Final Project Submission

Please fill out:

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- Student pace: full time
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- Blog post URL:

Your code here - remember to use markdown cells for comments as well!

MICROSOFT MOVIE STUDIO DATA ANALYSIS PROJECT

1.Business Understanding

In my project Microsoft wants to start a movie studio and my analysis is based on my objectives, which will enable microsoft to come up with a profitable competative movie studio.

Objectives

- Find the top movie genre
- Find the most popular genre
- Calculate profit and loss for a movie
- Find Distribution locally and worldwide
- Find which is the best movie and what are the features of the Movie

2.Data Understanding

In my project i need to get data that shows movie categories and sales

Collecting Our Data

In [209]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sqlite3
%matplotlib inline
import csv
```

2.1 Loading The data sets to see which datasets suits our project.

2.1.1 bom.movie_gross.csv File

In [210]:
```
df = pd.read_csv('bom.movie_gross.csv')
df.head()
```

Out[210]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [211]:
```
df.shape
```

Out[211]:
```
(3387, 5)
```

In [212]:
```
df.isna().sum()
```

Out[212]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

2.1.2 tn.movie_budgets.csv File

In [213]:
```
df2 = pd.read_csv('tn.movie_budgets.csv',index_col=0)
df2.head()
```

Out[213]:

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
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

In [214]:
```
# Convert "$" amounts to int64

df2["production_budget"] = df2.production_budget.str.replace('[\$\,]',"").astype(
df2["domestic_gross"] = df2.domestic_gross.str.replace('[\$\,]',"").astype("int64
df2["worldwide_gross"] = df2.worldwide_gross.str.replace('[\$\,]',"").astype("int
```

In [215]:
```
df2.head()
```

Out[215]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
1	Dec 18, 2009	Avatar	425000000	760507625	2776345279
2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875
3	Jun 7, 2019	Dark Phoenix	350000000	42762350	149762350
4	May 1, 2015	Avengers: Age of Ultron	330600000	459005868	1403013963
5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747

In [216]:
```
df2.isna().sum()
```

Out[216]:
```
release_date         0
movie                0
production_budget    0
domestic_gross       0
worldwide_gross      0
dtype: int64
```

2.1.3 `tmdb.movies.csv` File

In [217]:
```
df3 = pd.read_csv('tmdb.movies.csv',index_col=0)
df3.head()
```

Out[217]:

	genre_ids	id	original_language	original_title	popularity	release_date	title	vote_avera
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	7
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	7
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	6
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	7
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	8

In [218]:
```
df3.rename(columns= {'id':'movie_id','title':'movie_title'}, inplace=True)
df3.head()
```

Out[218]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title	vote_
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [219]:
```
df3.isna().sum()
```

Out[219]:
```
genre_ids            0
movie_id             0
original_language    0
original_title       0
popularity           0
release_date         0
movie_title          0
vote_average         0
vote_count           0
dtype: int64
```

2.1.4 rt.movie_info.tsv File

In [220]:
```
df4 = pd.read_csv('rt.movie_info.tsv',
                   sep='\t')
df4.head()
```

Out[220]:

	id	synopsis	rating	genre	director	writer	theater_date	dvd_
0	1	This gritty, fast-paced, and innovative police...	R	Action and Adventure|Classics|Drama	William Friedkin	Ernest Tidyman	Oct 9, 1971	Se
1	3	New York City, not-too-distant-future: Eric Pa...	R	Drama|Science Fiction and Fantasy	David Cronenberg	David Cronenberg|Don DeLillo	Aug 17, 2012	J
2	5	Illeana Douglas delivers a superb performance ...	R	Drama|Musical and Performing Arts	Allison Anders	Allison Anders	Sep 13, 1996	Ap
3	6	Michael Douglas runs afoul of a treacherous su...	R	Drama|Mystery and Suspense	Barry Levinson	Paul Attanasio|Michael Crichton	Dec 9, 1994	Au
4	7	NaN	NR	Drama|Romance	Rodney Bennett	Giles Cooper	NaN	

In [221]:
```
df4.isna().sum()
```

Out[221]:
```
id                 0
synopsis          62
rating             3
genre              8
director         199
writer           449
theater_date     359
dvd_date         359
currency        1220
box_office      1220
runtime           30
studio          1066
dtype: int64
```

2.1.5 `im.db` File

In [222]:
```
conn =sqlite3.connect("im.db")
```

Selected data data files for my analysis .

- `tmdb.movies.csv`
- `tn.movie_budgets.csv`
- `im.db`
- `bom.movie_gross.csv`

2.2 Cleaning the selected data

2.2.1 cleaning `tmdb.movies.csv` (df3)

In [223]:
```
df3
df3.isna().sum()
```

Out[223]:
```
genre_ids            0
movie_id             0
original_language    0
original_title       0
popularity           0
release_date         0
movie_title          0
vote_average         0
vote_count           0
dtype: int64
```

In [224]:
```
df3.tail()
df3["vote_average"]
df3.drop(index=df3[df3["vote_average"] == 0.0].index,inplace=True)
df3.drop(index=df3[df3["vote_count"] < 2].index,inplace=True)
df3.tail()
```

Out[224]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title
26486	[80, 18, 9648]	564776	en	Driver	0.6	2018-11-20	Driver
26487	[27]	505498	en	Parched	0.6	2018-01-02	Parched
26488	[27]	546914	en	The Crescent Moon Clown	0.6	2018-10-17	The Crescent Moon Clown
26489	[99]	522825	en	The Real Princess Diaries: From Diana to Meghan	0.6	2018-05-07	The Real Princess Diaries: From Diana to Meghan
26492	[]	582641	en	Dying Embers	0.6	2018-12-28	Dying Embers

In [225]:
```
df3['release_date'] = pd.to_datetime(df3['release_date'])
df3['release_year'] = df3['release_date'].dt.year
```

In [226]:
```
df3.head()
```

Out[226]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title	vote_
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

2.2.2 `tn.movie_budgets.csv` AS (df2)

In [227]:
```
df2.isna().sum()
df2.tail()
```

Out[227]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross
78	Dec 31, 2018	Red 11	7000	0	0
79	Apr 2, 1999	Following	6000	48482	240495
80	Jul 13, 2005	Return to the Land of Wonders	5000	1338	1338
81	Sep 29, 2015	A Plague So Pleasant	1400	0	0
82	Aug 5, 2005	My Date With Drew	1100	181041	181041

In [228]:
```
df2.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   int64 
 3   domestic_gross     5782 non-null   int64 
 4   worldwide_gross    5782 non-null   int64 
dtypes: int64(3), object(2)
memory usage: 271.0+ KB
```

In [229]:
```
df2['release_date'] = pd.to_datetime(df2['release_date'])
df2['release_year'] = df2['release_date'].dt.year
```

2.2.3: `bom.movie_gross.csv` (df)

In [230]:
```
df.head()
```

Out[230]:

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010

In [231]:
```
df.tail()
```

Out[231]:

	title	studio	domestic_gross	foreign_gross	year
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

In [232]:
```
df.isna().sum()
```

Out[232]:
```
title                0
studio               5
domestic_gross      28
foreign_gross     1350
year                 0
dtype: int64
```

In [233]:
```
df['foreign_gross'] = df['foreign_gross'].replace(np.nan, 0)
df['domestic_gross'] = df['domestic_gross'].replace(np.nan, 0)
df['studio'] = df['studio'].replace(np.nan, "no_studio")
```

In [234]:
```
# checking for changes made
df.isna().sum()
```

Out[234]:
```
title             0
studio            0
domestic_gross    0
foreign_gross     0
year              0
dtype: int64
```

In [235]:
```
df.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          3387 non-null   object 
 2   domestic_gross  3387 non-null   float64
 3   foreign_gross   3387 non-null   object 
 4   year            3387 non-null   int64  
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

