A DATA ANALYSIS FOR MICROSOFT MOVIE STUDIO

Problem

Microsoft want to enter the movie industry and create a new movie studio. However, they have limited knowledge about the industry and they need to understand the market and what type of films and genres are successful.

In doing so, they will be able to make a decision on how to proceed and what steps to take to make a successful studio.

Goals:

1. Assist Microsoft in creating a successful movies studio.
2. Identify films and genres that are successful in the box office.
3. Translate this analysis into recommendations that can guide decision making

In [1]:
```
#importing the required libraries
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
import sqlite3
import string
import random
import requests
from bs4 import BeautifulSoup
```

In [2]:
```
#1. opening bom.movie_gross file and creating a dataframe
bom_movie_gross = pd.read_csv('.data/bom.movie_gross.csv')

#2. opening rt.movie_info file and creating a dataframe
rt_movie_info = pd.read_csv('.data/rt.movie_info.tsv', sep = '\t', index_col=0)

#3. opening rt.reviews file and creating a dataframe
rt_reviews = pd.read_csv('.data/rt.reviews.tsv', encoding = 'unicode_escape', sep = '\t', index_col=0)

#4. opening tmdb.movies file and creating a dataframe
```

```
tmdb_movies = pd.read_csv('.data/tmdb.movies.csv', index_col=0)

#5. opening tn.movie_budgets file and creating a dataframe
tn_movie_budgets = pd.read_csv('.data/tn.movie_budgets.csv', index_col=0)

#5. opening imdb_movies file and creating a dataframe
movies_year = pd.read_csv('.data/imdb_movies.tsv', delimiter='\t', usecols=['titleType', 'primaryTitle',
                          'startYear', 'runtimeMinutes'], encoding='utf-8')

#6. opening imdb file and creating a dataframe
    #query the database and join the tables movie basics and movie ratings
conn = sqlite3.connect('.data/im.db')
```

Function for checking various information about a dataframe

In [3]:
```
def df_info(df):
    df_shape = df.shape
    missing_sum = df.isna().sum()
    names = df.columns
    info = df.info()
    print('\033[95m' + f'Column names: {names}' +  '\033[0m')
    print(f'Shape: {df_shape}')
    print(f'Df info: {info}')
    print('\033[94m' + 'Missing sum:' + '\033[0m')
    print('\033[94m' + f' {missing_sum}' + '\033[0m')
    return
```

Joining movie basics table with movie ratings and movie akas tables

In [4]:
```
#joining tables and creating a dataframe
imdb = pd.read_sql('''SELECT *
                      FROM movie_basics
                      JOIN ( SELECT averagerating, numvotes, region, movie_id
                             FROM movie_ratings
                             JOIN movie_akas
                             USING(movie_id)
                           ) ratings
                       USING(movie_id)
''', conn)
```

cleaning the dataframe formed after joining the tables

In [5]:
```
imdb
```

Out[5]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	None
1	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
2	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
3	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
4	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
...	...	...	...	...	...	...	...	...	...
261801	tt9905462	Pengalila	Pengalila	2019	111.0	Drama	8.4	600	IN
261802	tt9905462	Pengalila	Pengalila	2019	111.0	Drama	8.4	600	IN
261803	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365	None
261804	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365	IN
261805	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365	IN

261806 rows × 9 columns

In [6]:
```
#removing duplicated rows
imdb = imdb.drop_duplicates()

#removing null rows in region rows with the string none
imdb = imdb[(imdb['region'].notna()) & (imdb['region'] != 'None')]

#drop duplicated rows while merging the region values
imdb = imdb.groupby('movie_id', as_index=False).agg({'primary_title': 'first',
                                                     'original_title': 'first',
                                                     'start_year': 'first',
                                                     'runtime_minutes': 'first',
                                                     'genres': 'first',
                                                     'averagerating': 'first',
                                                     'numvotes': 'first',
                                                     'region': ', '.join})
```

```
imdb
```

Out[6]:

	movie_id	primary_title	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	tt0063540	Sunghursh	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
1	tt0066787	One Day Before the Rainy Season	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43	IN, XWW
2	tt0069049	The Other Side of the Wind	The Other Side of the Wind	2018	122.0	Drama	6.9	4517	AR, BR, DE, ES, FR, GB, IT, PL, PT, RU, US, VE
3	tt0069204	Sabse Bada Sukh	Sabse Bada Sukh	2018	NaN	Comedy,Drama	6.1	13	IN
4	tt0100275	The Wandering Soap Opera	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119	CL, PL, XWW
...	...	...	...	...	...	...	...	...	...
69547	tt9899860	Watching This Movie Is a Crime	Didan in film jorm ast	2019	100.0	Drama,Thriller	8.1	7	IR, XWW
69548	tt9899880	Columbus	Columbus	2018	85.0	Comedy	5.8	5	IR
69549	tt9903952	BADMEN with a good behavior	BADMEN with a good behavior	2018	87.0	Comedy,Horror	9.2	5	DE
69550	tt9905462	Pengalila	Pengalila	2019	111.0	Drama	8.4	600	IN
69551	tt9911774	Padmavyuhathile Abhimanyu	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365	IN

69552 rows × 9 columns

In [7]:
```
#checking which columns have missing data
imdb.isna().sum()
```

Out[7]:
```
movie_id             0
primary_title        0
original_title       0
start_year           0
runtime_minutes    6741
genres              637
averagerating         0
numvotes              0
```

```
region                0
dtype: int64
```

In [8]:
```
#checking missing percentage
missing_percentage_genres = imdb.genres.isna().sum() * 100 / len(imdb.genres)
missing_percentage_minutes = imdb.runtime_minutes.isna().sum() * 100 / len(imdb.runtime_minutes)
print('Missing data for genres', format(missing_percentage_genres, '.2f'))
print('Missing data for runtime', format(missing_percentage_minutes, '.2f'))
```

```
Missing data for genres 0.92
Missing data for runtime 9.69
```

In [9]:
```
#removing all rows in genre and runtime minutes as their percentage is negligible
imdb['genres'] = imdb.genres.dropna()
imdb['runtime_minutes'] = imdb.runtime_minutes.dropna()
imdb = imdb[imdb['runtime_minutes'] <= 200]
imdb = imdb[imdb['runtime_minutes'] >= 59]
imdb = imdb.dropna(subset=['genres', 'runtime_minutes'])
imdb = imdb.drop('movie_id', axis=1)

#dropping a column
imdb = imdb.drop('primary_title', axis=1)
imdb
```

Out[9]:

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	Sunghursh	2013	175.0	Action,Crime,Drama	7.0	77	IN
1	Ashad Ka Ek Din	2019	114.0	Biography,Drama	7.2	43	IN, XWW
2	The Other Side of the Wind	2018	122.0	Drama	6.9	4517	AR, BR, DE, ES, FR, GB, IT, PL, PT, RU, US, VE
4	La Telenovela Errante	2017	80.0	Comedy,Drama,Fantasy	6.5	119	CL, PL, XWW
6	Joe Finds Grace	2017	83.0	Adventure,Animation,Comedy	8.1	263	CA
...	...	...	...	...	...	...	...
69547	Didan in film jorm ast	2019	100.0	Drama,Thriller	8.1	7	IR, XWW
69548	Columbus	2018	85.0	Comedy	5.8	5	IR
69549	BADMEN with a good behavior	2018	87.0	Comedy,Horror	9.2	5	DE
69550	Pengalila	2019	111.0	Drama	8.4	600	IN

	original_title	start_year	runtime_minutes	genres	averagerating	numvotes	region
69551	Padmavyuhathile Abhimanyu	2019	130.0	Drama	8.4	365	IN

