss
4036           4.8          40 -35000000       Loss
4720           6.5         178   7361566     Profit
3249           7.5          18         0     Profit
3302           7.0         129  -8000000       Loss

                      genre_names  \
4592                      [Drama]
4661        [Drama, Romance, War]
2638     [Drama, Science Fiction]
4457  [Drama, Thriller, Romance]
4594      [Drama, Music, Romance]
…                               …
2273                      [Drama]
4036                     [Horror]
4720                      [Drama]
3249                  [Adventure]
3302                      [Drama]

                                         production_company  \
4592  [Triangle Film Corporation, Wark Producing Corp.]
```

```
4661                         [Metro-Goldwyn-Mayer (MGM)]
2638         [Paramount Pictures, Universum Film (UFA)]
4457                                        [Nero Films]
4594                         [Metro-Goldwyn-Mayer (MGM)]
…                                                  …
2273  [Weinstein Company, The, La Piedra Films, Fueg…
4036  [Hideaway Pictures, Traverse Media, Culminatio…
4720  [Phantom Four, Mandalay Pictures, Bron Studios…
3249  [Bystorm Films, Animal Kingdom, Bow and Arrow …
3302  [Envision Media Arts, Cinelou Films, Shenghua …

              country_original
4592  United States of America
4661  United States of America
2638                   Germany
4457                   Germany
4594  United States of America
…                          …
2273                    Panama
4036  United States of America
4720  United States of America
3249  United States of America
3302  United States of America

[4427 rows x 16 columns]
```

Definning period range

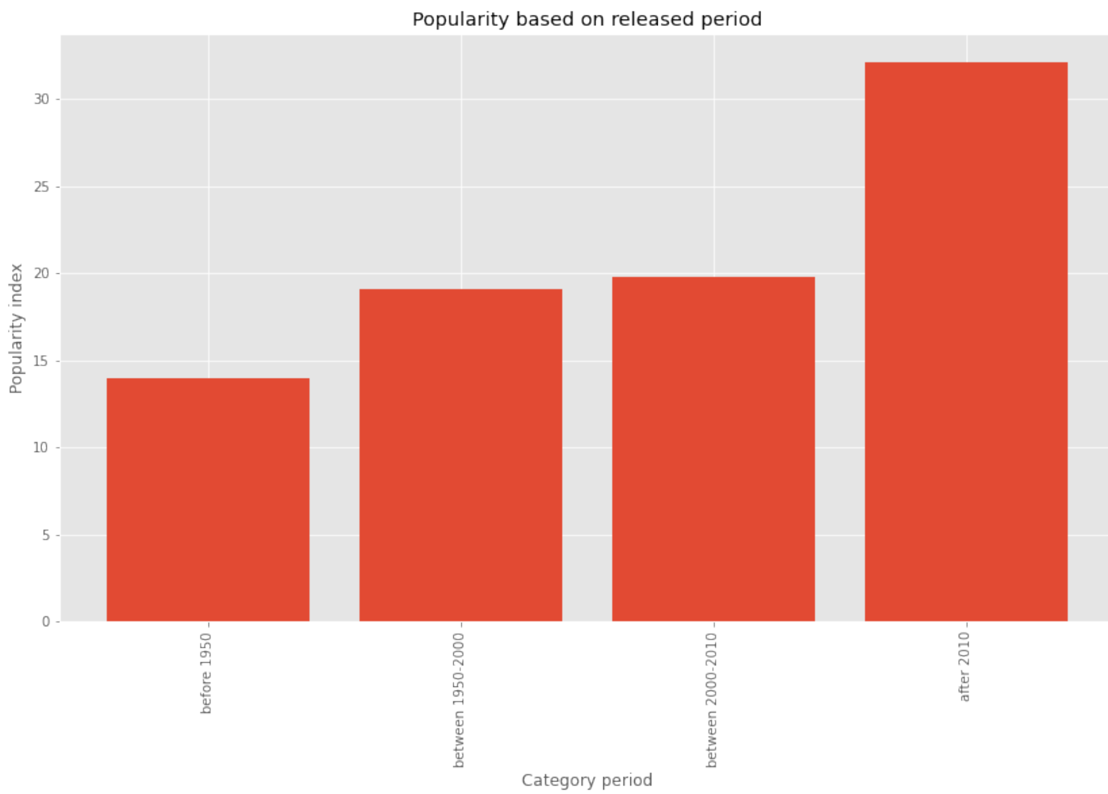
[36]:
```
# movies released before 1949
range_df1 = ( movies_df['release_date'] >= '1916-09-04') &␣
↪(movies_df['release_date']  <= '1949-12-31')