In [236]:
```
# changing foreign gross to int64
# Removing the ","
df["foreign_gross"] = df['foreign_gross'].str.replace(',',"")
# Replace "nan" with 0
df['foreign_gross'] = df['foreign_gross'].replace(np.nan, 0)
# Change type to float64
df['foreign_gross'] = df['foreign_gross'].astype("float64")
```

In [237]:
```
df.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          3387 non-null   object
 2   domestic_gross  3387 non-null   float64
 3   foreign_gross   3387 non-null   float64
 4   year            3387 non-null   int64
dtypes: float64(2), int64(1), object(2)
memory usage: 132.4+ KB
```

3.1 Analysing `tmdb.movies.csv` AS df3

In [238]:
```
# Viewing the data once again
df3.head()
```

Out[238]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title	vote_
0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19	Harry Potter and the Deathly Hallows: Part 1	
1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2010-03-26	How to Train Your Dragon	
2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2010-05-07	Iron Man 2	
3	[16, 35, 10751]	862	en	Toy Story	28.005	1995-11-22	Toy Story	
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception	

In [239]:
```
# Describing our data
df3.describe()
```

Out[239]:

	movie_id	popularity	vote_average	vote_count	release_year
count	19942.000000	19942.000000	19942.000000	19942.000000	19942.000000
mean	272380.082690	3.911647	5.893481	257.928493	2013.878598
std	151327.460944	4.764390	1.458278	1100.708858	3.784668
min	27.000000	0.600000	0.500000	2.000000	1930.000000
25%	128345.750000	0.901000	5.000000	4.000000	2012.000000
50%	284700.000000	1.987000	6.000000	11.000000	2014.000000
75%	397834.750000	5.654750	6.900000	52.000000	2016.000000
max	602754.000000	80.773000	10.000000	22186.000000	2019.000000

In [240]:
```
# view the shape of the data
df3.shape
```

Out[240]: (19942, 10)

Questions for the data set df3

3.1.1 Which Movies has the highest vote_rating?

In [241]:
```
df3.sort_values(by="vote_average", ascending=False)[:10]
```

Out[241]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_t
13292	[99]	305019	en	Campaign of Hate: Russia and Gay Propaganda	0.600	2014-06-22	Campaign Hate: Rus and G Propagan
13302	[]	298267	en	Virtus	0.600	2014-07-27	Vir
19615	[18]	397512	en	Last Man Club	0.665	2016-05-27	Last Man C
16535	[]	384518	en	Aubade	0.600	2015-04-10	Auba
19605	[28, 35]	444371	en	The Last Box	0.666	2016-08-02	The Last B
23184	[99]	433073	en	Tell Them We Are Rising: The Story of Black Co...	0.600	2017-01-23	Tell Them Are Rising: T Story of Bla C
23185	[10402, 99]	433053	en	Give Me Future: Major Lazer in Cuba	0.600	2017-01-21	Give Future: Ma Lazer in Cu
26079	[]	564296	en	When Calls the Heart: The Greatest Christmas B...	0.754	2018-12-25	When Calls Heart: T Great Christmas
16532	[18, 878, 53]	413367	en	Psychoacoustic	0.600	2015-10-23	Psychoacou
16526	[]	427932	en	I've Always Been Here	0.600	2015-01-25	I've Alwa Been H

In [242]:
```
# Does the movie average vote affected by it's popularity?
df3["popularity"].corr(df3["vote_average"])
```

Out[242]: 0.14814062866978023

The relationship is a very week positive correlation, so it doesn't affect.

In [243]:
```
# Does the the vote count affect the rating?
df3["vote_count"].corr(df3["vote_average"])
```

Out[243]: 0.14307217931922264

The movie rating of a movie is not affected by vote count

3.1.2: Which movie has the highest popularity?

In [244]:
```
# Finding the most watched movie
df3.sort_values(by="popularity", ascending=False)[:10]
```

Out[244]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title
23811	[12, 28, 14]	299536	en	Avengers: Infinity War	80.773	2018-04-27	Avengers Infinity War
11019	[28, 53]	245891	en	John Wick	78.123	2014-10-24	John Wick
23812	[28, 12, 16, 878, 35]	324857	en	Spider-Man: Into the Spider-Verse	60.534	2018-12-14	Spider-Man: Into the Spider-Verse
11020	[28, 12, 14]	122917	en	The Hobbit: The Battle of the Five Armies	53.783	2014-12-17	The Hobbit The Battle of the Five Armies
5179	[878, 28, 12]	24428	en	The Avengers	50.289	2012-05-04	The Avengers
11021	[28, 878,	118340	en	Guardians of	49.606	2014-08-01	Guardians of the

In [245]:
```
df3["vote_count"].corr(df3["vote_average"])
```

Out[245]: 0.14307217931922264

3.1.3: Which movie has the highest vote count?