58998 rows × 7 columns

In [10]:
```
imdb =imdb.rename(columns={'original_title': 'movie'})
```

In [11]:
```
#confirming if there are missing values
imdb.isna().sum()
```

Out[11]:
```
movie              0
start_year         0
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
region             0
dtype: int64
```

In [12]:
```
df_info(imdb)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58998 entries, 0 to 69551
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   movie            58998 non-null  object 
 1   start_year       58998 non-null  int64  
 2   runtime_minutes  58998 non-null  float64
 3   genres           58998 non-null  object 
 4   averagerating    58998 non-null  float64
 5   numvotes         58998 non-null  int64  
 6   region           58998 non-null  object 
dtypes: float64(2), int64(2), object(3)
memory usage: 3.6+ MB
Column names: Index(['movie', 'start_year', 'runtime_minutes', 'genres', 'averagerating',
       'numvotes', 'region'],
      dtype='object')
Shape: (58998, 7)
Df info: None
Missing sum:
 movie              0
start_year         0
```

```
runtime_minutes    0
genres             0
averagerating      0
numvotes           0
region             0
dtype: int64
```

Merging and cleaning bom movie gross and tn mov ie budgets data

In [13]:
```
#viewing information about the dataframe
tn_movie_budgets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5782 entries, 1 to 82
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   release_date       5782 non-null   object
 1   movie              5782 non-null   object
 2   production_budget  5782 non-null   object
 3   domestic_gross     5782 non-null   object
 4   worldwide_gross    5782 non-null   object
dtypes: object(5)
memory usage: 271.0+ KB
```

In [14]:
```
#viewing information about the dataframe
bom_movie_gross.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   title           3387 non-null   object 
 1   studio          3382 non-null   object 
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [15]:
```
#renaming a column in the dataframe
bom_movie_gross = bom_movie_gross.rename(columns={'title': 'movie'})
```

In [16]:
```
#viewing the dataframe
tn_movie_budgets.head(4)
```

Out[16]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963

In [17]:
```
#merging bom gross and tn budgets
bom_and_tn = pd.merge(bom_movie_gross, tn_movie_budgets, on='movie', how='outer')
```

In [18]:
```
bom_and_tn.tail()
```

Out[18]:

	movie	studio	domestic_gross_x	foreign_gross	year	release_date	production_budget	domestic_gross_y	worldwide_gross
7926	Red 11	NaN	NaN	NaN	NaN	Dec 31, 2018	$7,000	$0	$0
7927	Following	NaN	NaN	NaN	NaN	Apr 2, 1999	$6,000	$48,482	$240,495
7928	Return to the Land of Wonders	NaN	NaN	NaN	NaN	Jul 13, 2005	$5,000	$1,338	$1,338
7929	A Plague So Pleasant	NaN	NaN	NaN	NaN	Sep 29, 2015	$1,400	$0	$0
7930	My Date With Drew	NaN	NaN	NaN	NaN	Aug 5, 2005	$1,100	$181,041	$181,041

In [19]:
```
#information about the merged dataframe
bom_and_tn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7931 entries, 0 to 7930
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              7931 non-null   object 
 1   studio             3391 non-null   object 
 2   domestic_gross_x   3368 non-null   float64
 3   foreign_gross      2044 non-null   object 
 4   year               3396 non-null   float64
 5   release_date       5782 non-null   object 
 6   production_budget  5782 non-null   object 
```

```
 7   domestic_gross_y   5782 non-null   object
 8   worldwide_gross    5782 non-null   object
dtypes: float64(2), object(7)
memory usage: 619.6+ KB
```

In [20]:
```
bom_and_tn.isna().sum()
```

Out[20]:
```
movie                  0
studio              4540
domestic_gross_x    4563
foreign_gross       5887
year                4535
release_date        2149
production_budget   2149
domestic_gross_y    2149
worldwide_gross     2149
dtype: int64
```

In [21]:
```
#removing dollar signs and commas in this columns
bom_and_tn['production_budget'] = bom_and_tn['production_budget'].str.replace('[$,]', '').astype(float)
bom_and_tn['domestic_gross_y'] = bom_and_tn['domestic_gross_y'].str.replace('[$,]', '').astype(float)
bom_and_tn['worldwide_gross'] = bom_and_tn['worldwide_gross'].str.replace('[$,]', '').astype(float)

# fill missing values in 'domestic gross y' column with values from 'domestic gross x' column
bom_and_tn['domestic_gross_y'] = bom_and_tn['domestic_gross_y'].fillna(bom_and_tn['domestic_gross_x'])
```

In [22]:
```
bom_and_tn.tail()
```

Out[22]:

	movie	studio	domestic_gross_x	foreign_gross	year	release_date	production_budget	domestic_gross_y	worldwide_gross
7926	Red 11	NaN	NaN	NaN	NaN	Dec 31, 2018	7000.0	0.0	0.0
7927	Following	NaN	NaN	NaN	NaN	Apr 2, 1999	6000.0	48482.0	240495.0
7928	Return to the Land of Wonders	NaN	NaN	NaN	NaN	Jul 13, 2005	5000.0	1338.0	1338.0
7929	A Plague So Pleasant	NaN	NaN	NaN	NaN	Sep 29, 2015	1400.0	0.0	0.0
7930	My Date With Drew	NaN	NaN	NaN	NaN	Aug 5, 2005	1100.0	181041.0	181041.0

In [23]:
```
#changing to datetime data type and keeping the year only
bom_and_tn['release_date'] = pd.to_datetime(bom_and_tn['release_date']).dt.strftime('%Y')
```

In [24]:
```
#replacing nan with year from the column release date
bom_and_tn['year'] = bom_and_tn['year'].fillna(bom_and_tn['release_date'])
```

In [25]:
```
bom_and_tn.tail()
```

Out[25]:

	movie	studio	domestic_gross_x	foreign_gross	year	release_date	production_budget	domestic_gross_y	worldwide_gross
7926	Red 11	NaN	NaN	NaN	2018	2018	7000.0	0.0	0.0
7927	Following	NaN	NaN	NaN	1999	1999	6000.0	48482.0	240495.0
7928	Return to the Land of Wonders	NaN	NaN	NaN	2005	2005	5000.0	1338.0	1338.0
7929	A Plague So Pleasant	NaN	NaN	NaN	2015	2015	1400.0	0.0	0.0
7930	My Date With Drew	NaN	NaN	NaN	2005	2005	1100.0	181041.0	181041.0

In [26]:
```
bom_and_tn.studio.value_counts().head(10)
```

Out[26]:
```
IFC      166
Uni.     149
WB       141
Fox      137
Magn.    137
SPC      123
Sony     111
BV       106
LGF      103
Par.     102
Name: studio, dtype: int64
```

In [27]:
```
missing_percentage_studio = bom_and_tn['domestic_gross_y'].isna().sum() * 100 / len(bom_and_tn.domestic_gross_y)
missing_percentage_studio
```

Out[27]:
```
0.3278275122935317
```

In [28]:
```
bom_and_tn["studio"] = np.where(bom_and_tn["studio"].isna(),
                            pd.Series([random.choice(["IFC", "Uni.", "WB", "Magn", "Fox", "SPC", "Sony", "BV", "LGF", "F
                            for i in range(len(bom_and_tn))]),
                            bom_and_tn["studio"])
```

In [29]:
```
#removing scientific notation
pd.options.display.float_format = '{:.2f}'.format
```

In [30]:
```
#removing the columns not needed
bom_and_tn = bom_and_tn.drop(columns=[ 'domestic_gross_x', 'release_date', 'foreign_gross'])
```

In [31]:
```
#renaming the column domestic_gross_y to domestic_gross
bom_and_tn =bom_and_tn.rename(columns={'domestic_gross_y': 'domestic_gross'})