# movies released between 1950 to 1999
range_df2=( movies_df['release_date'] >= '1950-01-01') &␣
↪(movies_df['release_date']  <= '1999-12-31')

# movies released between 2000 to 2010
range_df3 = ( movies_df['release_date'] >= '2000-01-01') &␣
↪(movies_df['release_date']  <= '2009-12-31')

# movies released after 2010
range_df4 = ( movies_df['release_date'] >= '2010-01-01') &␣
↪(movies_df['release_date']  <= '2022-12-31'),
```

[37]:
```
# movies released period dictionary
period_data={'before 1950':movies_df.loc[range_df1]['popularity'].mean(),
             'between 1950-2000':movies_df.loc[range_df2] ['popularity'].mean(),
             'between 2000-2010':movies_df.loc[range_df3]['popularity'].mean(),
```

```
            'after 2010':movies_df.loc[range_df4]['popularity'].mean()}
period_data
```

[37]:
```
{'before 1950': 13.936031066666667,
 'between 1950-2000': 19.036122541010773,
 'between 2000-2010': 19.79205343494624,
 'after 2010': 32.107002219011406}
```

[38]:
```
plt.bar(period_data.keys(),period_data.values())
plt.title('Popularity based on released period')
plt.xlabel('Category period')
plt.ylabel('Popularity index')
plt.xticks(rotation=90);
plt.show()
```



Bar graph shows that the movies popularity increased as the time goes on. The movies average popularity of movies before 1950 is around 14 while the ones between 1950 to 2000 have average popularity around 19 while the ones from 2000 to 2010 have average popularity around 20 while the ones after 2010 are more popular with average popularity 33 of popularity index.

1.1.5 Research Question 3 : Which production companies have most popular movies ?

Creating top 30 movies production companies in dataset with average popularity of their movies

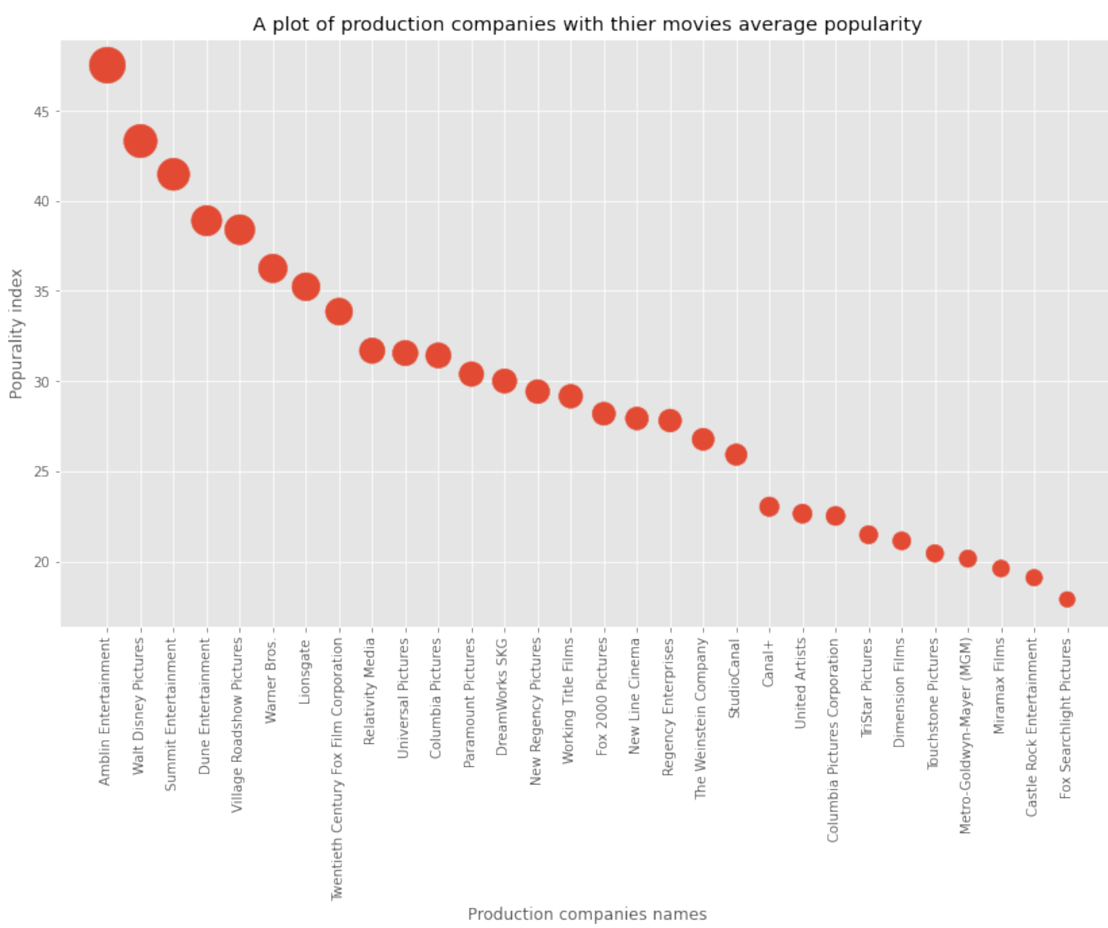
[39]:
```
"""
The loop will Create top 30 movies production companies in dataset with average␣
↪popularity of their movies
"""