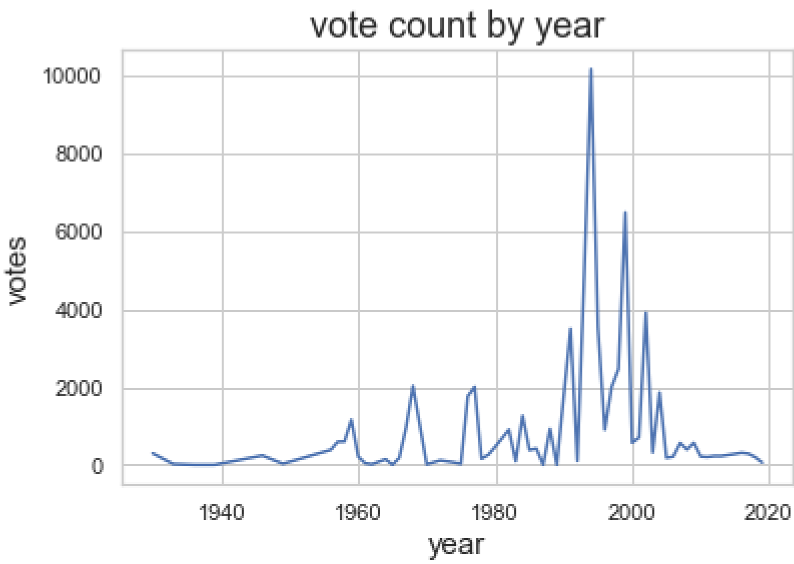
In [246]:
```
df3.sort_values(by="vote_count", ascending=False)[:10]
```

Out[246]:

	genre_ids	movie_id	original_language	original_title	popularity	release_date	movie_title
4	[28, 878, 12]	27205	en	Inception	27.920	2010-07-16	Inception
17383	[28, 12, 35]	293660	en	Deadpool	35.067	2016-02-12	Deadpool
5179	[878, 28, 12]	24428	en	The Avengers	50.289	2012-05-04	The Avengers
6	[28, 12, 14, 878]	19995	en	Avatar	26.526	2009-12-18	Avatar
11032	[12, 18, 878]	157336	en	Interstellar	28.440	2014-11-05	Interstellar
11021	[28, 878, 12]	118340	en	Guardians of the Galaxy	49.606	2014-08-01	Guardians of the Galaxy
5189	[18, 37]	68718	en	Django Unchained	21.260	2012-12-25	Django Unchained
5235	[878, 12, 14]	70160	en	The Hunger Games	14.212	2012-03-23	The Hunger Games
14177	[28, 12, 878]	76341	en	Mad Max: Fury Road	28.099	2015-05-15	Mad Max: Fury Road
7881	[28, 12, 878]	68721	en	Iron Man 3	32.093	2013-05-03	Iron Man 3

3.1.4: What is the distribution vote_count and year?

In [247]:
```
sns.set(style="whitegrid")
sns.lineplot(data=df3, x="release_year", y="vote_count", ci=None)
plt.title("vote count by year",fontsize=18)
plt.xlabel("year",fontsize=15)
plt.ylabel("votes",fontsize=15)
plt.show()
```



3.2: Analysing `tmdb.movies.csv` (df2)

In [248]:
```
df2.head()
```

Out[248]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
1	2009-12-18	Avatar	425000000	760507625	2776345279	2009
2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017

3.2.1: Which movie has the highest Worldwide gross?

In [249]:
```
df2.sort_values(by="worldwide_gross", ascending=False)
df2.head()
```

Out[249]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
1	2009-12-18	Avatar	425000000	760507625	2776345279	2009
2	2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000	241063875	1045663875	2011
3	2019-06-07	Dark Phoenix	350000000	42762350	149762350	2019
4	2015-05-01	Avengers: Age of Ultron	330600000	459005868	1403013963	2015
5	2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000	620181382	1316721747	2017

3.2.2: Which movies made the highest gross profit world_wide and locally?

In [250]:
```
# Calculating and creating a new column "world_wide_gross_profit"
df2['world_wide_gross_profit'] = df2['worldwide_gross']-df2['production_budget']
```

In [251]:
```
# Calculating and creating a new column "worldwide_percentage-profit"
df2['worldwide_percentage_profit'] = (df2['world_wide_gross_profit']/df2['product
```

In [252]:
```
# Sorting the data to view the movies with the highest worldwide profit
df2.sort_values(by="worldwide_percentage_profit", ascending=False)[:10]
```

Out[252]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
46	1972-06-30	Deep Throat	25000	45000000	45000000	1972
14	1980-03-21	Mad Max	200000	8750000	99750000	1980
93	2009-09-25	Paranormal Activity	450000	107918810	194183034	2009
80	2015-07-10	The Gallows	100000	22764410	41656474	2015
7	1999-07-14	The Blair Witch Project	600000	140539099	248300000	1999
10	2004-05-07	Super Size Me	65000	11529368	22233808	2004

In [253]:
```
# Calculating and creating a new column "domestic_gross_profit"
df2['domestic_gross_profit'] = df2['domestic_gross']-df2['production_budget']
```

In [254]:
```
# Calculating and creating a new column "domestic_percentage-profit"
df2['domestic_percentage_profit'] = df2['domestic_gross']/df2['production_budget'
```

In [255]:
```
# Sorting the data to view the movies with the highest domestic profit
df2.sort_values(by="domestic_percentage_profit", ascending=False)[:10]
```

Out[255]:

id	release_date	movie	production_budget	domestic_gross	worldwide_gross	release_year
46	1972-06-30	Deep Throat	25000	45000000	45000000	1972
74	1993-02-26	El Mariachi	7000	2040920	2041928	1993
93	2009-09-25	Paranormal Activity	450000	107918810	194183034	2009
7	1999-07-14	The Blair Witch Project	600000	140539099	248300000	1999
80	2015-07-10	The Gallows	100000	22764410	41656474	2015
16	1995-08-09	The Brothers McMullen	50000	10426506	10426506	1995
66	1974-10-18	The Texas Chainsaw Massacre	140000	26572439	26572439	1974
10	2004-05-07	Super Size Me	65000	11529368	22233808	2004
82	2005-08-05	My Date With Drew	1100	181041	181041	2005
73	1973-08-11	American Graffiti	777000	115000000	140000000	1973

3.2.3: What is the relationship between a movie budget and the reception it gets?

