Average Movie Ratings for Box Office Underperformers

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Dataset

Which dataset did you use of the following:

- Soccer Dataset
- **IMDB Movie Dataset**
- World Development Indicators Dataset

Motivation

- The performance and verdict of movies at the box office is based on a variety of factors apart from the content such as word of mouth publicity, promotions and several others.
- Sometimes, general audience tend to miss out on some great movies typically because they are declared underperformers in their initial box office verdict.
- This study aims at analysing the average rating for some of these movies and the findings can then be used by producers to re-release those movies in the theatres which underperformed at the time of release but then have become cult classics over the years.

Research Question(s)

- Do box office underperformers necessarily have low audience ratings?
- Are there any of those movies which underperformed at the time of the release but have gained popularity amongst the masses over the years?

Domain Specifics

- For the analysis, the below movies from the dataset have been considered[1]:

- Annihilation (2018)
- The Assassination of Jesse James by the Coward Robert Ford (2007)
- Blade Runner 2049 (2017)
- Bottle Rocket (1996)
- Children of Men (2006)
- Cloud Atlas (2012)
- Dredd 3D (2012)
- Fight Club (1999)
- The Fountain (2006)
- Grindhouse (2007)

1 https://www.indiewire.com/gallery/best-films-box-office-bombs

Categorization

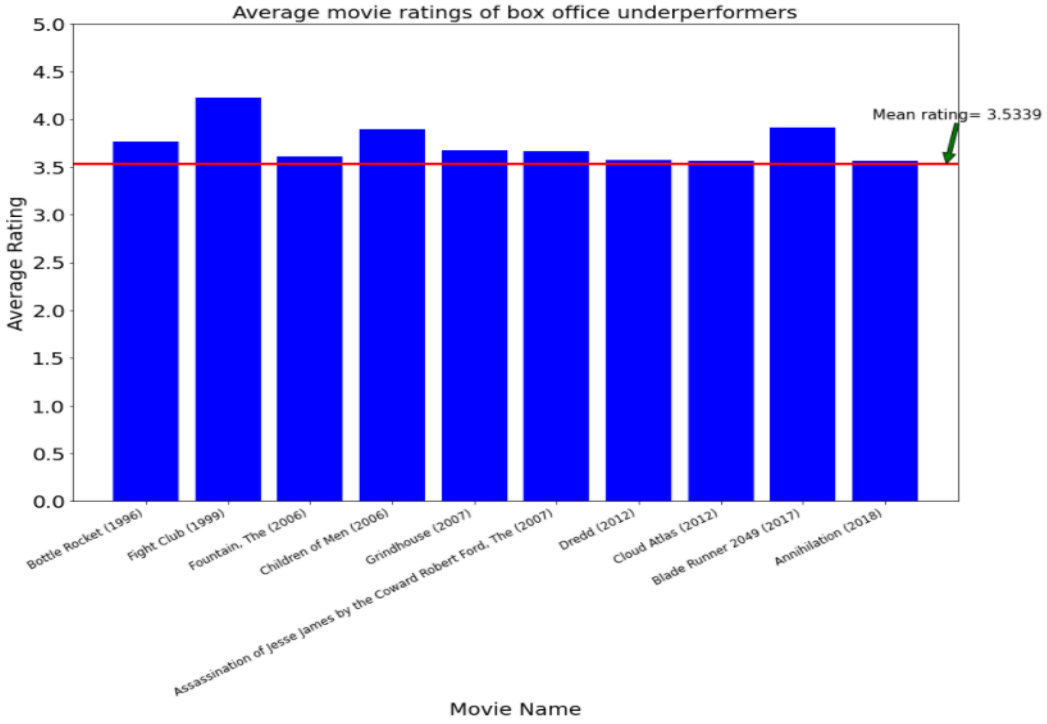
- The ratings dataset range is between 0.5-5.
- Considering this fact, 3 categories of ratings can be defined for movies.