production_mean=[]
for i in pd.DataFrame(movies_df['production_company'].
↪explode())['production_company'].value_counts().head(30).index:
    production_mean.append(movies_df[movies_df['production_company'].str.
↪contains(i,regex=False)]['popularity'].mean())

# top 30 movies production companies dictionary
production_mean_dict=dict(zip(pd.DataFrame(movies_df['production_company'].
↪explode())['production_company'].value_counts().head(30).
↪index,production_mean))
production_mean_dict = OrderedDict(sorted(production_mean_dict.items(),␣
↪key=lambda x: x[1],reverse=True))
production_mean_dict
```

[39]:
```
OrderedDict([('Amblin Entertainment', 47.51972583673469),
             ('Walt Disney Pictures', 43.310791876106194),
             ('Summit Entertainment', 41.46614390384615),
             ('Dune Entertainment', 38.89317925423729),
             ('Village Roadshow Pictures', 38.39371525925926),
             ('Warner Bros.', 36.247154263322884),
             ('Lionsgate', 35.22953926785714),
             ('Twentieth Century Fox Film Corporation', 33.85089831081081),
             ('Relativity Media', 31.68398799019607),
             ('Universal Pictures', 31.55245160967742),
             ('Columbia Pictures', 31.421506597014925),
             ('Paramount Pictures', 30.385787207017543),
             ('DreamWorks SKG', 30.00171408974359),
             ('New Regency Pictures', 29.4139214),
             ('Working Title Films', 29.15677835849056),
             ('Fox 2000 Pictures', 28.18877576363636),
             ('New Line Cinema', 27.924684091463412),
             ('Regency Enterprises', 27.806324768115942),
             ('The Weinstein Company', 26.7687935952381),
             ('StudioCanal', 25.91613763414634),
             ('Canal+', 23.027730146666663),
             ('United Artists', 22.644047733333334),
             ('Columbia Pictures Corporation', 22.51928042105263),
```