In [256]:
```
# Finding the relationship between a movies' production budget and how it sells w
df2['production_budget'].corr(df2['world_wide_gross_profit'])
```

Out[256]: 0.6087521471718846

There is a positive relationship between a movies budget and the reception it gets worldwide
The higher the movie budget the high positive reception it gets.

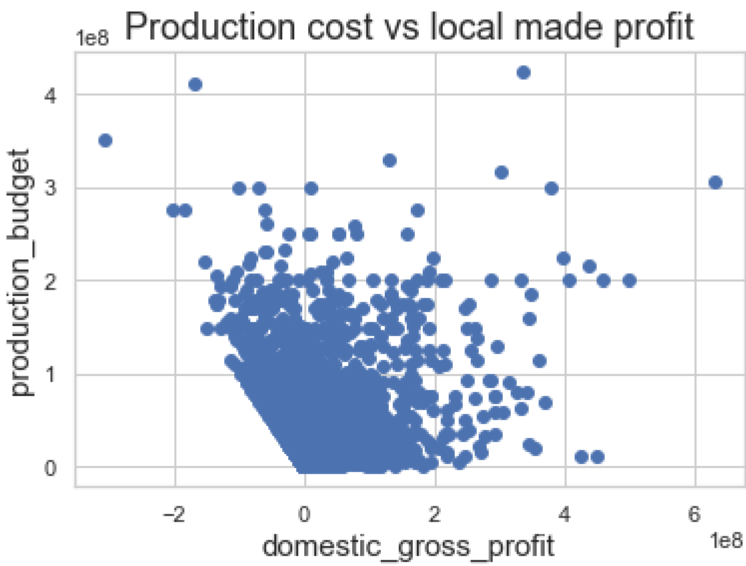
In [257]:
```
# Plotting a scatter plot to visualize
plt.scatter(df2.world_wide_gross_profit, df2.production_budget)
plt.title('Production_budget vs world_wide_profit',fontsize=16)
plt.xlabel("world_wide_gross_profit",fontsize=15)
plt.ylabel("production_budget",fontsize=15)
plt.show();
```

In [258]:
```
# Finding the relationship between a movies' production budget and how it sells l
df2['production_budget'].corr(df2['domestic_gross_profit'])
```

Out[258]: 0.09974209165512304

We can interprate this to movies with high budget do not do sell domestically

In [259]:
```
# Plotting a scatter plot to visualize
plt.scatter(df2.domestic_gross_profit, df2.production_budget)
plt.title("Production cost vs local made profit",fontsize=18)
plt.xlabel("domestic_gross_profit",fontsize=15)
plt.ylabel("production_budget",fontsize=15)
plt.show();
```



3.3 Analysing `bom.movie_gross.csv` AS df

In [260]:
```
df.tail()
```

Out[260]:

	title	studio	domestic_gross	foreign_gross	year
3382	The Quake	Magn.	6200.0	0.0	2018
3383	Edward II (2018 re-release)	FM	4800.0	0.0	2018
3384	El Pacto	Sony	2500.0	0.0	2018
3385	The Swan	Synergetic	2400.0	0.0	2018
3386	An Actor Prepares	Grav.	1700.0	0.0	2018

In [261]:
```
# How many studios does the data set have?
df['studio'].nunique()
```

Out[261]: 258

3.3.1: Which studios generates the highest gross?

In [262]:
```
# Studio with the heighest Domestic gross
studio_with_highest_dom_gross = df.groupby(['studio'])["domestic_gross"].sum()
studio_with_highest_dom_gross.sort_values(ascending=False)
```

Out[262]:
```
studio
BV            1.841903e+10
Uni.          1.290239e+10
WB            1.216805e+10
Fox           1.094950e+10
Sony          8.459683e+09
                  ...
ALP           2.800000e+03
Synergetic    2.400000e+03
DR            8.000000e+02
PI            0.000000e+00
Myr.          0.000000e+00
Name: domestic_gross, Length: 258, dtype: float64
```

In [263]:
```
# Studio with the heighest foreign gross
studio_with_highest_for_gross = df.groupby(['studio'])["foreign_gross"].sum()
studio_with_highest_for_gross.sort_values(ascending=False)
```

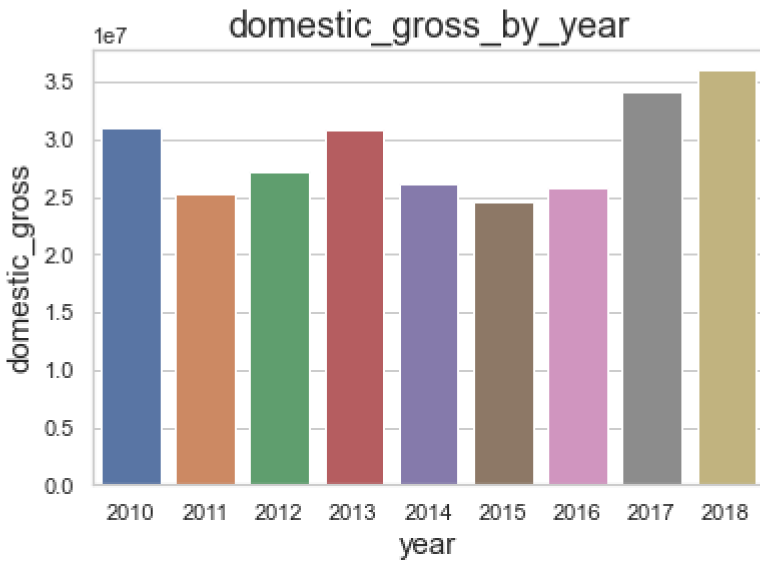
Out[263]:
```
studio
BV        2.579385e+10
Fox       2.005587e+10
WB        1.866790e+10
Uni.      1.685477e+10
Sony      1.394535e+10
              ...
DLA       0.000000e+00
RME       0.000000e+00
Rel.      0.000000e+00
KS        0.000000e+00
CFilms    0.000000e+00
Name: foreign_gross, Length: 258, dtype: float64
```

3.3.2: Whats the gross distribution per year?