- High Rated Movies: [4.0,5.0]
- Average Rated Movies: [2.0,4.0)
- Low Rated Movies: [0.5,2.0)

Findings

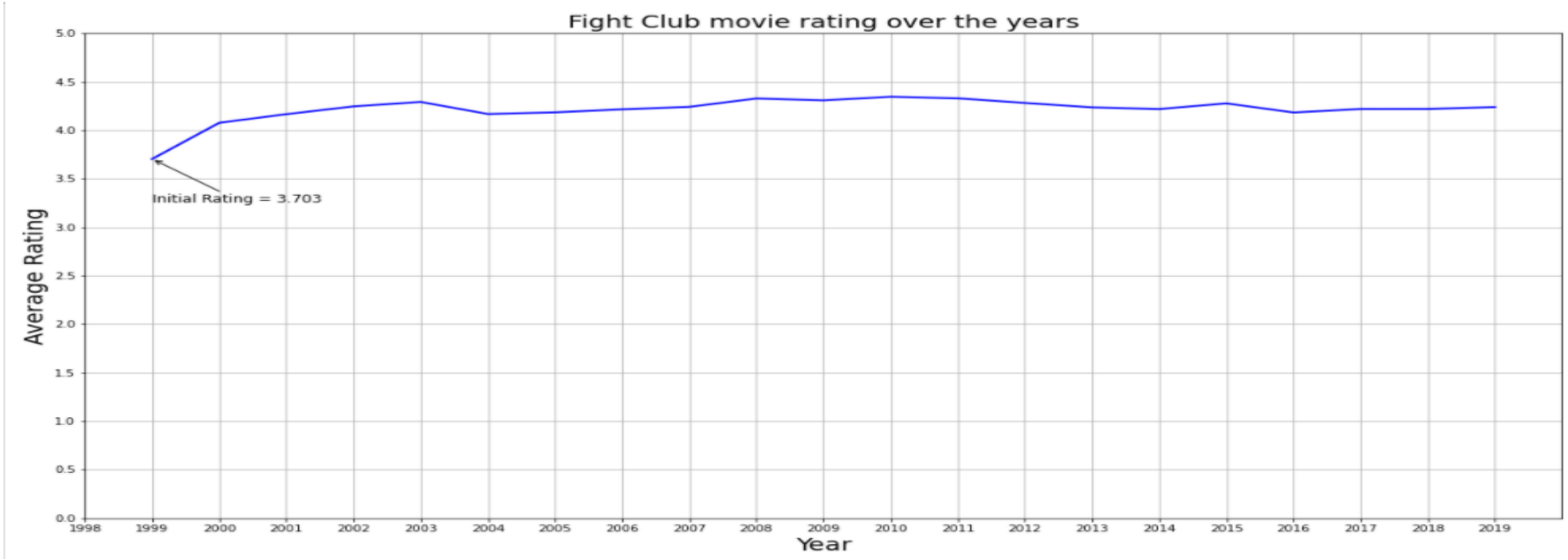
From the adjacent bar chart of average movie ratings for underperformers, it can be concluded that :

- All of the selected movies have an average rating above 3.534 (mean of the entire ratings dataset).
- It means that they belong to the average rated movies according to the categorization in the previous slide.
- Additionally, Fight Club (1999) which has a movie average rating over 4 is a high rated movie and seemingly an outlier.



This analysis answers the first research question that box office underperformers are not necessarily low rated movies.

Findings



From the above line graph of the average ratings for Fight Club movie over the years, it can be inferred that:

- Fight Club movie had the lowest average rating (3.703) at the time of it's release(1999).
- The rating increased and went up to beyond 4 in the very next year(2000).
- Since then, the rating has remained above 4 till 2019 with some minor fluctuations.

This answers the second research question that among the underperformers, there are a select few movies like Fight Club(1999) which gained great ratings and became cult classics post their release till date.

Acknowledgements

- Instructors Ilkay Altintas and Leo Porter for the great content taught in this class.
- Zack Sharf for the IndieWire article on Box Office Underperformers.