```
('TriStar Pictures', 21.47307623636364),
('Dimension Films', 21.133551314814813),
('Touchstone Pictures', 20.44103031355932),
('Metro-Goldwyn-Mayer (MGM)', 20.15020059836065),
('Miramax Films', 19.60111504255319),
('Castle Rock Entertainment', 19.0914079),
('Fox Searchlight Pictures', 17.887086484375)])
```

Movies production companies with their average popularity

[40]:
```
z=production_mean_dict.keys()
y=production_mean_dict.values()
n=production_mean_dict.keys()
fig,ax=plt.subplots()
ax.scatter(z,y,s=[i**1.7 for i in list(y)])
plt.title('A plot of production companies with thier movies average popularity')
plt.xlabel('Production companies names')
plt.ylabel('Popurality index')
plt.xticks(rotation=90);
plt.show()
```



The scatter plot above shows how the production companies produce popular movies. The movies from Amblin Entertainment occupies the first place around 47 popularity index, followed by Walt Disney Pictures, Summit Entertainment occupies the third place and Dune Pictures occupies the fourth place while Village Roadshow Pictures occupies the fifth place . In the top thirty the 30th is Fox Searchlight Pictures

1.1.6 Research Question 4 : Which genre of the movies are most popular ?

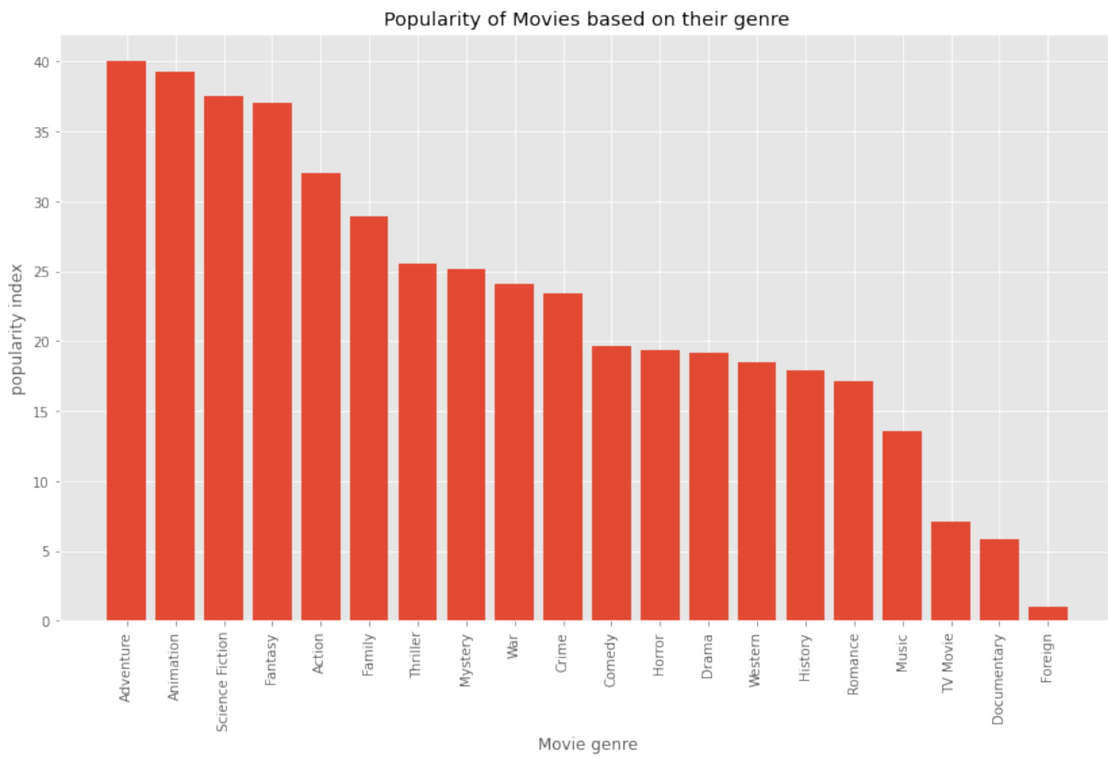
Getting the average popularity of each genre movies

[41]:
```
"""
The loop is going to get every genre of the movie and their average popularity␣
↪index
"""
Genre_means=[]
for genre in pd.DataFrame(movies_df['genre_names'].explode())['genre_names'].
↪value_counts().index:
    Genre_means.append(movies_df[movies_df['genre_names'].str.
↪contains(genre,regex=False)]['popularity'].mean())

