

First of all, we decided to review the 1000 movies that have become famous in the digital world and here we will examine the priorities that make the movies high.

these are the important variables

missing data detected

For the right movie, we determine how the audience attaches importance to the longest-running movies.

```
In [46]: data[data['Runtime (Minutes)']>=180]['Title']
```

```
Out[46]: 82      The Wolf of Wall Street
88      The Hateful Eight
311     La vie d'Adèle
Name: Title, dtype: object
```

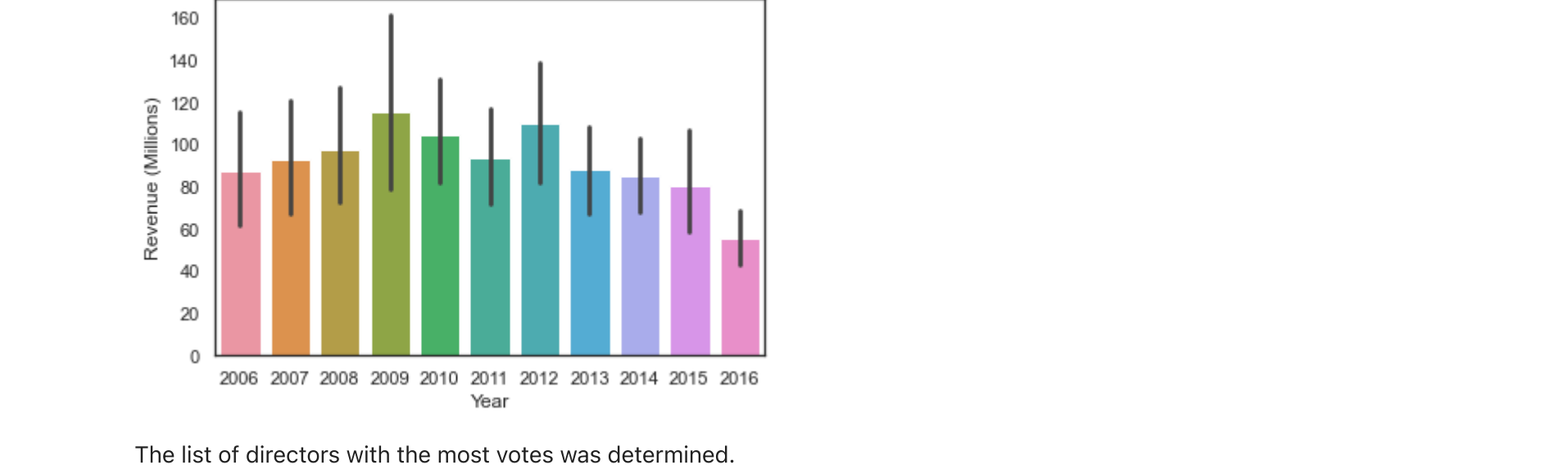
The participation rate of the audience according to the years will show us the order of importance of the film industry.

```
In [48]: data.groupby('Year')['Votes'].mean().sort_values(ascending=False)
```

```
Out[48]: Year
2012      290861.483871
2006      277232.219512
2009      267180.577778
2008      266580.145833
2007      266530.704545
2010      261082.929825
2011      259254.736842
2013      225531.892857
2014      211926.881720
2015      129512.651376
2016       68437.823232
Name: Votes, dtype: float64
```

The income increase over the years shows us how the film industry is in an economic race.

```
In [56]: sns.barplot(x='Year',y='Revenue (Millions)',data=data)
plt.title('Revenue By millions')
plt.show()
```



The list of directors with the most votes was determined.

```
In [58]: data.groupby('Director')['Rating'].mean().sort_values(ascending=False)
```

```
Out[58]: Director
Christopher Nolan      8.68
Olivier Nakache        8.60
Makoto Shinkai         8.60
Aamir Khan             8.50
Florian Henckel von Donnersmarck  8.50
...
Sam Taylor-Johnson     4.10
Joey Curtis            4.00
George Nolfi           3.90
James Wong             2.70
Jason Friedberg        1.90
Name: Rating, Length: 524, dtype: float64
```

Of course, the running time of the films is one of the most important factors.