References

- https://pandas.pydata.org/docs/
- https://matplotlib.org/3.3.2/contents.html
- https://www.indiewire.com/gallery/best-films-box-office-bombs/

In [1]:
```
# https://grouplens.org/datasets/movielens/25m/
# Folder: 'Movie Ratings Dataset'
```

In [2]:
```
# Importing Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Analysis of Average Movie Rating for Box Office Underperformers

Do box office underperformers necessarily have low audience ratings? Are there any of those movies which underperformed at the time of the release but have gained popularity amongst the masses over the years?

For the analysis, considering the below movies from the link https://www.indiewire.com/gallery/best-films-box-office-bombs

- Annihilation (2018)
- The Assassination of Jesse James by the Coward Robert Ford (2007)
- Blade Runner 2049 (2017)
- Bottle Rocket (1996)
- Children of Men (2006)
- Cloud Atlas (2012)
- Dredd 3D (2012)
- Fight Club (1999)
- The Fountain (2006)
- Grindhouse (2007)

In [3]:
```
# Reading ratings dataset

ratings = pd.read_csv('./Movie Ratings Dataset/ratings.csv')
ratings.shape
```

Out[3]:
```
(25000095, 4)
```

In [4]:
```
# Reading movies dataset

movies = pd.read_csv('./Movie Ratings Dataset/movies.csv')
movies.shape
```

Out[4]:
```
(62423, 3)
```

In [5]:
```
# Checking ratings records

ratings.head()
```

Out[5]:

	userId	movieId	rating	timestamp
0	1	296	5.0	1147880044
1	1	306	3.5	1147868817
2	1	307	5.0	1147868828
3	1	665	5.0	1147878820
4	1	899	3.5	1147868510

In [6]:
```
# Checking the range of the ratings

print(f'Ratings range: {ratings.rating.min()} - {ratings.rating.max()}')
```

```
Ratings range: 0.5 - 5.0
```

Considering the fact that the ratings range is between 0.5-5, we will define 3 types of ratings for movies

(i) High Rated Movies : [4.0,5.0]

(ii) Average Rated Movies : [2.0,4.0)

(iii) Low Rated Movies : [0.5,2.0)

In [7]:
```
# Checking movies records

movies.head()
```

Out[7]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

In [8]:
```
# Quick check to see if the underperformed movies mentioned in the link are present in the d
ataset.

print(movies[movies['title'].str.contains('Annihilation \(2018\)')]['title'].values)
print(movies[movies['title'].str.contains('Assassination of Jesse James by the Coward Robert
Ford, The \(2007\)')]['title'].values)
print(movies[movies['title'].str.contains('Blade Runner 2049 \(2017\)')]['title'].values)
print(movies[movies['title'].str.contains('Bottle Rocket \(1996\)')]['title'].values)
print(movies[movies['title'].str.contains('Children of Men \(2006\)')]['title'].values)
print(movies[movies['title'].str.contains('Cloud Atlas \(2012\)')]['title'].values)
print(movies[movies['title'].str.contains('Dredd \(2012\)')]['title'].values)
print(movies[movies['title'].str.contains('Fight Club \(1999\)')]['title'].values)
print(movies[movies['title'].str.contains('Fountain, The \(2006\)')]['title'].values)
print(movies[movies['title'].str.contains('Grindhouse \(2007\)')]['title'].values)
```

```
['Annihilation (2018)']
['Assassination of Jesse James by the Coward Robert Ford, The (2007)']
['Blade Runner 2049 (2017)']
['Bottle Rocket (1996)']
['Children of Men (2006)']
['Cloud Atlas (2012)']
['Dredd (2012)']
['Fight Club (1999)']
['Fountain, The (2006)']
['Grindhouse (2007)']
```

In [9]:
```
# Mask to filter out the above movies from the dataset

mask = ['Annihilation \(2018\)',
        'Assassination of Jesse James by the Coward Robert Ford, The \(2007\)',
        'Blade Runner 2049 \(2017\)',
        'Bottle Rocket \(1996\)',
        'Children of Men \(2006\)',
        'Cloud Atlas \(2012\)',
        'Dredd \(2012\)',
        'Fight Club \(1999\)',
        'Fountain, The \(2006\)',
        'Grindhouse \(2007\)'
       ]

box_office_underperformers = movies[movies.title.str.contains('|'.join(mask))]
```

In [10]:
```
# Checking the sub-dataframe of the underperformers from the movies dataset

box_office_underperformers
```

Out[10]:

	movieId	title	genres
99	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance
2867	2959	Fight Club (1999)	Action|Crime|Drama|Thriller
11075	48043	Fountain, The (2006)	Drama|Fantasy|Romance
11162	48774	Children of Men (2006)	Action|Adventure|Drama|Sci-Fi|Thriller
11509	52281	Grindhouse (2007)	Action|Crime|Horror|Sci-Fi|Thriller
11874	55363	Assassination of Jesse James by the Coward Rob...	Crime|Drama|Western
18491	96737	Dredd (2012)	Action|Sci-Fi
18703	97752	Cloud Atlas (2012)	Drama|Sci-Fi|IMAX
48302	176371	Blade Runner 2049 (2017)	Sci-Fi
51241	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller

In [11]:
```
# Creating a dataframe of all ratings for the underperformers.
# This can be done by inner join of the sub-dataframe created in the above cell and the rati
ngs dataset with movieId as key.