# average genre popularity index  dictionary
Genre_means_dict=dict(zip(pd.DataFrame(movies_df['genre_names'].
↪explode())['genre_names'].value_counts().index,Genre_means))
Genre_means_dict = OrderedDict(sorted(Genre_means_dict.items(), key=lambda x:␣
↪x[1],reverse=True))
Genre_means_dict
```

[41]:
```
OrderedDict([('Adventure', 40.022213994832036),
             ('Animation', 39.30202294805195),
             ('Science Fiction', 37.532599949903656),
             ('Fantasy', 37.04356345432692),
             ('Action', 32.03698656834532),
             ('Family', 28.971218751527495),
             ('Thriller', 25.507213375205257),
             ('Mystery', 25.128864323529413),
             ('War', 24.09604402112676),
             ('Crime', 23.43035849187592),
             ('Comedy', 19.64457378192162),
             ('Horror', 19.39194707802875),
             ('Drama', 19.18519478605313),
             ('Western', 18.461373567901234),
             ('History', 17.899342136125657),
             ('Romance', 17.142549088484845),
             ('Music', 13.560474711864407),
             ('TV Movie', 7.140965571428572),
             ('Documentary', 5.812743071428572),
             ('Foreign', 0.967619611111111)])
```

Ploting the bar graphs

[42]:
```
plt.bar(Genre_means_dict.keys(),Genre_means_dict.values())
plt.title('Popularity of Movies based on their genre')
plt.xlabel('Movie genre')
plt.xticks(rotation=90)
plt.ylabel('popularity index')
plt.show()
```



From bar graph above, the adventure movies are most popular movies, followed by Animation, Science Fiction, Fantasy and then Action. Documentary movies and Foreign movies occupy the last two places.

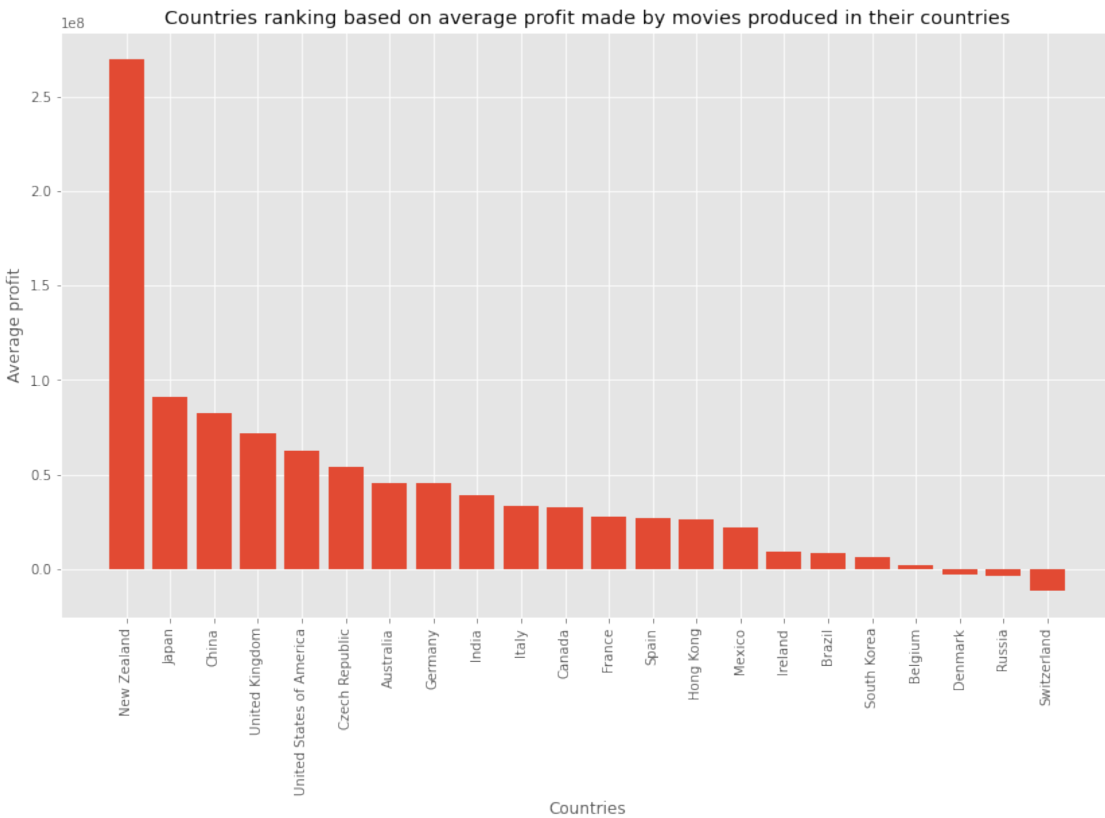
1.1.7 Research Question 5 : How countries are ranked in based on average profit of their movies ?

[43]:
```
"""
This loop will get the average profit for movies produced in certain Countries
"""
mean_popularity=[]
for i in country_original.index:
    mean_popularity.
↪append(movies_df[movies_df['country_original']==i]['profit'].mean())
```