#changing a column data typeJOIN 'Order'
bom_and_tn
```

Out[31]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross
0	Toy Story 3	BV	2010.00	200000000.00	415004880.00	1068879522.00
1	Alice in Wonderland (2010)	BV	2010.00	nan	334200000.00	nan
2	Harry Potter and the Deathly Hallows Part 1	WB	2010.00	nan	296000000.00	nan
3	Inception	WB	2010.00	160000000.00	292576195.00	835524642.00
4	Shrek Forever After	P/DW	2010.00	165000000.00	238736787.00	756244673.00
...	...	...	...	...	...	...
7926	Red 11	WB	2018	7000.00	0.00	0.00
7927	Following	Par.	1999	6000.00	48482.00	240495.00
7928	Return to the Land of Wonders	Par.	2005	5000.00	1338.00	1338.00
7929	A Plague So Pleasant	Fox	2015	1400.00	0.00	0.00
7930	My Date With Drew	LGF	2005	1100.00	181041.00	181041.00

7931 rows × 6 columns

In [32]:
```
#creating a new column foreign gross
bom_and_tn['foreign_gross'] = (bom_and_tn['worldwide_gross'] - bom_and_tn['domestic_gross'])
```

In [33]:
```
bom_and_tn.tail()
```

Out[33]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
7926	Red 11	WB	2018	7000.00	0.00	0.00	0.00
7927	Following	Par.	1999	6000.00	48482.00	240495.00	192013.00

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
7928	Return to the Land of Wonders	Par.	2005	5000.00	1338.00	1338.00	0.00
7929	A Plague So Pleasant	Fox	2015	1400.00	0.00	0.00	0.00
7930	My Date With Drew	LGF	2005	1100.00	181041.00	181041.00	0.00

In [34]:
```
bom_and_tn.isna().sum()
```

Out[34]:
```
movie                   0
studio                  0
year                    0
production_budget    2149
domestic_gross         26
worldwide_gross      2149
foreign_gross        2149
dtype: int64
```

In [35]:
```
#calculating the percentage of NaN in domestic gross
percent_nan = bom_and_tn['domestic_gross'].isna().sum() / len(bom_and_tn.domestic_gross) * 100
percent_nan
```

Out[35]:
```
0.3278275122935317
```

In [36]:
```
percent_nan_ww = (bom_and_tn['worldwide_gross'].isna().sum()) / len(bom_and_tn.worldwide_gross) * 100
percent_nan_ww
```

Out[36]:
```
27.09620476610768
```

In [37]:
```
percent_nan_ww = (bom_and_tn['foreign_gross'].isna().sum()) / len(bom_and_tn.foreign_gross) * 100
percent_nan_ww
```

Out[37]:
```
27.09620476610768
```

In [38]:
```
bom_and_tn = bom_and_tn.dropna(subset=['domestic_gross', 'production_budget', 'worldwide_gross'])
```

In [39]:
```
bom_and_tn
```

Out[39]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	Toy Story 3	BV	2010.00	200000000.00	415004880.00	1068879522.00	653874642.00

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
3	Inception	WB	2010.00	160000000.00	292576195.00	835524642.00	542948447.00
4	Shrek Forever After	P/DW	2010.00	165000000.00	238736787.00	756244673.00	517507886.00
5	The Twilight Saga: Eclipse	Sum.	2010.00	68000000.00	300531751.00	706102828.00	405571077.00
6	Iron Man 2	Par.	2010.00	170000000.00	312433331.00	621156389.00	308723058.00
...	...	...	...	...	...	...	...
7926	Red 11	WB	2018	7000.00	0.00	0.00	0.00
7927	Following	Par.	1999	6000.00	48482.00	240495.00	192013.00
7928	Return to the Land of Wonders	Par.	2005	5000.00	1338.00	1338.00	0.00
7929	A Plague So Pleasant	Fox	2015	1400.00	0.00	0.00	0.00
7930	My Date With Drew	LGF	2005	1100.00	181041.00	181041.00	0.00

5782 rows × 7 columns

In [40]:
```
bom_and_tn.isna().sum()
```

Out[40]:
```
movie              0
studio             0
year               0
production_budget  0
domestic_gross     0
worldwide_gross    0
foreign_gross      0
dtype: int64
```

In [41]:
```
imdb
```

Out[41]:

	movie	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	Sunghursh	2013	175.00	Action,Crime,Drama	7.00	77	IN
1	Ashad Ka Ek Din	2019	114.00	Biography,Drama	7.20	43	IN, XWW
2	The Other Side of the Wind	2018	122.00	Drama	6.90	4517	AR, BR, DE, ES, FR, GB, IT, PL, PT, RU, US, VE
4	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy	6.50	119	CL, PL, XWW
6	Joe Finds Grace	2017	83.00	Adventure,Animation,Comedy	8.10	263	CA

	movie	start_year	runtime_minutes	genres	averagerating	numvotes	region
...	...	...	...	...	...	...	...
69547	Didan in film jorm ast	2019	100.00	Drama,Thriller	8.10	7	IR, XWW
69548	Columbus	2018	85.00	Comedy	5.80	5	IR
69549	BADMEN with a good behavior	2018	87.00	Comedy,Horror	9.20	5	DE
69550	Pengalila	2019	111.00	Drama	8.40	600	IN
69551	Padmavyuhathile Abhimanyu	2019	130.00	Drama	8.40	365	IN

58998 rows × 7 columns

In [42]:
```
bom_and_tn.head(5)
```

Out[42]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	Toy Story 3	BV	2010.00	200000000.00	415004880.00	1068879522.00	653874642.00
3	Inception	WB	2010.00	160000000.00	292576195.00	835524642.00	542948447.00
4	Shrek Forever After	P/DW	2010.00	165000000.00	238736787.00	756244673.00	517507886.00
5	The Twilight Saga: Eclipse	Sum.	2010.00	68000000.00	300531751.00	706102828.00	405571077.00
6	Iron Man 2	Par.	2010.00	170000000.00	312433331.00	621156389.00	308723058.00

In [43]:
```
#merging bom gross and tn budgets
imdb_n_bom = pd.merge(bom_and_tn, imdb, on='movie', how='inner')
```

In [44]:
```
imdb_n_bom.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2446 entries, 0 to 2445
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   movie              2446 non-null   object 
 1   studio             2446 non-null   object 
 2   year               2446 non-null   object 
 3   production_budget  2446 non-null   float64
 4   domestic_gross     2446 non-null   float64
```