underperformer_ratings = box_office_underperformers.merge(ratings,on='movieId',how='inner')
```

In [12]:
```
# Checking the created dataframe

underperformer_ratings.head()
```

Out[12]:

	movieId	title	genres	userId	rating	timestamp
0	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	12	4.0	1255359683
1	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	57	4.5	1142400226
2	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	171	4.5	1074594930
3	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	201	4.0	938860807
4	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	226	3.5	1059575181

In [13]:
```
# Quick check on the number of ratings for each movie.

underperformer_ratings.groupby(['movieId','title']).rating.count()
```

Out[13]:
```
movieId  title
101      Bottle Rocket (1996)                                                  4438
2959     Fight Club (1999)                                                    58773
48043    Fountain, The (2006)                                                  4536
48774    Children of Men (2006)                                               15063
52281    Grindhouse (2007)                                                     5324
55363    Assassination of Jesse James by the Coward Robert Ford, The (2007)    2627
96737    Dredd (2012)                                                          3495
97752    Cloud Atlas (2012)                                                    5750
176371   Blade Runner 2049 (2017)                                              5119
182715   Annihilation (2018)                                                   2017
Name: rating, dtype: int64
```

In [14]:
```
# Reviewing the ratings statistics for the underpeformers

underperformer_ratings.groupby(['movieId','title']).rating.describe()
```

Out[14]:

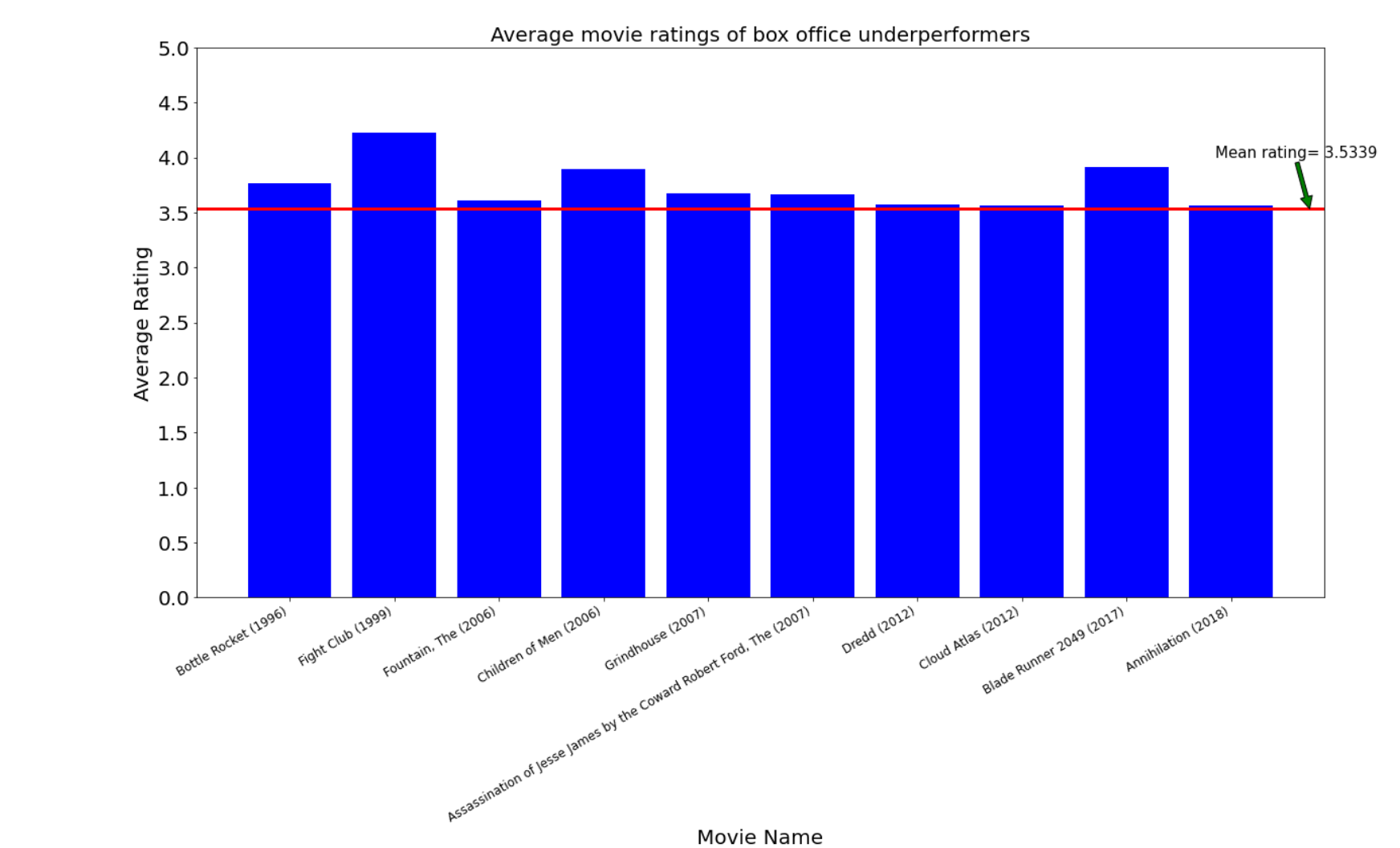
movieId	title	count	mean	std	min	25%	50%	75%	max