```
means_by_country=dict(zip(country_original.index,mean_popularity))
means_by_country = OrderedDict(sorted(means_by_country.items(), key=lambda x:␣
↪x[1],reverse=True))
means_by_country
```

[43]:
```
OrderedDict([('New Zealand', 270077563.95238096),
             ('Japan', 90925710.0),
             ('China', 82604548.48648648),
             ('United Kingdom', 71660680.28055556),
             ('United States of America', 62913271.694435075),
             ('Czech Republic', 54085828.23529412),
             ('Australia', 45453358.03488372),
             ('Germany', 45189326.89795918),
             ('India', 38729338.428571425),
             ('Italy', 33479999.208333332),
             ('Canada', 32734174.047393367),
             ('France', 27326890.277108435),
             ('Spain', 26967893.454545453),
             ('Hong Kong', 26503358.636363637),
             ('Mexico', 21919210.095238097),
             ('Ireland', 8799116.0),
             ('Brazil', 8135280.666666667),
             ('South Korea', 6224687.384615385),
             ('Belgium', 1862752.6470588236),
             ('Denmark', -2787057.0),
             ('Russia', -3549098.4545454546),
             ('Switzerland', -11779491.8)])
```

[44]:
```
plt.bar(means_by_country.keys(),means_by_country.values())
plt.title('Countries ranking based on average profit made by movies produced in␣
↪their countries')
plt.xlabel('Countries')
plt.ylabel('Average profit')
plt.xticks(rotation=90)
plt.show()
```



Movies from New Zealand made most of the profit based on average , followed by Japan, China,United Kingdom and USA. Movies from Denmark, Russia and Switzerland are in losses

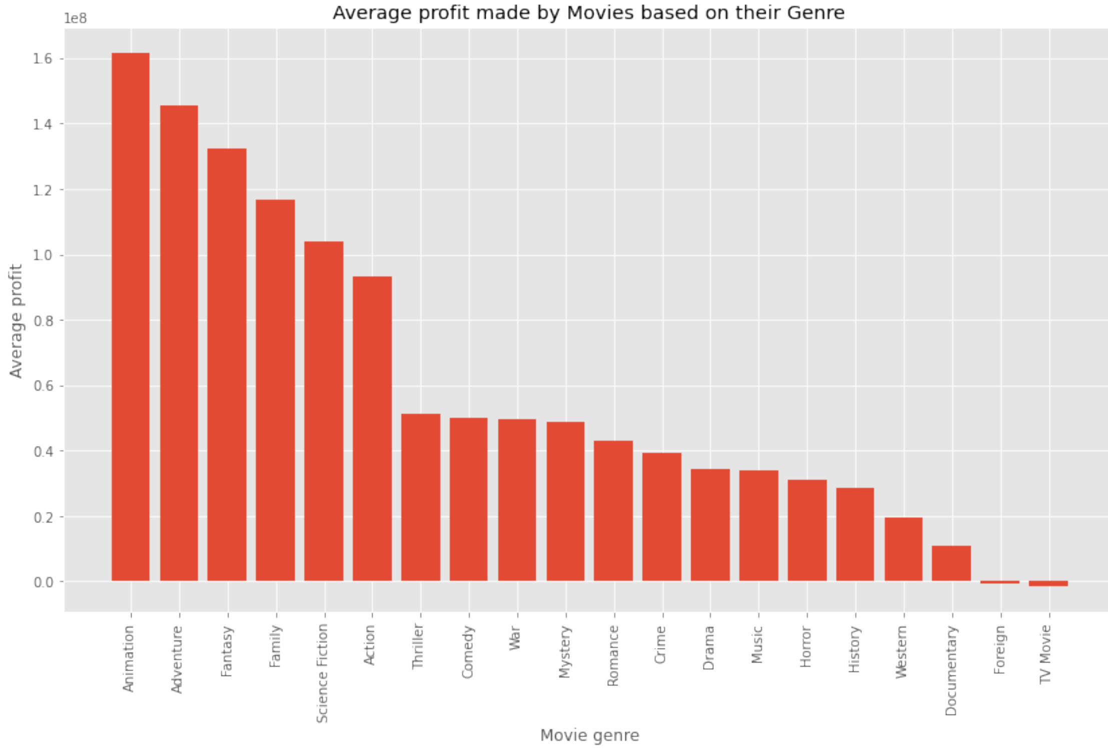
1.1.8 Research Question 5 : How movie genre are ranked in based on average profit of made?

[45]:
```
"""
The loop will get the average profit made by each genre of the movie
"""
Genre_means=[]
for genre in pd.DataFrame(movies_df['genre_names'].explode())['genre_names'].
↪value_counts().index:
    Genre_means.append(movies_df[movies_df['genre_names'].str.
↪contains(genre,regex=False)]['profit'].mean())