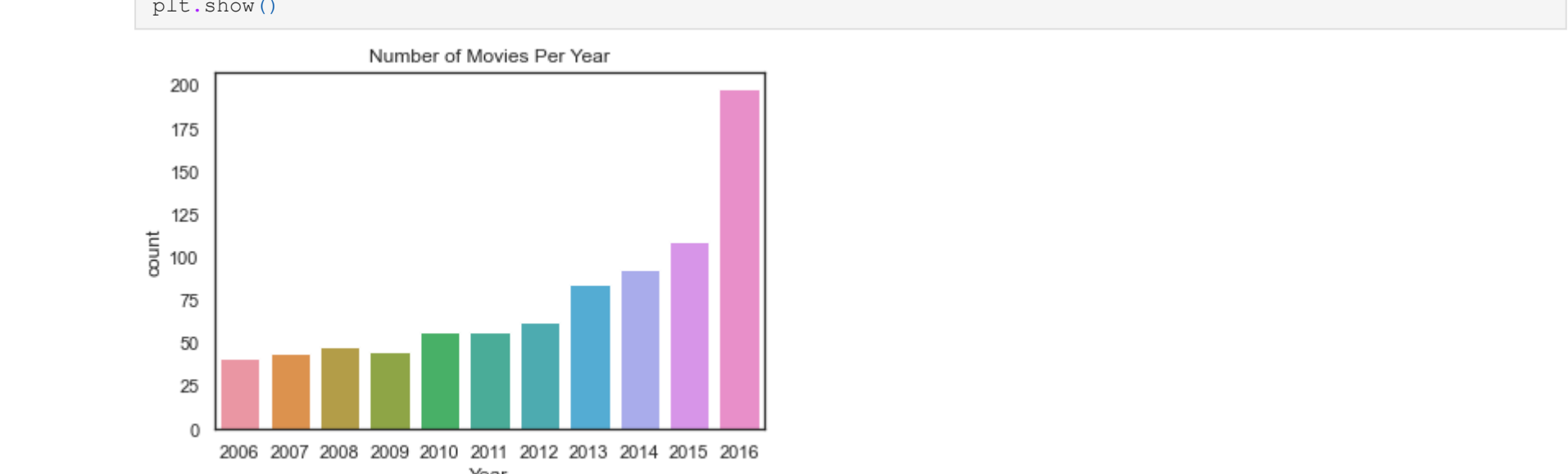
```
In [63]: top10_len=data.nlargest(10,'Runtime (Minutes)')[['Title','Runtime (Minutes)']]
top10_len
```

	Title	Runtime (Minutes)
88	The Hateful Eight	187
82	The Wolf of Wall Street	180
311	La vie d'Adèle	180
267	Cloud Atlas	172
430	3 Idiots	170
36	Interstellar	169
75	Pirates of the Caribbean: At World's End	169
271	The Hobbit: An Unexpected Journey	169
425	The Curious Case of Benjamin Button	166
126	Transformers: Age of Extinction	165

```
In [70]: data['Year'].value_counts()
```

```
Out[70]: 2016      198
2015      109
2014       93
2013       84
2012       62
2011       57
2010       57
2008       48
2009       45
2007       44
2006       41
Name: Year, dtype: int64
```

```
In [72]: sns.countplot(x='Year',data=data)
plt.title('Number of Movies Per Year')
plt.show()
```



```
In [77]: data[data['Revenue (Millions)'].max()==data['Revenue (Millions)']]['Title']
```

```
Out[77]: 50      Star Wars: Episode VII - The Force Awakens
Name: Title, dtype: object
```

When we look at the most voted movies, action science fiction movies are at the forefront.

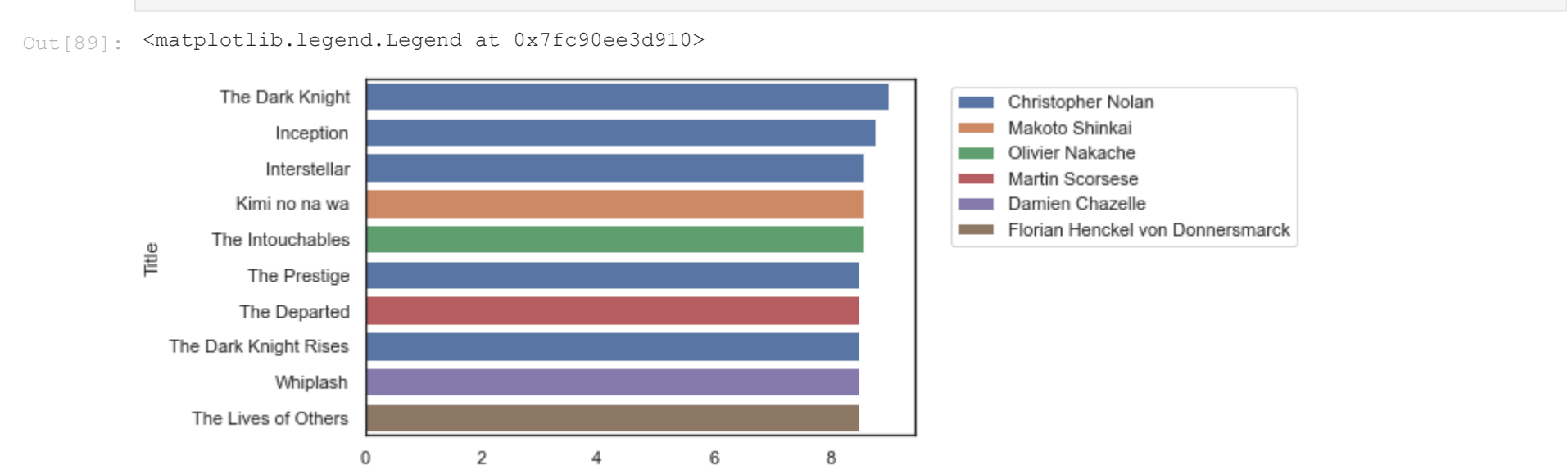
```
In [86]: top10_len=data.nlargest(10,'Rating')[['Title','Rating','Director']]
.set_index('Title')
top10_len
```