101	Bottle Rocket (1996)	4438.0	3.767350	0.881794	0.5	3.0	4.0	4.5	5.0
2959	Fight Club (1999)	58773.0	4.228311	0.870319	0.5	4.0	4.5	5.0	5.0
48043	Fountain, The (2006)	4536.0	3.607694	1.098224	0.5	3.0	4.0	4.5	5.0
48774	Children of Men (2006)	15063.0	3.897896	0.871526	0.5	3.5	4.0	4.5	5.0
52281	Grindhouse (2007)	5324.0	3.677029	0.962270	0.5	3.0	4.0	4.5	5.0
55363	Assassination of Jesse James by the Coward Robert Ford, The (2007)	2627.0	3.661401	0.949519	0.5	3.0	4.0	4.5	5.0
96737	Dredd (2012)	3495.0	3.569671	0.981699	0.5	3.0	3.5	4.0	5.0
97752	Cloud Atlas (2012)	5750.0	3.567913	1.055408	0.5	3.0	3.5	4.5	5.0
176371	Blade Runner 2049 (2017)	5119.0	3.914827	0.937565	0.5	3.5	4.0	4.5	5.0
182715	Annihilation (2018)	2017.0	3.564948	0.938721	0.5	3.0	3.5	4.0	5.0

In [15]:
```
# Checking the mean of the entire ratings dataset

np.mean(ratings.rating)
```

Out[15]:
```
3.533854451353085
```

In [16]:
```
# Comparing the average ratings for the above movies against the average rating of the entir
e ratings dataset.
# Using a bar chart to visualize the same and the threshold for the mean of the ratings data
set is annotated

avg = underperformer_ratings.groupby(['movieId','title']).rating.mean()

# Movie Names on the X-axis and Average Ratings on the Y-axis
x = [title for _,title in avg.index.values]
y = avg.values

plt.figure(figsize=(20,10))
plt.bar(x, y, color = 'blue')

# Y-axis going from 0 to 5 as per the ratings to create an honest visualization.
plt.xticks(rotation=30,fontsize=12,horizontalalignment='right')
plt.yticks(np.arange(0.0,5.01,0.5),fontsize=20)

# Setting the Axes labels and title of the bar chart
plt.xlabel(xlabel = 'Movie Name',fontsize=20,horizontalalignment='center')
plt.ylabel(ylabel = 'Average Rating',fontsize=20)
plt.title('Average movie ratings of box office underperformers',fontsize=20)

# Plotting a horizontal line to indicate the mean rating of the entire ratings dataset and c
reating an annotation for the same.