```
 5   worldwide_gross    2446 non-null   float64
 6   foreign_gross      2446 non-null   float64
 7   start_year         2446 non-null   int64
 8   runtime_minutes    2446 non-null   float64
 9   genres             2446 non-null   object
 10  averagerating      2446 non-null   float64
 11  numvotes           2446 non-null   int64
 12  region             2446 non-null   object
dtypes: float64(6), int64(2), object(5)
memory usage: 267.5+ KB
```

In [45]:
```
imdb.head(5)
```

Out[45]:

	movie	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	Sunghursh	2013	175.00	Action,Crime,Drama	7.00	77	IN
1	Ashad Ka Ek Din	2019	114.00	Biography,Drama	7.20	43	IN, XWW
2	The Other Side of the Wind	2018	122.00	Drama	6.90	4517	AR, BR, DE, ES, FR, GB, IT, PL, PT, RU, US, VE
4	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy	6.50	119	CL, PL, XWW
6	Joe Finds Grace	2017	83.00	Adventure,Animation,Comedy	8.10	263	CA

Visualization

Visualization of imdb dataframe

In [46]:
```
imdb.head(5)
```

Out[46]:

	movie	start_year	runtime_minutes	genres	averagerating	numvotes	region
0	Sunghursh	2013	175.00	Action,Crime,Drama	7.00	77	IN
1	Ashad Ka Ek Din	2019	114.00	Biography,Drama	7.20	43	IN, XWW
2	The Other Side of the Wind	2018	122.00	Drama	6.90	4517	AR, BR, DE, ES, FR, GB, IT, PL, PT, RU, US, VE
4	La Telenovela Errante	2017	80.00	Comedy,Drama,Fantasy	6.50	119	CL, PL, XWW
6	Joe Finds Grace	2017	83.00	Adventure,Animation,Comedy	8.10	263	CA

What are the top rated genres?

In [47]:
```
#creating a new dataframe with only the columns needed for this question.
genre_rating = imdb[['genres', 'averagerating']]
```

In [48]:
```
genre_rating = genre_rating.groupby('genres')['averagerating'].mean()
genre_rating = genre_rating.reset_index(name='averagerating')
genre_rating = genre_rating[genre_rating['averagerating'] >= 7.6]
```

In [49]:
```
genre_rating
```

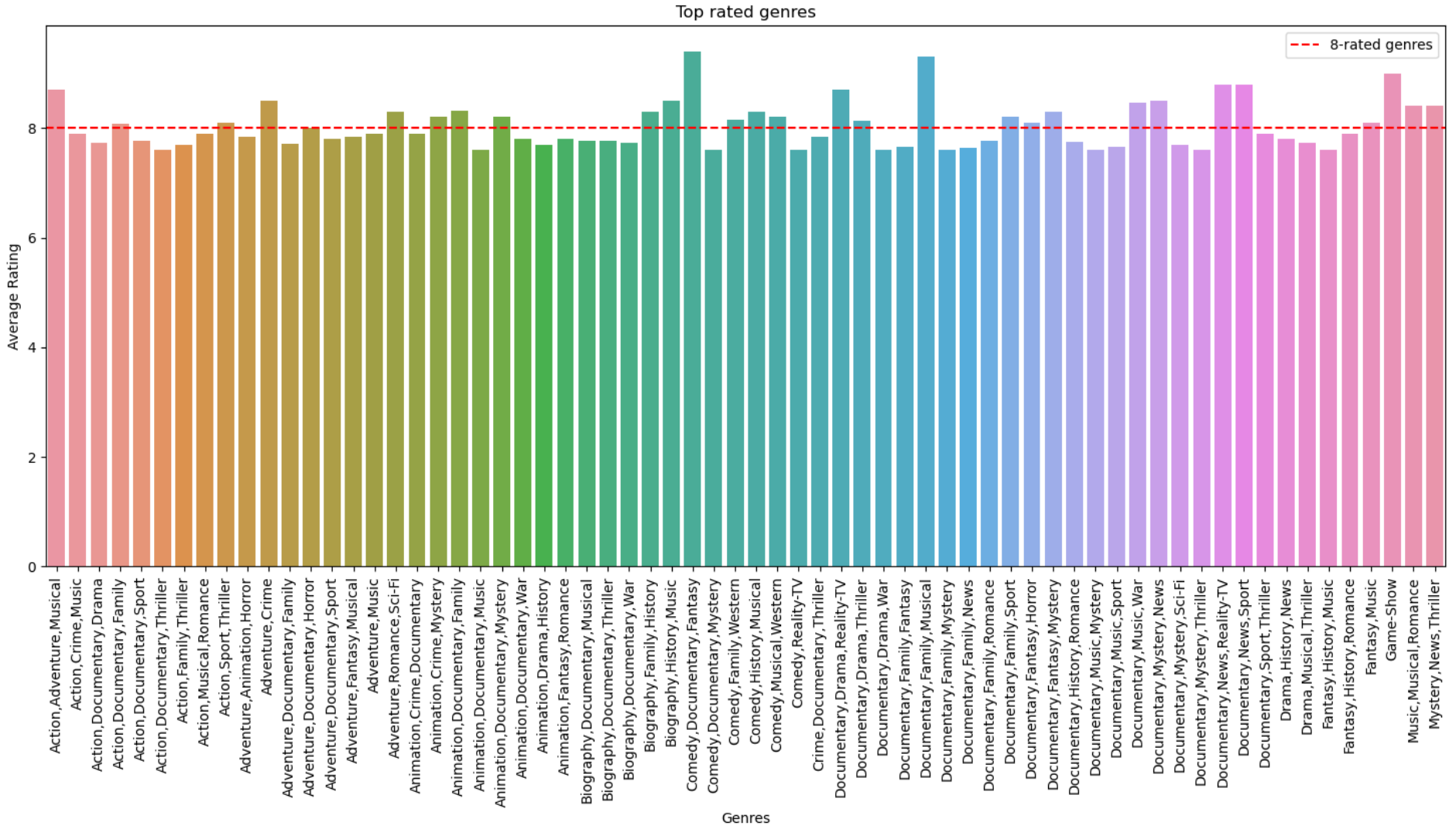
Out[49]:

	genres	averagerating
14	Action,Adventure,Musical	8.70
63	Action,Crime,Music	7.90
72	Action,Documentary,Drama	7.74
73	Action,Documentary,Family	8.08
77	Action,Documentary,Sport	7.78
...	...	...
785	Fantasy,History,Romance	7.90
794	Fantasy,Music	8.10
808	Game-Show	9.00
850	Music,Musical,Romance	8.40
860	Mystery,News,Thriller	8.40

66 rows × 2 columns

In [50]:
```
#bar graph of top rated genres
big = (18,7)
fig, ax = plt.subplots(figsize = big )
sns.barplot(x = 'genres', y = 'averagerating',  data = genre_rating)
plt.axhline(y=8, color='r', linestyle='--', label = '8-rated genres')
plt.xticks(rotation = 90 )
plt.legend()
plt.xlabel('Genres')
```