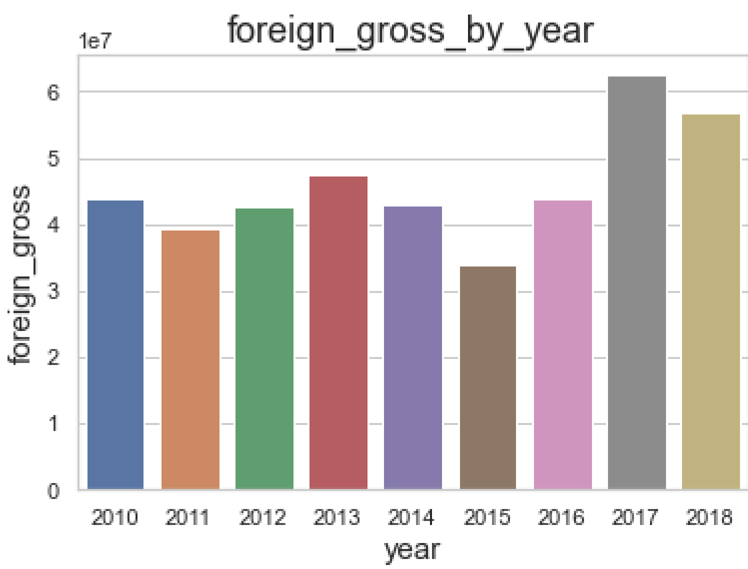
In [264]:
```
# Finding the years in the dataset
df['year'].unique()
```

Out[264]:
```
array([2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018], dtype=int64)
```

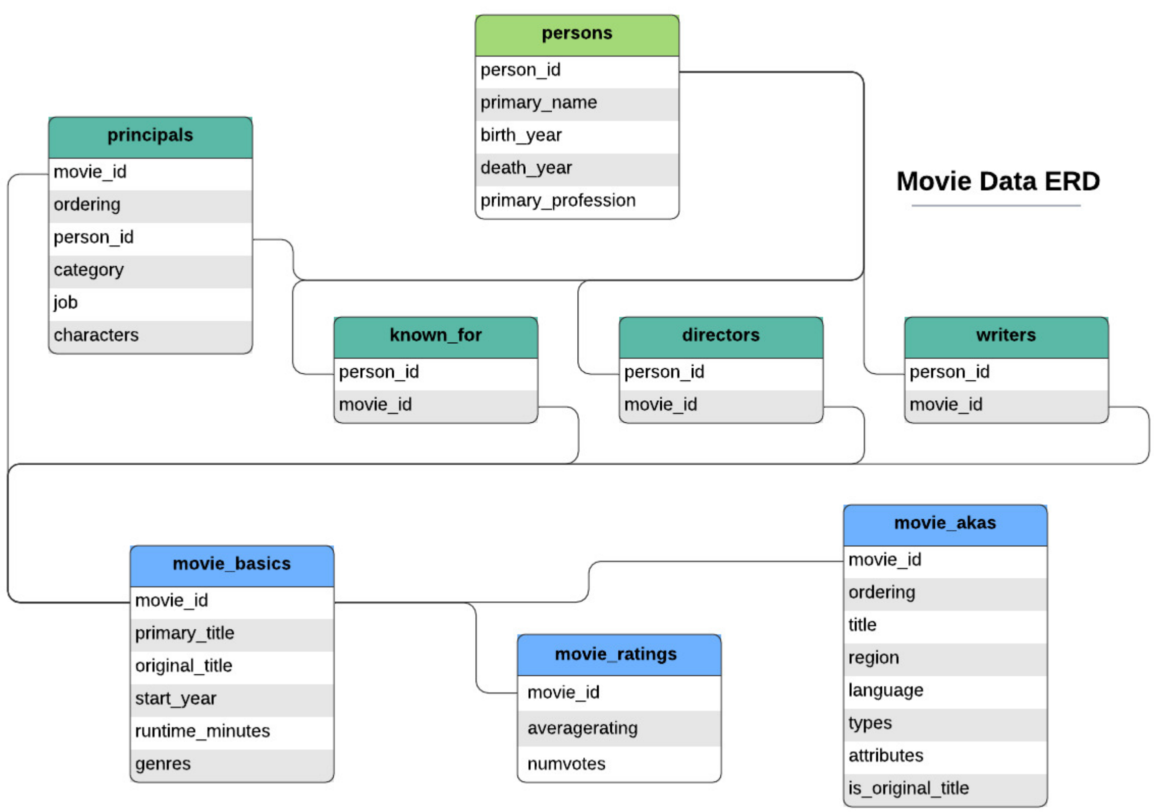
In [265]:
```
# domestic gross
sns.barplot(x="year", y="domestic_gross", data=df, ci=None)
plt.title("domestic_gross_by_year",fontsize=18)
plt.xlabel("year",fontsize=15)
plt.ylabel("domestic_gross",fontsize=15)
plt.show()
```



In [266]:
```
# foreign gross
sns.barplot(x="year", y="foreign_gross", data=df, ci=None)
plt.title("foreign_gross_by_year",fontsize=18)
plt.xlabel("year",fontsize=15)
plt.ylabel("foreign_gross",fontsize=15)
plt.show()
```



3.4: Analysing `im.db` tables



In [267]:
```
conn = sqlite3.connect('im.db')
```

In [268]:
```
# Selecting the table names
tables_name = """SELECT name
                     AS 'Table Names'
                     FROM sqlite_master
                     WHERE type='table';"""

pd.read_sql(tables_name, conn)
```

Out[268]:

	Table Names
0	movie_basics
1	directors
2	known_for
3	movie_akas
4	movie_ratings
5	persons
6	principals
7	writers

In [287]:
```
# Lets see how many genre do we have do we have
genres = """
   SELECT genres
     FROM movie_basics
 GROUP BY genres

;
"""
data = pd.read_sql(genres ,conn).dropna()
data.count()
```

Out[287]:
```
genres    1085
dtype: int64
```

3.4.1: Which Are The Top Genres?