plt.axhline(y=ratings.rating.mean(), color='r', linestyle='solid',linewidth=3)

plt.annotate(f'Mean rating= {np.mean(ratings.rating):1.4f}',
             xy=(9.75,np.mean(ratings.rating)),
             xycoords='data',
             xytext=(8.85, 4.0),
             textcoords='data',
             fontsize=15,
             arrowprops=dict(facecolor='green'))
```

Out[16]:
```
Text(8.85, 4.0, 'Mean rating= 3.5339')
```



A quick glance at the results shows that:
(i) All of the selected movies have an average rating above 3.534 (mean of ratings dataset)
(ii) It means that they belong to the average rated movies according to the categorization earlier.
(iii) Also, in the range of average rated movies, they are in the top 25% percent (3.5-4).
(iv) Additionally, Fight Club (1999) which has an movie average rating over 4 is a high rated movie and seemingly an outlier.

In [17]:
```
# Continuing further analysis for Fight Club Movie which has the highest average rating
# Converting UNIX timestamp to datetime and adding as a column to the sub-dataframe

underperformer_ratings['parsed_time'] = pd.to_datetime(underperformer_ratings['timestamp'],u
nit='s')
```

In [18]:
```
underperformer_ratings
```

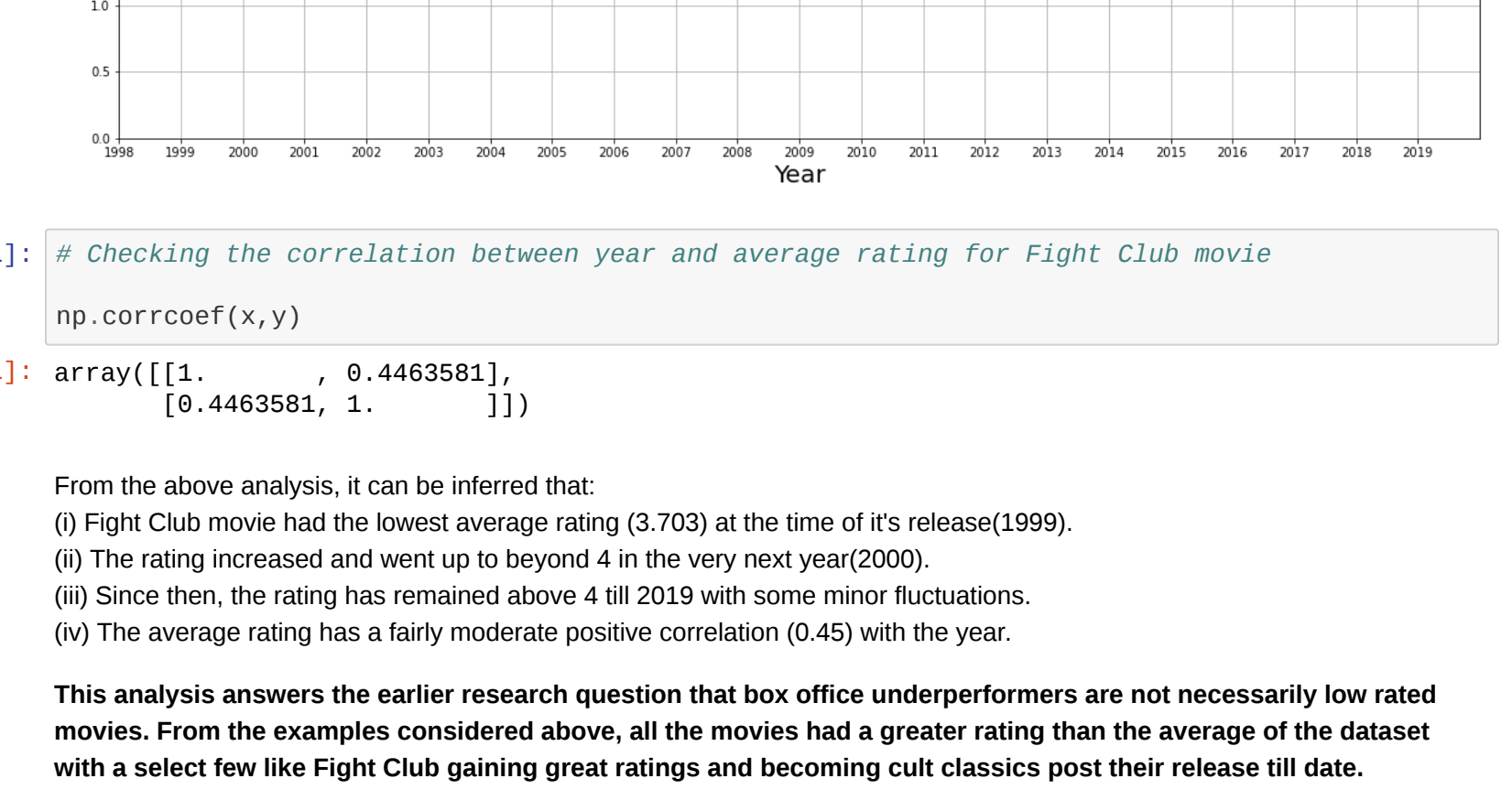
Out[18]:

	movieId	title	genres	userId	rating	timestamp	parsed_time
0	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	12	4.0	1255359683	2009-10-12 15:01:23
1	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	57	4.5	1142400226	2006-03-15 05:23:46
2	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	171	4.5	1074594930	2004-01-20 10:35:30
3	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	201	4.0	938860807	1999-10-02 10:40:07
4	101	Bottle Rocket (1996)	Adventure|Comedy|Crime|Romance	226	3.5	1059575181	2003-07-30 14:26:21
...	...	...	...	...	...	...	...
107137	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller	162335	4.5	1571016207	2019-10-14 01:23:27
107138	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller	162349	5.0	1551623659	2019-03-03 14:34:19
107139	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller	162400	4.0	1558853777	2019-05-26 06:56:17
107140	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller	162516	3.5	1531712401	2018-07-16 03:40:01
107141	182715	Annihilation (2018)	Adventure|Mystery|Sci-Fi|Thriller	162534	2.5	1526748381	2018-05-19 16:46:21

107142 rows × 7 columns

In [19]:
```
# Getting all the ratings for Fight Club movie.