```
plt.ylabel('Average Rating')
plt.title('Top rated genres')
plt.show()
```



From the data provided, there are many ratings and for this plot we needed the highest rated movies. I therefore trimmed the data to contain only ratings that were above a 7.6 rating. From the available data, movies in Comedy, Documentary, Fantasy, Musical, Family, Game-show, Action, Adventure, Crime, War and Reality-TV seem to be the best performing genres. This are just a few of the top rated genre as there are many.

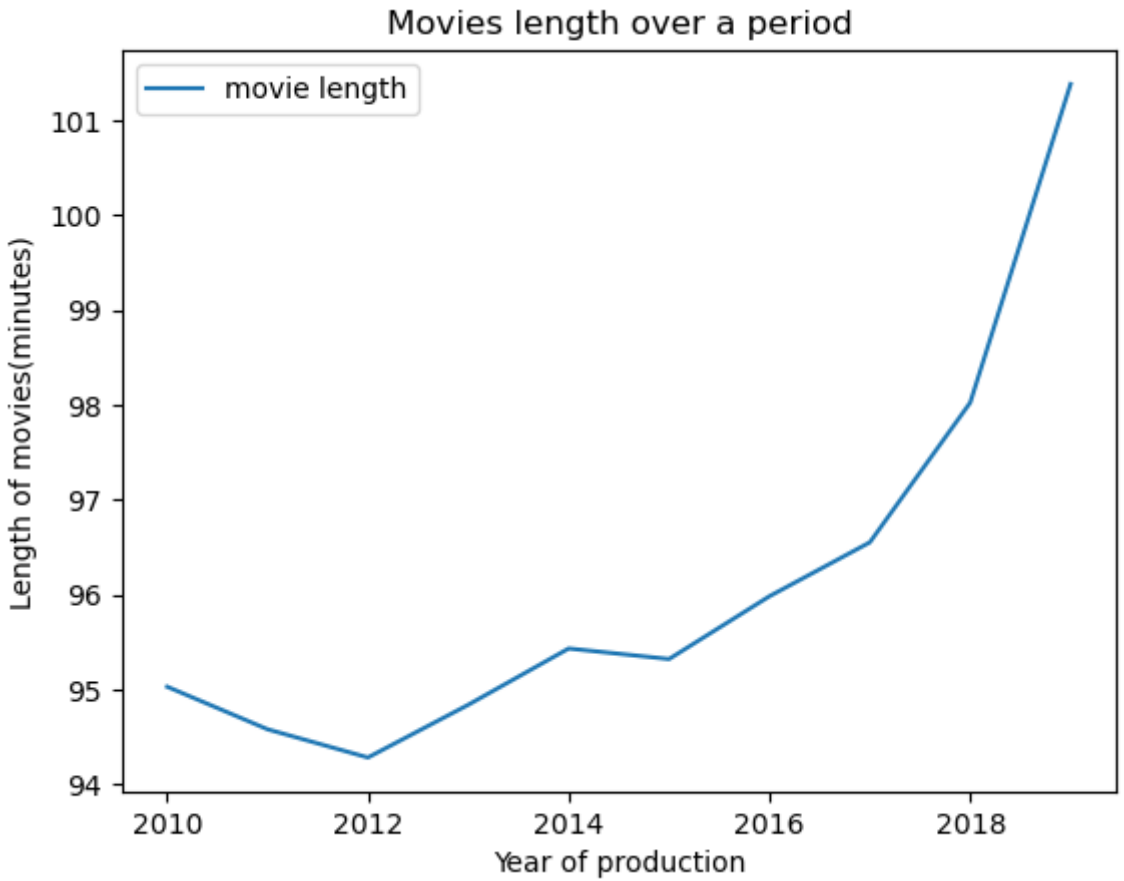
What is the trend of movie length over the years?

In [51]:
```
#new dataframe with required values
run_years = imdb[['start_year', 'runtime_minutes']]
run_years = run_years.groupby('start_year')['runtime_minutes'].mean()
run_years = run_years.reset_index(name='minutes')
run_years
```

Out[51]:

	start_year	minutes
0	2010	95.03
1	2011	94.58
2	2012	94.28
3	2013	94.84
4	2014	95.43
5	2015	95.32
6	2016	95.98
7	2017	96.55
8	2018	98.02
9	2019	101.38

In [52]:
```
#plot showing movie runtime over the years
sns.lineplot(data=run_years, x='start_year', y='minutes', label = 'movie length')
plt.ylabel('Length of movies(minutes)')
plt.xlabel('Year of production')
plt.title('Movies length over a period')
plt.show()
```

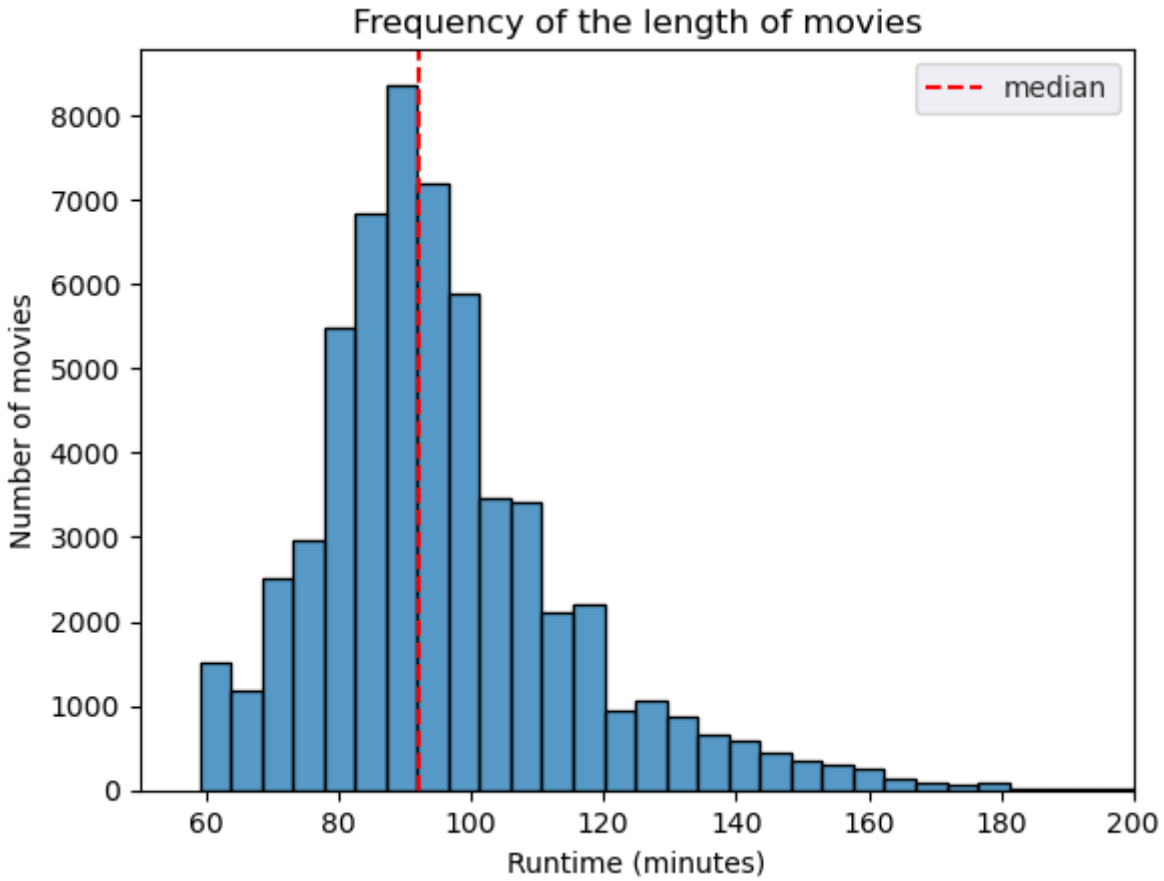


It seems that the movie length is increasing over the years. This may due to many factors but it is evident that longer movies are being produced as the years go by

Which is the most common runtime?

In [53]:
```
#histogram for most common runtime
sns.histplot(data=imdb, x='runtime_minutes', bins = 30)
sns.set_style('darkgrid')
plt.axvline(imdb['runtime_minutes'].median(), color='red', linestyle='--', label = 'median')
plt.title('Frequency of the length of movies')
plt.xlabel('Runtime (minutes)')
plt.ylabel('Number of movies')
plt.legend()
```