	Rating	Director
	Title	
	The Dark Knight	Christopher Nolan
	Inception	Christopher Nolan
	Interstellar	Christopher Nolan
	Kimi no na wa	Makoto Shinkai
	The Intouchables	Olivier Nakache
	The Prestige	Christopher Nolan
	The Departed	Martin Scorsese
	The Dark Knight Rises	Christopher Nolan
	Whiplash	Damien Chazelle
	The Lives of Others	Florian Henckel von Donnersmarck

Christopher Nolan movies grab our attention

```
In [89]: sns.barplot(x='Rating',y=top10_len.index,data=top10_len,hue="Director",dodge=False)
plt.legend(bbox_to_anchor=(1.05,1),loc=2)
```

```
Out[89]: <matplotlib.legend.Legend at 0x7fc90ee3d910>
```



```
In [91]: data.nlargest(10,'Revenue (Millions)')['Title']
```

```
Out[91]: 50      Star Wars: Episode VII - The Force Awakens
87      Avatar
85      Jurassic World
76      The Avengers
54      The Dark Knight
12      Rogue One
119     Finding Dory
94      Avengers: Age of Ultron
124     The Dark Knight Rises
578     The Hunger Games: Catching Fire
Name: Title, dtype: object
```

```
In [93]: top_10=data.nlargest(10,'Revenue (Millions)')[['Title','Revenue (Millions)']].\
.set_index('Title')
top_10
```

```

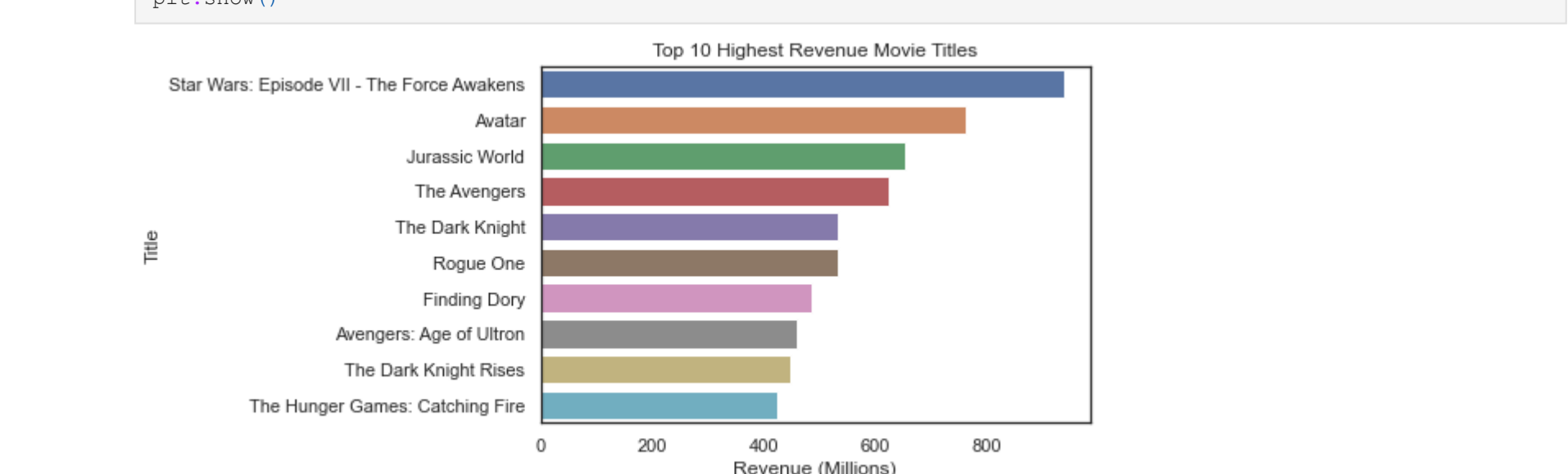
set_index("Title")
top_10