fight_club_movie_ratings = underperformer_ratings[underperformer_ratings.title.str.contains(
'Fight Club')]
```

In [20]:
```
# Plotting the average ratings for Fight Club movie over the years using a line chart.
avg = fight_club_movie_ratings.groupby(fight_club_movie_ratings['parsed_time'].dt.year).rati
ng.mean()

# Year on the X-axis and Average rating on the Y-axis
x = avg.index.values
y = avg.values

plt.figure(figsize=(20,10))

plt.xlabel('Year',fontsize=20)
plt.ylabel('Average Rating',fontsize=20)
plt.title('Fight Club movie rating over the years',fontsize=20)

plt.xticks(np.arange(1998,2020,1),fontsize=10)
plt.yticks(np.arange(0.0,5.01,0.5),fontsize=10)

plt.plot(x,y,linewidth=2,color='blue')

plt.axis([1998, 2020,0,5])

plt.grid(True)

# Annotating the Initial Rating in release year 1999
plt.annotate(f'Initial Rating = {y[0]:1.3f}',
             xy=(1999,y[0]),
             xycoords='data',
             xytext=(1999, 3.25),
             textcoords='data',
             fontsize=12,
             arrowprops=dict(arrowstyle='->',color='black',connectionstyle='arc3'))

plt.show()
```



In [21]:
```
# Checking the correlation between year and average rating for Fight Club movie

np.corrcoef(x,y)
```

Out[21]:
```
array([[1.       , 0.4463581],
       [0.4463581, 1.       ]])
```

From the above analysis, it can be inferred that:
(i) Fight Club movie had the lowest average rating (3.703) at the time of it's release(1999).
(ii) The rating increased and went up to beyond 4 in the very next year(2000).
(iii) Since then, the rating has remained above 4 till 2019 with some minor fluctuations.
(iv) The average rating has a fairly moderate positive correlation (0.45) with the year.

This analysis answers the earlier research question that box office underperformers are not necessarily low rated movies. From the examples considered above, all the movies had a greater rating than the average of the dataset with a select few like Fight Club gaining great ratings and becoming cult classics post their release till date.