```
plt.xlim(50, 200)
plt.show()
```



From the visualization, it appears movies with a runtime of arounf 90 minutes are very popular. This means that most movies are between 1 hour to 1 hour 30 minutes.

How does the runtime influence rating?

In [54]:
```
#dataframe for runtime and average rating
runtime_vs_rating = imdb[['runtime_minutes', 'averagerating', 'movie']]
```

In [55]:
```
runtime_vs_rating = runtime_vs_rating.groupby('runtime_minutes')['averagerating'].mean()
runtime_vs_rating = runtime_vs_rating.reset_index(name='averagerating')
```

In [56]:
```
runtime_vs_rating
```

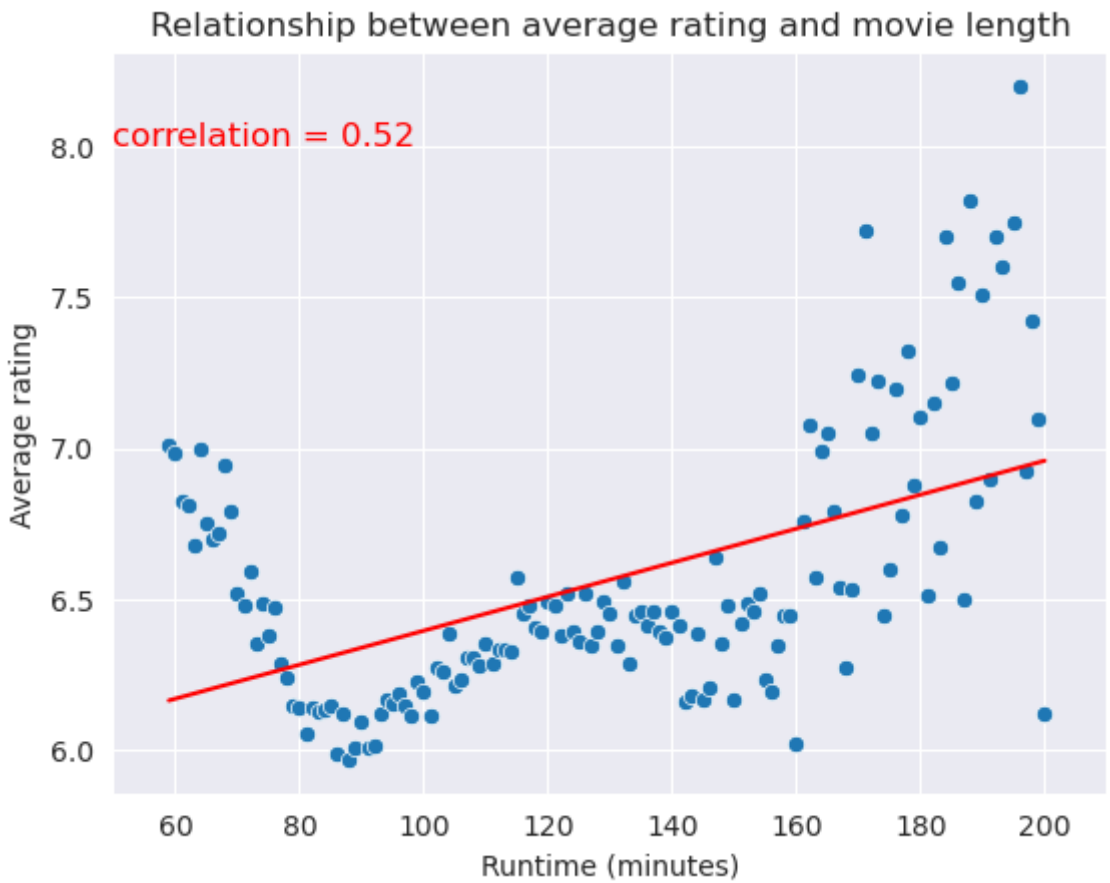
Out[56]:

	runtime_minutes	averagerating
0	59.00	7.01
1	60.00	6.98
2	61.00	6.83
3	62.00	6.82
4	63.00	6.68
...	...	...
136	196.00	8.20
137	197.00	6.93
138	198.00	7.43
139	199.00	7.10
140	200.00	6.12

141 rows × 2 columns

In [57]:
```
#correlation between average rating and movie length
corr = runtime_vs_rating['runtime_minutes'].corr(runtime_vs_rating['averagerating'])
```

In [58]:
```
#plot showing runtime vs average rating
sns.scatterplot(data=runtime_vs_rating, x='runtime_minutes', y='averagerating')
plt.text(50, 8, f"correlation = {corr:.2f}", fontsize=12, color='red')
sns.set_style('darkgrid')
x = runtime_vs_rating['runtime_minutes']
y = runtime_vs_rating['averagerating']
plt.plot(np.unique(x),
         np.poly1d(np.polyfit(x, y, 1))
         (np.unique(x)), color='red')
plt.title('Relationship between average rating and movie length')
plt.xlabel('Runtime (minutes)')
plt.ylabel('Average rating')
plt.xlim(50, 210)
plt.show()
```



It seems that as runtime increases so does the average rating. The correlation indicates a moderate positive relationship between the two. This means that as runtime increases, the average rating tends to increase and vice versa which is further visible in the scatter plot There could be other factors affecting this.

Visualization of bom and tn dataframe

In [59]:
```
bom_and_tn.head(5)
```

Out[59]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
0	Toy Story 3	BV	2010.00	200000000.00	415004880.00	1068879522.00	653874642.00
3	Inception	WB	2010.00	160000000.00	292576195.00	835524642.00	542948447.00

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross
4	Shrek Forever After	P/DW	2010.00	165000000.00	238736787.00	756244673.00	517507886.00
5	The Twilight Saga: Eclipse	Sum.	2010.00	68000000.00	300531751.00	706102828.00	405571077.00
6	Iron Man 2	Par.	2010.00	170000000.00	312433331.00	621156389.00	308723058.00

What is the relationship between production budget and worldwide gross?

In [60]:
```
#dataframe with specific data for this question
yearly_stats = bom_and_tn[['year', 'worldwide_gross', 'production_budget']].copy()
yearly_stats['year'] = yearly_stats['year'].astype(str).str[:4]

yearly_stats['year'] = pd.to_datetime(yearly_stats['year']).dt.strftime('%Y')
yearly_stats = yearly_stats[yearly_stats['worldwide_gross'] >= 1000000]
yearly_stats = yearly_stats.reset_index(drop=True)
```

In [61]:
```
yearly_stats = yearly_stats.groupby('year')[['worldwide_gross', 'production_budget']].mean()

yearly_stats
```

Out[61]:

year	worldwide_gross	production_budget
1915	11000000.00	110000.00
1916	8000000.00	200000.00
1920	3000000.00	100000.00
1925	15500000.00	2072500.00
1929	4358000.00	379000.00
...	...	...
2015	155188302.59	45489502.76
2016	153508731.00	47597967.91
2017	185497901.75	53530823.53
2018	201508558.21	51018604.65
2019	148337734.11	62662222.22

91 rows × 2 columns

In [62]:
```
corr_yr = yearly_stats['production_budget'].corr(yearly_stats['worldwide_gross'])
corr_yr
```

Out[62]: 0.7395243968583006

In [63]:
```
#plot illustrating relationship between production budget and worldwide gross
big = (10,7)
fig, ax = plt.subplots(figsize = big )

sns.scatterplot(data=yearly_stats, y='production_budget', x='worldwide_gross')
plt.text(8, (5 * 1e7), f"correlation = {corr_yr:.2f}", fontsize=12, color='red')
sns.set_style('darkgrid')
y = yearly_stats['production_budget']
x = yearly_stats['worldwide_gross']
plt.plot(np.unique(x),
         np.poly1d(np.polyfit(x, y, 1))
         (np.unique(x)), color='red')
plt.title('Relationship between production budget and worldwide gross')
plt.ticklabel_format(style='plain', axis='y')
plt.ticklabel_format(style='plain', axis='x')
plt.xlabel('Worldwide gross')
plt.ylabel('Production budget')
plt.xticks(rotation = 45 )

plt.show()
```


Relationship between production budget and worldwide gross
correlation = 0.74
Production budget
Worldwide gross
0
10000000
20000000
30000000
40000000
50000000
60000000
0
25000000
50000000
75000000
100000000
125000000
150000000
175000000
200000000

From the above visualization, there is a notable trend where when the production budget is increased, the worldwide gross also increases. The correlation also supports this as it is a positive correlation 0f 0.73 which means that there is a high likelihood of worldwide gross increasing when production budget is increased. This however does not mean production budget is the only thing that influences production budget.

How has time influenced production budget and worldwide gross?

In [64]:
```
yr_budget = yearly_stats.reset_index()

# convert 'year' to int
yr_budget['year'] = yr_budget['year'].astype(int)
```

In [65]:
```
yr_budget
```

Out[65]:

	year	worldwide_gross	production_budget
0	1915	11000000.00	110000.00
1	1916	8000000.00	200000.00
2	1920	3000000.00	100000.00
3	1925	15500000.00	2072500.00
4	1929	4358000.00	379000.00
...	...	...	...
86	2015	155188302.59	45489502.76
87	2016	153508731.00	47597967.91
88	2017	185497901.75	53530823.53
89	2018	201508558.21	51018604.65
90	2019	148337734.11	62662222.22

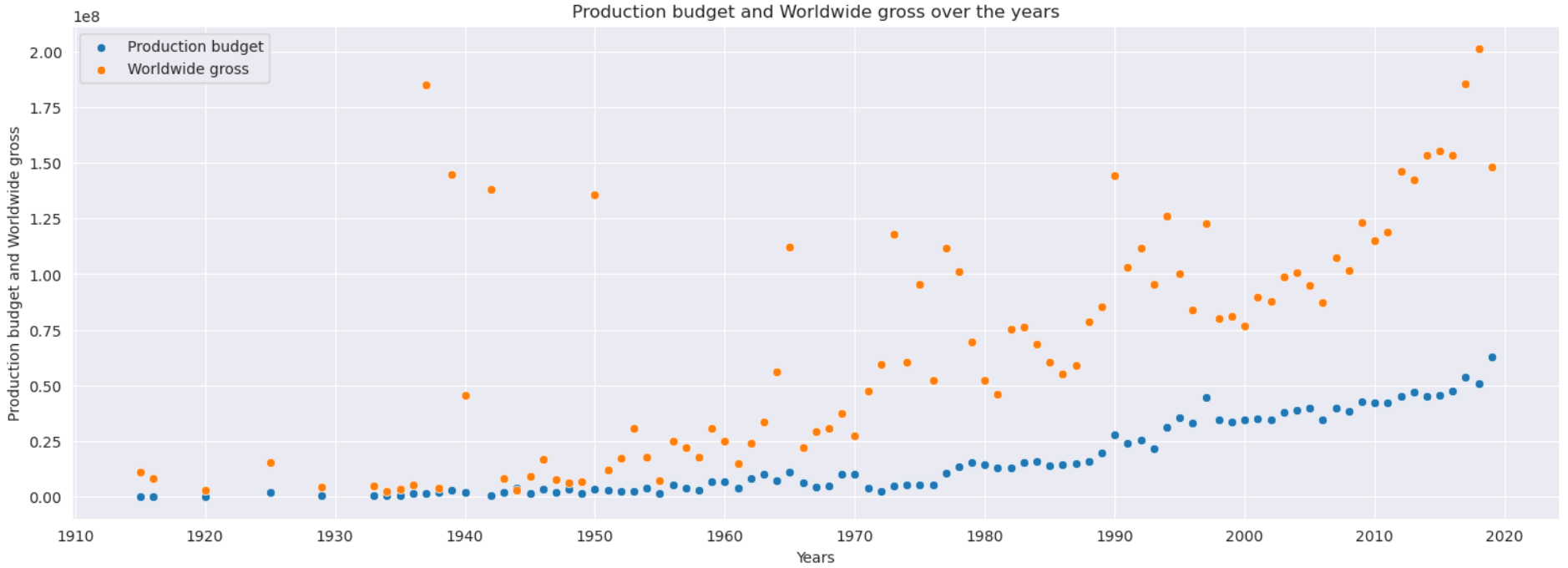
91 rows × 3 columns

In [66]:
```
#plot illustrating relationship between production budget and worldwide gross over the years
fig, ax = plt.subplots(figsize = (18,6))
sns.scatterplot(data=yr_budget, x='year', y='production_budget', label = 'Production budget')
sns.scatterplot(data=yr_budget, x='year', y='worldwide_gross', label = 'Worldwide gross')

ax.set_xlabel('Years')
```

```
ax.set_ylabel('Production budget and Worldwide gross')
ax.set_title('Production budget and Worldwide gross over the years')
plt.legend()
plt.xticks(np.arange(1910, 2022, 10))


plt.show()
```



Here we can summarise that over the years, the movie industry has continued injecting more money into production. The worldwide gross has also risen over the years which is reflected in the data. This however does not mean there are no other factors influencing this.

Visualization of both dataframes combined

In [67]:
```
imdb_n_bom.head(5)
```

Out[67]:

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross	start_year	runtime_minutes	genr
0	Toy Story 3	BV	2010.00	200000000.00	415004880.00	1068879522.00	653874642.00	2010	103.00	Adventure,Animation,Come

	movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross	start_year	runtime_minutes	genr
1	Inception	WB	2010.00	160000000.00	292576195.00	835524642.00	542948447.00	2010	148.00	Action,Adventure,Sci
2	Shrek Forever After	P/DW	2010.00	165000000.00	238736787.00	756244673.00	517507886.00	2010	93.00	Adventure,Animation,Come
3	The Twilight Saga: Eclipse	Sum.	2010.00	68000000.00	300531751.00	706102828.00	405571077.00	2010	124.00	Adventure,Drama,Fanta
4	Iron Man 2	Par.	2010.00	170000000.00	312433331.00	621156389.00	308723058.00	2010	124.00	Action,Adventure,Sci

movie	studio	year	production_budget	domestic_gross	worldwide_gross	foreign_gross	start_year	runtime_minutes	genr

Does studio budget affect movie gross?

In [68]:
```
studio_money = imdb_n_bom[['studio', 'worldwide_gross', 'production_budget']]
```

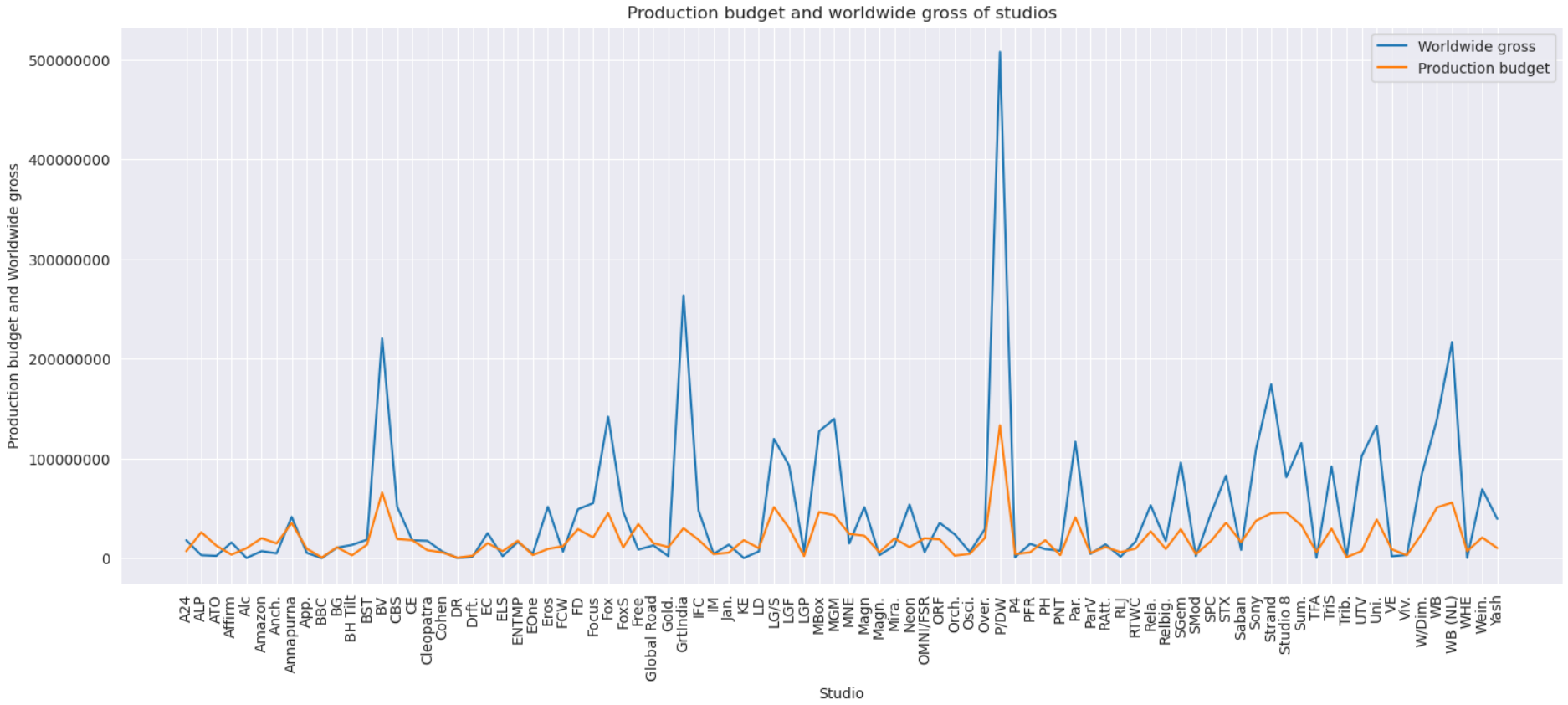
In [69]:
```
studio_money = studio_money.groupby('studio')[['worldwide_gross', 'production_budget']].mean()
studio_money
```

Out[69]:

studio	worldwide_gross	production_budget
A24	17977546.15	6980000.00
ALP	2923959.00	26000000.00
ATO	2272186.00	12500000.00
Affirm	15735746.00	3500000.00
Alc	161097.00	10000000.00
...	...	...
WB	139175487.70	50912354.17
WB (NL)	216790496.34	55697560.98
WHE	382946.00	7000000.00
Wein.	69159160.49	20688372.09
Yash	39398223.50	10100000.00

88 rows × 2 columns

In [70]:
```
fig, ax = plt.subplots(figsize = (18,7))
sns.lineplot(data=studio_money, x= 'studio', y='worldwide_gross', label = 'Worldwide gross')
sns.lineplot(data=studio_money, x= 'studio', y='production_budget', label = 'Production budget')
plt.ticklabel_format(style='plain', axis='y')
plt.xticks(rotation = 90)
ax.set_xlabel('Studio')
ax.set_ylabel('Production budget and Worldwide gross')
ax.set_title('Production budget and worldwide gross of studios')
plt.show()
```



The various studios have different budgets as is evident in the plot. It seems that a higher budget does play a role on the worlwide gross of the studio. This however is not the case in all the studios. This can be influenced by factors such as movie reception in the market.

What is the trend of movies produced per year?

In [71]:
```
# drop rows where titleType is not 'movie' or 'tvMovie'
movies_year = movies_year[movies_year['titleType'].isin(['movie', 'tvMovie'])]