In [289]:
```
genre_ratings = """
   SELECT genres,avg(averagerating) AS average_ratings
     FROM movie_basics
     JOIN movie_ratings
    USING(movie_id)
 GROUP BY genres
 ORDER BY average_ratingS DESC




;
"""
pd.read_sql(genre_ratings, conn).dropna()
```

Out[289]:

	genres	average_ratings
0	Comedy,Documentary,Fantasy	9.4
1	Documentary,Family,Musical	9.3
2	History,Sport	9.2
3	Music,Mystery	9.0
4	Game-Show	9.0
...	...	...
919	Crime,Music	2.4
920	History,Sci-Fi,Thriller	2.3
921	Adventure,Crime,Romance	2.3
922	Adult,Horror	2.0
923	Comedy,Musical,Sport	1.4

923 rows × 2 columns

3.4.2: Which are the most viewed genres?

In [291]:
```
genre_ratings = """
   SELECT genres,sum(numvotes) AS People_viewed
     FROM movie_basics
     JOIN movie_ratings
    USING(movie_id)
 GROUP BY genres
 ORDER BY people_viewed desc





;
"""
pd.read_sql(genre_ratings, conn).dropna()
```

Out[291]:

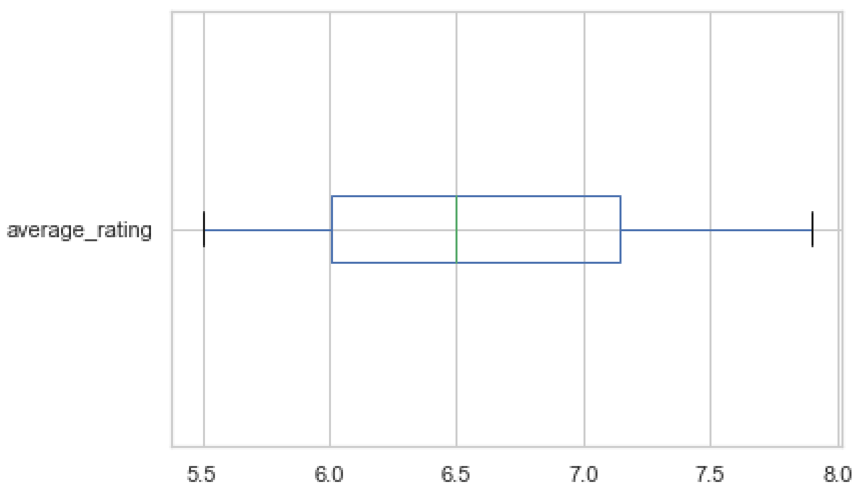
	genres	People_viewed
0	Action,Adventure,Sci-Fi	23023248
1	Action,Adventure,Fantasy	9658883
2	Adventure,Animation,Comedy	8687435
3	Drama	8395521
4	Comedy,Drama,Romance	7665463
...	...	...
919	Family,War	5
920	Crime,Western	5
921	Comedy,Documentary,Fantasy	5
922	Action,Documentary,Horror	5
923	Action,Crime,Musical	5

923 rows × 2 columns

3.4.1: Does the numbers of viewers relate with the ratings?

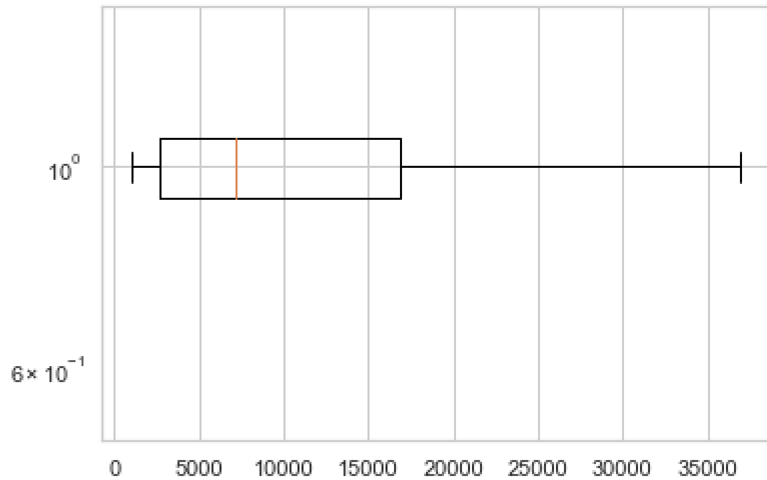
In [292]:
```
genre_counts = """
   SELECT genres, sum(numvotes) AS people_viewed, avg(averagerating) as average_r
     FROM movie_basics
     JOIN movie_ratings
    USING(movie_id)
 GROUP BY genres
 HAVING people_viewed  between 1000 and 50000
   AND average_rating  between 5.5 and 8
 ORDER BY people_viewed desc




;
"""
pd.read_sql(genre_counts, conn)
data = pd.read_sql(genre_counts, conn).dropna()
```

In [273]:
```
# Find outliers from ratings
data["average_rating"].plot(kind='box',vert=False,showfliers=False);
```



In [293]:
```
# find outliers from people viewed
plt.boxplot(x=data['people_viewed'], vert=False,showfliers=False);
plt.semilogy()
```