```

Out[93]:

	Revenue (Millions)
Title	
Star Wars: Episode VII - The Force Awakens	936.63
Avatar	760.51
Jurassic World	652.18
The Avengers	623.28
The Dark Knight	533.32
Rogue One	532.17
Finding Dory	486.29
Avengers: Age of Ultron	458.99
The Dark Knight Rises	448.13
The Hunger Games: Catching Fire	424.65

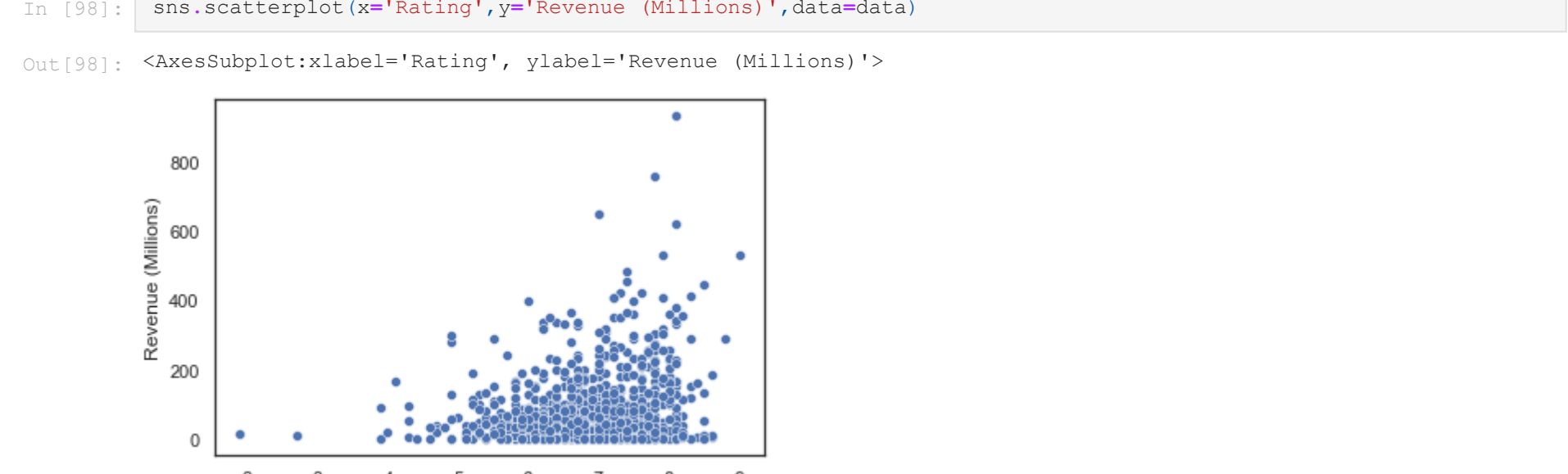
```
In [95]: sns.barplot(x='Revenue (Millions)',y=top_10.index,data=top_10)
plt.title('Top 10 Highest Revenue Movie Titles')
plt.show()
```



Does Rating Affect the Revenue ? its looking yes

```
In [98]: sns.scatterplot(x='Rating',y='Revenue (Millions)',data=data)
```

```
Out[98]: <AxesSubplot:xlabel='Rating', ylabel='Revenue (Millions)'>
```



```
In [99]: def rating(rating):
if rating>=7.0:
    return "Excellent"
elif rating>=6.0:
    return "Good"
else:
    return "Average"
```

```
In [106... data['Genre']
```

```
Out[106... 0      Action,Adventure,Sci-Fi
1      Adventure,Mystery,Sci-Fi
2      Horror,Thriller
3      Animation,Comedy,Family
4      Action,Adventure,Fantasy
...
993     Action,Adventure,Horror
994      Comedy
996      Horror
997      Drama,Music,Romance
999      Comedy,Family,Fantasy
Name: Genre, Length: 838, dtype: object
```

```
In [117... from collections import Counter
Counter(one_d)
```

```
Out[117... Counter({'Action': 277,
'Adventure': 244,
'Sci-Fi': 107,
'Mystery': 86,
'Horror': 87,
'Thriller': 148,
'Animation': 45,
'Comedy': 250,
'Family': 48,
'Fantasy': 92,
'Drama': 419,
'Music': 15,
'Biography': 67,
'Romance': 120,
'History': 25,
'Western': 4,
'Crime': 126,
'War': 10,
'Musical': 5,
'Sport': 15})
```

If we consider the data, it would be right for us to invest in genre science fiction movies, when the runtime is 180.

```
In [ ]:
```