# convert non-numeric runtimeMinutes to NaN
movies_year['runtimeMinutes'] = pd.to_numeric(movies_year['runtimeMinutes'], errors='coerce')

# filter runtimeMinutes to only include values greater than or equal to 60
movies_year = movies_year[movies_year['runtimeMinutes'].notnull() & (movies_year['runtimeMinutes'] >= 60) ]
```

In [72]:
```
#customizing the dataframe to be used
grouped = movies_year.groupby('startYear')['primaryTitle'].count().reset_index(name='movie_count')
grouped['startYear'] = grouped['startYear'].replace('\\N', 0)
grouped['startYear'] = grouped['startYear'].astype(int)
grouped_filtered = grouped[grouped['startYear'] <= 2022]
movies_per_year = grouped_filtered.reset_index(drop=True)
movies_per_year = movies_per_year.drop(movies_per_year[movies_per_year['startYear'] == 0].index)

movies_per_year
```

Out[72]:

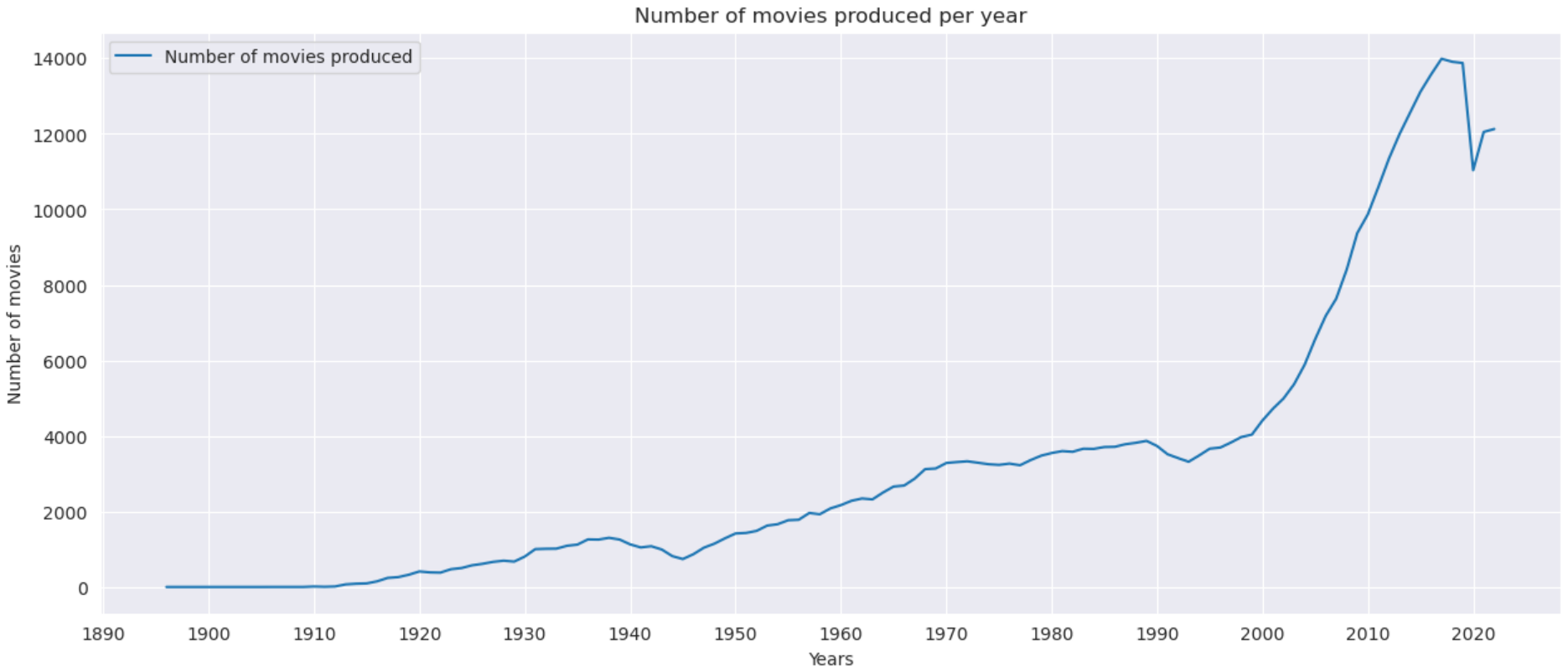
	startYear	movie_count
0	1896	1
1	1897	1
2	1899	1
3	1900	1
4	1903	1
...	...	...
119	2018	13909
120	2019	13875
121	2020	11037
122	2021	12050
123	2022	12128

124 rows × 2 columns

In [73]:
```
#plot for movies produced each year
fig, ax = plt.subplots(figsize = (15,6))
sns.lineplot(data=movies_per_year, x='startYear', y='movie_count', label = 'Number of movies produced')

plt.ticklabel_format(style='plain', axis='y')
ax.set_xlabel('Years')
ax.set_ylabel('Number of movies')
ax.set_title('Number of movies produced per year')
plt.legend()
plt.xticks(np.arange(1890, 2022, 10))

plt.show()
```



From this, an upward trajectory is clearly visible from 1900 to 2019. After 2019, the number of movies produced dropped which can be explained by Covid-19 as it caused shutdown of studios and there was no filming ongoing. However, after 2020, the trajectory starts going upwards after filming resumes. This shows that there are more movies being produced each year.