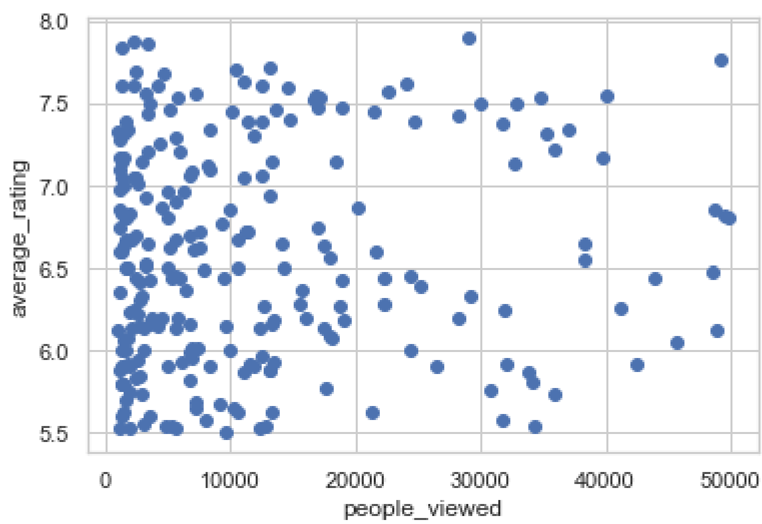
Out[293]: []



In [275]:
```
data["average_rating"].corr(data["people_viewed"])
```

Out[275]: 0.06824764666660994

In [294]:
```
plt.scatter(data.people_viewed, data.average_rating)
plt.xlabel("people_viewed")
plt.ylabel("average_rating")
plt.show();
```



There is no relationship between number of people viewing a genre and it's rating

3.4.2: Does a movie length affect its rating?

In [295]:
```
movie_length = """
  SELECT movie_id, runtime_minutes AS length, averagerating AS rating
    FROM movie_basics
    JOIN movie_ratings
    USING(movie_id)
GROUP BY movie_id
HAVING length < 200
LIMIT 1000







"""
data2 = pd.read_sql(movie_length, conn).dropna()
```

In [278]:
```
data2.describe()
```

Out[278]:

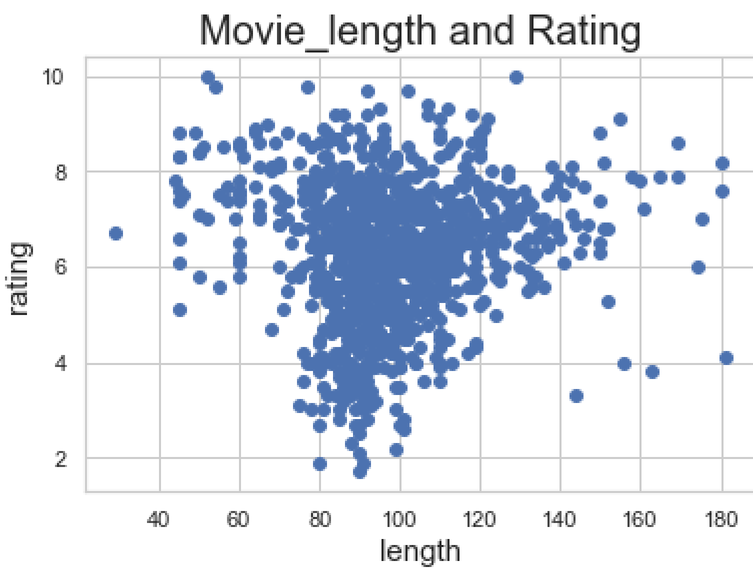
	length	rating
count	1000.000000	1000.000000
mean	98.485000	6.266500
std	19.809144	1.439396
min	29.000000	1.700000
25%	88.000000	5.400000
50%	96.000000	6.400000
75%	108.000000	7.200000
max	181.000000	10.000000

In [296]:
```
# Finding relationship between movie rating and legnth
data = pd.read_sql(movie_length,conn).dropna()
data2["rating"].corr(data2["length"])
```

Out[296]:
```
0.06685514663923223
```

In [297]:
```
# Plotting a scatter plot
plt.scatter(data2.length, data2.rating)
plt.xlabel("length",fontsize=15)
plt.ylabel("rating",fontsize=15)
plt.title("Movie_length and Rating",fontsize=20)
```

Out[297]:
```
Text(0.5, 1.0, 'Movie_length and Rating')
```



A movie legnth does not affect its rating

3.4.3: Who are the best directors?

In [298]:
```
# first lets find how many directors we have
directors_details = """
  SELECT person_id AS director_id, primary_name AS director_name
    FROM directors
    JOIN persons
   USING(person_id)
GROUP BY person_id
;
"""
data3 = pd.read_sql(directors_details,conn)
```

In [299]:
```
data3.count()
```

Out[299]:
```
director_id      109251
director_name    109251
dtype: int64
```

In [300]:
```
data3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 109251 entries, 0 to 109250
Data columns (total 2 columns):
 #   Column         Non-Null Count   Dtype 
---  ------         --------------   ----- 
 0   director_id    109251 non-null  object
 1   director_name  109251 non-null  object
dtypes: object(2)
memory usage: 1.7+ MB
```

We have 109,251 directors is our data set.

3.4.4: Out of the Director Movie rated which director has the heighest rating?

In [301]:
```
directors_ratings = """
  SELECT person_id AS director_id, primary_name As director_name, COUNT(movie_id)
    FROM directors
LEFT JOIN persons
USING(person_id)
    JOIN movie_ratings
    USING(movie_id)
GROUP BY director_id
HAVING movies_rated > 5
ORDER BY director_movies_average_rating DESC







;
"""
data4 = pd.read_sql(directors_ratings,conn)
```

3.4.5: Out of the Director Movie rated which director has the heighest number of movies?

In [304]:
```
rs_ratings = """
T person_id AS director_id, primary_name As director_name, COUNT(movie_id) AS mov
M directors
IN persons
erson_id)
N movie_ratings
NG(movie_id)
Y director_id
movies_rated > 5
Y movies_rated desc







 pd.read_sql(directors_ratings,conn)
```

3.4.6: Do we have a relationship between movie ratings and number of movie rated?