Genre_means_dict=dict(zip(pd.DataFrame(movies_df['genre_names'].
↪explode())['genre_names'].value_counts().index,Genre_means))
```

```
Genre_means_dict = OrderedDict(sorted(Genre_means_dict.items(), key=lambda x:␣
↪x[1],reverse=True))
Genre_means_dict
```

[45]:
```
OrderedDict([('Animation', 161450279.92640692),
             ('Adventure', 145317565.97545218),
             ('Fantasy', 132344290.8125),
             ('Family', 116717133.75763747),
             ('Science Fiction', 103739185.9884393),
             ('Action', 93149627.50089929),
             ('Thriller', 51367304.52545156),
             ('Comedy', 50153200.208596714),
             ('War', 49561774.873239435),
             ('Mystery', 48685533.26764706),
             ('Romance', 43105553.16969697),
             ('Crime', 39361804.14475628),
             ('Drama', 34293625.65227704),
             ('Music', 34066261.79096045),
             ('Horror', 30902223.147843942),
             ('History', 28573205.130890053),
             ('Western', 19403895.185185187),
             ('Documentary', 10876810.028571429),
             ('Foreign', -533369.2777777778),
             ('TV Movie', -1314285.7142857143)])
```

[46]:
```
plt.bar(Genre_means_dict.keys(),Genre_means_dict.values())
plt.title('Average profit made by Movies based on their Genre')
plt.xlabel('Movie genre')
plt.ylabel('Average profit')
plt.xticks(rotation=90);
plt.show()
```



From the plot, Animation movies have high average profit, the second is Adventure and Fantasy as the third. Foreign Movies and Tv Movies have average losses

Conclusions

- **The movies popularity increased as the time goes on. The average popularity of movies before 1950 is around 14 while the ones between 1950 to 2000 have average popularity around 19 while the ones from 2000 to 2010 have average popularity around 20 while the ones after 2010 are more popular with average popularity 33 of popularity index.**
- **Movies from New Zealand made most of the profit based on average , followed by Japan, China,United Kingdom and USA. Movies from Denmark, Russia and Switzerland are in losses**
- **The adventure movies are most popular movies, followed by Animation, Science Fiction, Fantasy and then Action. Documentary movies and Foreign movies occupy the last two places.**
- **The movies from Amblin Entertainment occupies the first place around 47 popularity index, followed by Walt Disney Pictures, Summit Entertainment occupies the third place and Dune Pictures occupies the fourth place while Village Roadshow Pictures occupies the fifth place . In the top thirty the 30th is Fox Searchlight Pictures**
- **The movies from New Zeland are most popular and are much ahead than others**

around 50 of popularity index, the second is United Kingdom with around 27, followed by Spain and Japan. The united State of America occupy the 8th position while Denmark and Russia movies occupy the 21st and 22nd places respectively. Another insight is that despite having a lot of movies in the dataset, United State of America movies are not popular as expected, therefore the popularity of the movie do not deppend on how much movies are produced in the country.

[ ]:

```

```