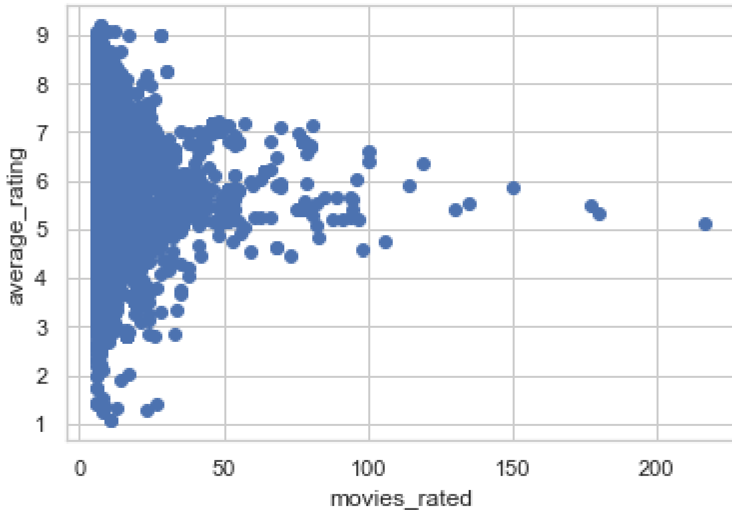
In [305]:
```
data5["director_movies_average_rating"].corr(data5["movies_rated"])
```

Out[305]:
```
-0.023868139052040636
```

No relationship between directors_movies_rated and the movies rating

In [306]:
```
plt.scatter(data5.movies_rated, data5.director_movies_average_rating)
plt.xlabel("movies_rated")
plt.ylabel("average_rating")
```

Out[306]:
```
Text(0, 0.5, 'average_rating')
```



3.4.7: What is the average movie length?

In [307]:
```
movie_durations = """
  SELECT movie_id,avg(runtime_minutes) AS average_runtime,start_year
    FROM movie_basics
 GROUP BY start_year







;
"""
data7 = pd.read_sql(movie_durations,conn)
data7.dropna()
```

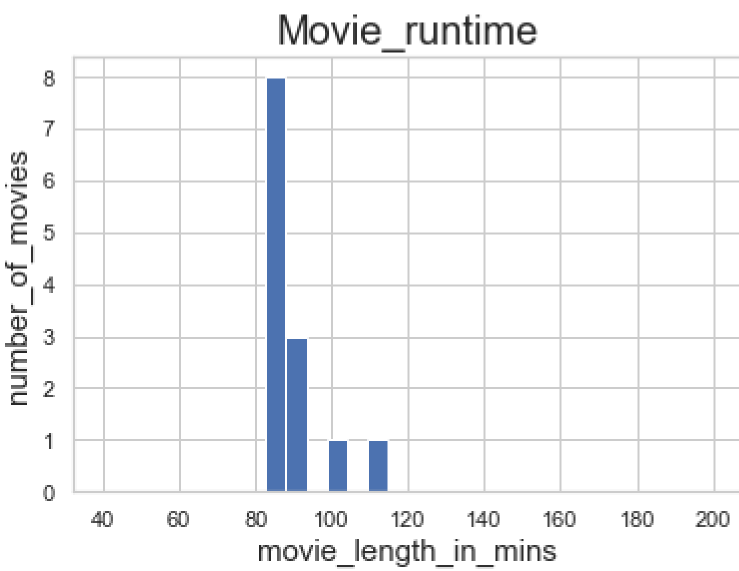
Out[307]:

	movie_id	average_runtime	start_year
0	tt0146592	85.495694	2010
1	tt0176694	86.410106	2011
2	tt0139613	89.208856	2012
3	tt0063540	84.931670	2013
4	tt0329539	84.541500	2014
5	tt0283440	85.407108	2015
6	tt0315642	84.974249	2016
7	tt0100275	85.732214	2017
8	tt0069049	87.661099	2018
9	tt0066787	90.887358	2019
10	tt0499097	91.280488	2020
11	tt0293429	101.750000	2021
12	tt10042446	109.666667	2022

In [308]:
```
# runtime by movies
plt.hist(data7['average_runtime'],range=(40,200),bins=30)
plt.title("Movie_runtime",fontsize=20)
plt.xlabel("movie_length_in_mins",fontsize=15)
plt.ylabel("number_of_movies",fontsize=15)
```

```
C:\Users\abel1\anaconda3\envs\learn-env\lib\site-packages\numpy\lib\histograms.
py:839: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
C:\Users\abel1\anaconda3\envs\learn-env\lib\site-packages\numpy\lib\histograms.
py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

Out[308]: Text(0, 0.5, 'number_of_movies')

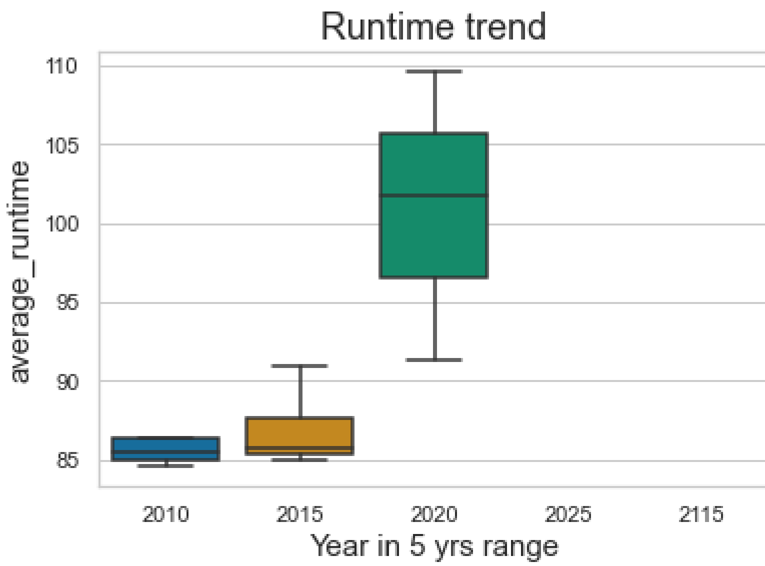


In [309]:
```
# Create year range of 5 years
runtime_by_year = data7.copy()
```

In [310]:
```
runtime_by_year["start_year"] = ((runtime_by_year['start_year']//5)*5).astype("ir
```

In [311]:
```
# Plotting boxplot to visualize
sns.boxplot(x="start_year",y="average_runtime",data=runtime_by_year, palette='col
plt.title("Runtime trend",fontsize=18)
plt.xlabel('Year in 5 yrs range',fontsize=15)
plt.ylabel("average_runtime",fontsize=15)
```

Out[311]:
```
Text(0, 0.5, 'average_runtime')
```



In [ ]: