Project 2: Investigate TMDb movie data from kaggle

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Introduction

> The film industry is in full swing. The emergence of new multimedia platforms such as netflix or amazong prime, requires a redefinition and replacement of its structure and direction. The big Hollywood productions have a new competitor in a new format that day after day absorbs their expectations and customers. What are the characteristics of the sector? Is it really in decline? Throughout this document, we will prepare the database and describe the characteristics of this market. Using descriptive and inferential statistics we will try to establish a diagnosis of the sector
>
> A study on the last years of film productions is an interesting exercise to understand the sector and the impact of new platforms on it. We propose to describe this market through certain problems, make a diagnosis and infer certain measures

> To perfomr the analysis we will use the TMDb database This data set contains information about 10,000 movies collected from The Movie Database (TMDb),including user ratings and revenue.
>
> - Certain columns, like ‘cast’ and ‘genres’, contain multiple values separated by pipe (|) characters.
> - There are some odd characters in the ‘cast’ column. Don’t worry about cleaning them. You can leave them as is.
> - The final two columns ending with “_adj” show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

Problematics

- What are the main producers in the sector, in which genres did they invest the largest budgets? What results did they have?
- What are the most popular genres? How are they located in the valuation ranking? Are the most viewed the best valued too?
- On average, what is the most profitable genre? What is the least?
- What is the average budget for film productions? Is there a budget that ensures profitability?
- What are the movies with the most benefits, are they in the most popular genres?
- Is the scene dominated by a small number of directors or is there a diversity of production teams? Is there a director who ensures profitability?

In [1]:

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

%matplotlib inline
```

Data Wrangling

DataBase reconnition: In this section of the report, we will load in the data, check for cleanliness, and then trim and clean the dataset for analysis.

General Properties

In [2]:

```
df = pd.read_csv(r'database/tmdb-movies.csv')
df_copy = df
df.head(3)
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://w

3 rows × 21 columns

Characteristics

to have a better understanding of the database caracteristics, we perform some assesing descriptions of the data with the objective of build intuitions relatives to the **`problematics`** .

- First, we perform the functions shape and data types. to see the size of the dataset and the types of the columns. we notice that the column realise_Date is in fact a date that need to be changed. with this information we can easly understand if the data is quantitative o categorical.
- Next, we perform the info function to relate the null values for each column and the data types
- With the function nunique, we see the number of differents values in each variable.
- Value counts is a really handy function to understand if a columns messy or not.

In [3]:

```
df.shape
```

Out[3]:

```
(10866, 21)
```

In [4]:

```
df.dtypes
```

Out[4]:

```
id                        int64
imdb_id                  object
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
homepage                 object
director                 object
tagline                  object
keywords                 object
overview                 object
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
revenue_adj             float64
dtype: object
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    10866 non-null  int64  
 1   imdb_id               10856 non-null  object 
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64  
 4   revenue               10866 non-null  int64  
 5   original_title        10866 non-null  object 
 6   cast                  10790 non-null  object 
 7   homepage              2936 non-null   object 
 8   director              10822 non-null  object 
 9   tagline               8042 non-null   object 
 10  keywords              9373 non-null   object 
 11  overview              10862 non-null  object 
 12  runtime               10866 non-null  int64  
 13  genres                10843 non-null  object 
 14  production_companies  9836 non-null   object 
 15  release_date          10866 non-null  object 
 16  vote_count            10866 non-null  int64  
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64  
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [6]:

```
df.nunique()
```

Out[6]:

```
id                      10865
imdb_id                 10855
popularity              10814
budget                    557
revenue                  4702
original_title          10571
cast                    10719
homepage                 2896
director                 5067
tagline                  7997
keywords                 8804
overview                10847
runtime                   247
genres                   2039
production_companies     7445
release_date             5909
vote_count               1289
vote_average               72
release_year               56
budget_adj               2614
revenue_adj              4840
dtype: int64
```

In [7]:

```
df.production_companies.value_counts().head(25)
```

Out[7]:

```
Paramount Pictures                              156
Universal Pictures                              133
Warner Bros.                                     84
Walt Disney Pictures                             76
Columbia Pictures                                72
Metro-Goldwyn-Mayer (MGM)                        72
New Line Cinema                                  61
Touchstone Pictures                              51
20th Century Fox                                 50
Twentieth Century Fox Film Corporation           49
TriStar Pictures                                 45
Orion Pictures                                   42
Miramax Films                                    32
Columbia Pictures Corporation                    31
DreamWorks Animation                             31
Pixar Animation Studios                          30
Walt Disney Productions                          29
Dimension Films                                  28
United Artists                                   23
Imagine Entertainment|Universal Pictures         22
Marvel Studios                                   22
The Asylum                                       21
Lions Gate Films                                 21
New World Pictures                               17
Walt Disney Pictures|Pixar Animation Studios     17
Name: production_companies, dtype: int64
```

In [8]:

```
df.genres.value_counts().head(20)
```

Out[8]:

```
Drama                       712
Comedy                      712
Documentary                 312
Drama|Romance               289
Comedy|Drama                280
Comedy|Romance              268
Horror|Thriller             259
Horror                      253
Comedy|Drama|Romance        222
Drama|Thriller              138
Comedy|Family               102
Action|Thriller             101
Thriller                     93
Drama|Comedy                 92
Animation|Family             90
Crime|Drama|Thriller         81
Crime|Drama                  74
Comedy|Horror                72
Drama|Comedy|Romance         64
Action                       63
Name: genres, dtype: int64
```

ASSESS

- missing values: producction companies,cast..
- inaccured datatypes: release date
- inconsistency data: genres, porduction companies
- duplicated values
- the loc function is a perfect tool to filter the data and in ths case look after some inconsistencies in it.

In [9]:

```
df.loc[df.duplicated(subset='original_title')].shape
```

Out[9]:

```
(295, 21)
```

In [10]:

```
df.loc[df.popularity != 0].shape
```

Out[10]:

```
(10866, 21)
```

In [11]:

```
df.loc[(df.revenue == 0) & (df.budget == 0)].shape
```

Out[11]:

```
(4701, 21)
```

Data Cleaning

Data type correction

In [12]:

```
df['release_date'] = pd.to_datetime(df.release_date)
```

Droping duplicated values

In [13]:

```
df.drop_duplicates(subset='original_title', keep='first', inplace=True)
```

Reduce output values

In [14]:

```
df['genres'] = df['genres'].str.split('|', expand=True)[1]
```

In [15]:

```
df['production_companies'] = df['production_companies'].str.split('|', expand=True)[1]
```

Inconsistency between values

In [16]:

```
def conditional_change(col_name, value_in, value_out):
    df.loc[df[col_name].str.contains(value_in, case=False, na=False), col_name] = value
_out
    return df
```

In [17]:

```
conditional_change('production_companies', 'fox', 'Twentieth Century Fox Film Corporati
on')
conditional_change('production_companies', 'warner', 'Warner Bros')
conditional_change('production_companies', 'disney', 'Walt Disney Production')
```

Out[17]:

	id	imdb_id	popularity	budget	revenue	original_title	cas
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryc Dallas Howard|Irrfa Khan|Vi.
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charliz Theron|Hug Keays-Byrne|Nic.
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailen Woodley|The James|Kat Winslet|Ansel.
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mar Hamill|Carri Fisher|Adam D.
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Pau Walker|Jaso Statham|Michelle .
...	...	...	...	...	...	...	.
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michae Hynson|Robe August|Lord 'Tall Ho' B.
10862	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner|Ev Marie Saint|Yve Montand|Tosh.
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokenti Smoktunovskiy|Ole Efremov|Georgi Z.
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuy Mihashi|Akik Wakabayashi|Mi Hama|Joh.
10865	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold F Warren|Tor Neyman|Joh Reynolds|Dian.

10571 rows × 21 columns

In [18]:

```
df.production_companies.value_counts().head(70)
```

Out[18]:

```
Warner Bros                                 224
Twentieth Century Fox Film Corporation       74
Touchstone Pictures                          63
Metro-Goldwyn-Mayer (MGM)                    62
Walt Disney Production                       57
                                           ...
Robert Simonds Productions                    9
British Broadcasting Corporation (BBC)        9
Lakeshore Entertainment                       9
Stage 6 Films                                 9
Vertigo Entertainment                         9
Name: production_companies, Length: 70, dtype: int64
```

Innacurates values (original title)

In [19]:

```
df.loc[df.duplicated(subset='original_title')]
```

Out[19]:

id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline

0 rows × 21 columns

In [20]:

```
df.drop_duplicates(subset='original_title' , keep='first', inplace=True)
```

Innacurates values (release_date)

> there are 328 movies registred with the wrong year, to correct them we use an apply function combined with a lambda function to replace the values that are wrong

In [21]:

```
df.loc[df.release_date.dt.year > 2015].shape
```

Out[21]:

```
(328, 21)
```

In [22]:

```
df['release_date'] = df['release_date'].apply(lambda x: x.replace(year = x.year -100) i
f x.year>2015 else x)
```

the revenue and budget column have almost half of the registred values indicating 0. This represents almost half of the dataset. here we have differents options:

- to use the mean of each year and each genre to aproximante a value
- to consider them as a null values and drop them.

In [23]:

```
df_2 = df.loc[(df.revenue != 0) & (df.budget != 0)]
```

- We generate a new dataframe df2 with completes observations for each row.
- This new df is generated to study te evolution and direction of the budget and revenues of the film industrie al over the las 60 years.

Drop unnecesaries columns

In [24]:

```
df_2.columns
```

Out[24]:

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_titl
e',
       'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview',
       'runtime', 'genres', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
       'revenue_adj'],
      dtype='object')
```

In [25]:

```
df_2.drop(columns=['imdb_id','cast', 'homepage','tagline', 'keywords', 'overview', 'run
time'], inplace=True)
```

```
c:\program files\python38\lib\site-packages\pandas\core\frame.py:3987: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

In [26]:

```
df_2.head()
```

Out[26]:

	id	popularity	budget	revenue	original_title	director	genres	productio
0	135397	32.985763	150000000	1513528810	Jurassic World	Colin Trevorrow	Adventure	Amblin
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	George Miller	Adventure	K
2	262500	13.112507	110000000	295238201	Insurgent	Robert Schwentke	Science Fiction	Ma
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	J.J. Abrams	Adventure	Truenort
4	168259	9.335014	190000000	1506249360	Furious 7	James Wan	Crime	

Describe values

In [27]:

```
df_2.describe().T
```

Out[27]:

	count	mean	std	min	25%	50%
id	3756.0	4.055726e+04	6.786629e+04	5.000000	6.430000e+03	1.137050e+04
popularity	3756.0	1.194688e+00	1.486161e+00	0.001117	4.631333e-01	7.983430e-01
budget	3756.0	3.752862e+07	4.244601e+07	1.000000	1.000000e+07	2.400000e+07
revenue	3756.0	1.082386e+08	1.770478e+08	2.000000	1.358668e+07	4.483448e+07
vote_count	3756.0	5.307348e+02	8.857413e+02	10.000000	7.100000e+01	2.050000e+02
vote_average	3756.0	6.164004e+00	7.949363e-01	2.200000	5.675000e+00	6.200000e+00
release_year	3756.0	2.001538e+03	1.106193e+01	1960.000000	1.996000e+03	2.004000e+03
budget_adj	3756.0	4.436703e+07	4.498007e+07	0.969398	1.319180e+07	3.014881e+07
revenue_adj	3756.0	1.363931e+08	2.158969e+08	2.370705	1.830994e+07	6.092554e+07

Exploratory Data Analysis

with the data wrangling done with use differents datastes to find some insights. reated to the problematics that came out with the gather of the dataset.

What was the evolution of the profits of the film industry during the period 1960 - 2018?

to understand the evolution of the budget and the revenues of the industrie we use the function group by. and then, we plot it with a line plot using seaborn.

In [28]:

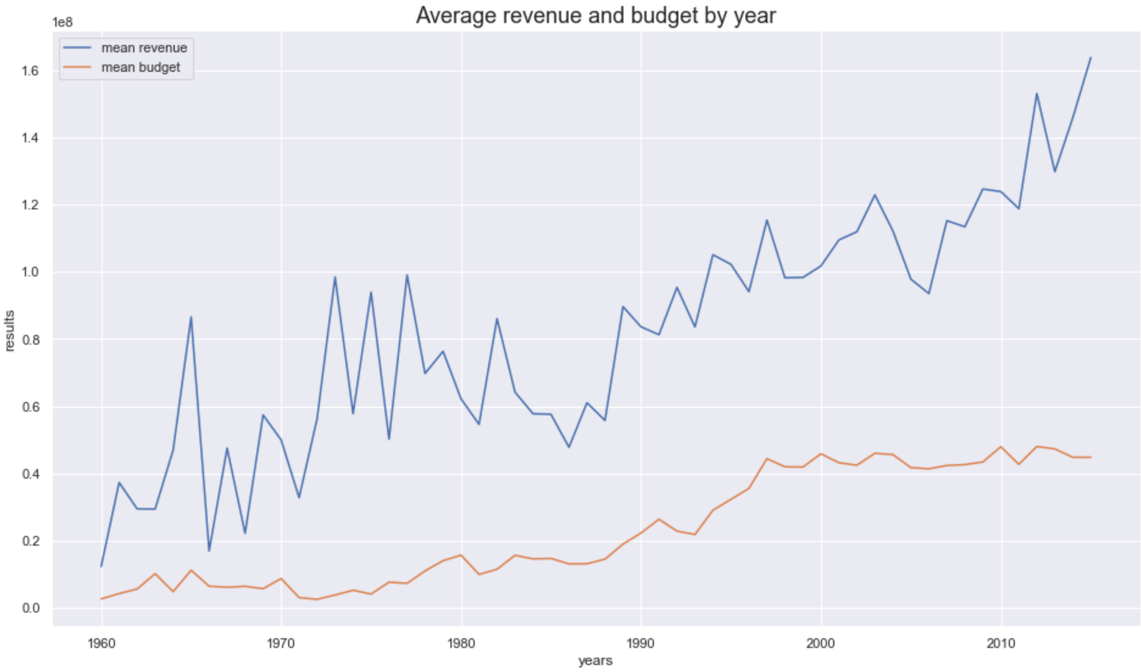
```
df_year = df_2.groupby(df['release_date'].dt.year).mean().reset_index()
```

In [29]:

```
def lineplot_x_2(x_axes, y1_axes, y2_axes, df):
    sns.set(style="darkgrid")
    plt.figure(figsize=(16,9))
    ax = sns.lineplot(x=x_axes, y=y1_axes, label=f"mean {y1_axes}", data=df)
    ax = sns.lineplot(x=x_axes, y=y2_axes, label=f"mean {y2_axes}", data=df)
    ax.set_title(f'Average {y1_axes} and {y2_axes} by year', fontsize=18)
    ax.set_xlabel('years')
    ax.set_ylabel('results');
```

In [30]:

```
lineplot_x_2('release_date', 'revenue', 'budget', df_year)
```



- the revenue curve is very intermittent. Growth processes last 2-3 years and are interrupted by abrupt falls. this pattern is reproduced throughout the study period
- at the end of the 80s, the amplitude of the volatility of the revenues is reduced and the difference between this curve and that of the budget that is maintained at around 450,000,000.00 is enlarged.
- The maximum recorded results are 1,600,000,000.00 relative to 2015, the last year with records.

In [31]:

```
df_year_sum = df_2.groupby(df['release_date'].dt.year).sum().reset_index()
df_year_sum['profit'] = df_year_sum['revenue'] - df_year_sum['budget']
df_year_sum.sort_values(by='profit', axis=0, ascending=False).head(10)
```

Out[31]:

	release_date	id	popularity	budget	revenue	vote_count	vote_average
55	2015	40164198	457.110856	7170777528	26202922801	155369	999.0
54	2014	32176813	416.406465	7393768000	24069969357	169922	1045.6
52	2012	12619538	222.580212	7587610525	24184456032	160629	946.3
51	2011	11301674	238.473152	8416550543	23404448100	121027	1203.1
53	2013	22144450	243.244332	8372922778	22974907074	177627	1097.4
49	2009	3425233	197.929015	7511827919	21563814641	102827	1046.3
50	2010	6327730	208.805990	8441108439	21802891959	115323	1074.1
48	2008	1824188	178.003082	6991556800	18599657891	85593	991.5
47	2007	1476451	159.612919	6740517892	18321062428	74054	980.8
44	2004	1267794	162.605879	6661999308	16381794281	71424	890.4

- In generals terms boths curves, are increasing. The revenue presents a higher volatility but the tendency shows how it is separating from the budget curve. In the last 20 years, there are two low bounces probably relates to the online piracy with web like piratebay or mega and in the erlies 2010 probaly related with the new multimedia plataforms.
- Even so, they revenues continue to grow in a faster than they budgets that stays leveled around the 400.000.000 for the all industrie
- To check for more granularity, we add the month value to the dataset, and we use the rolling function smooth the curves.

In [32]:

```
df_2['month_year'] = df_2['release_date'].dt.to_period('M')
df_y_m = df_2.groupby([df_2.month_year]).mean().reset_index()
df_y_m
```

```
<ipython-input-32-d9f477d823fc>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_2['month_year'] = df_2['release_date'].dt.to_period('M')
```

Out[32]:

	month_year	id	popularity	budget	revenue	vote_count	vote_
0	1960-06	284.000000	0.947307	3.000000e+06	2.500000e+07	235.000000	7
1	1960-10	966.000000	1.872132	2.000000e+06	4.905000e+06	224.000000	7
2	1960-12	18973.000000	0.055821	3.000000e+06	7.100000e+06	13.000000	7
3	1961-01	12230.000000	2.631987	4.000000e+06	2.158800e+08	913.000000	6
4	1961-03	18647.000000	0.173731	6.000000e+06	4.300000e+06	17.000000	6
...	...	...	...	...	...	...	
531	2015-08	254943.916667	1.903474	3.291667e+07	7.925642e+07	659.416667	6
532	2015-09	271716.041667	1.804688	3.292083e+07	1.050920e+08	701.875000	6
533	2015-10	264129.529412	2.141399	3.543706e+07	9.103131e+07	710.764706	6
534	2015-11	266496.000000	2.278568	4.359444e+07	1.108521e+08	658.888889	6
535	2015-12	264217.333333	4.516088	7.333333e+07	3.860243e+08	1765.222222	6

536 rows × 10 columns

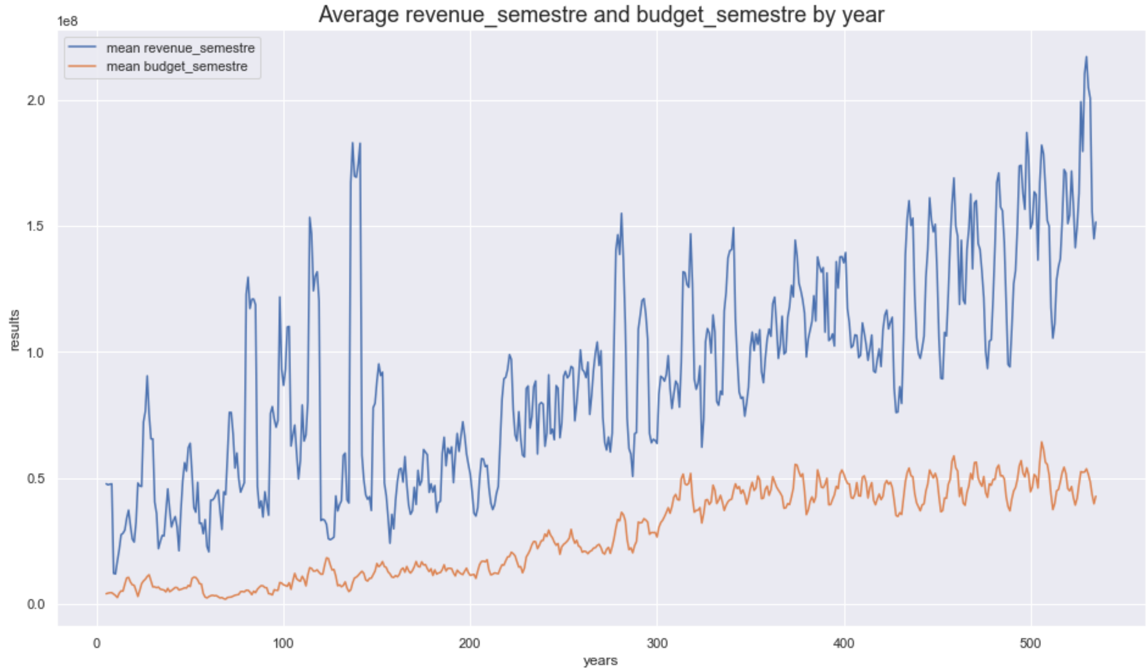
- before plotting the results, we use the rolling function to smooth the curve and make ir more readable

In [33]:

```
df_y_m['budget_semestre'] = df_y_m['budget'].rolling(6).mean()
df_y_m['revenue_semestre'] = df_y_m['revenue'].rolling(6).mean()
```

In [34]:

```
lineplot_x_2(df_y_m.index, 'revenue_semestre', 'budget_semestre', df_y_m)
```



- The two curves presents some paralalism. The tendency shows that when a budget breaks the market a big increase in the revenue happens.the movements in the budget curve exponentially affect the profit curve
- The last 8 years, presents the budgets expends with intermittent evolution follow by an intermittent revenue that in generals terms is increassing. Lets' make a zoom of it using plt.xlimt

In [35]:

```
df_y_m.sort_values(by='revenue', axis=0,ascending=False)
```

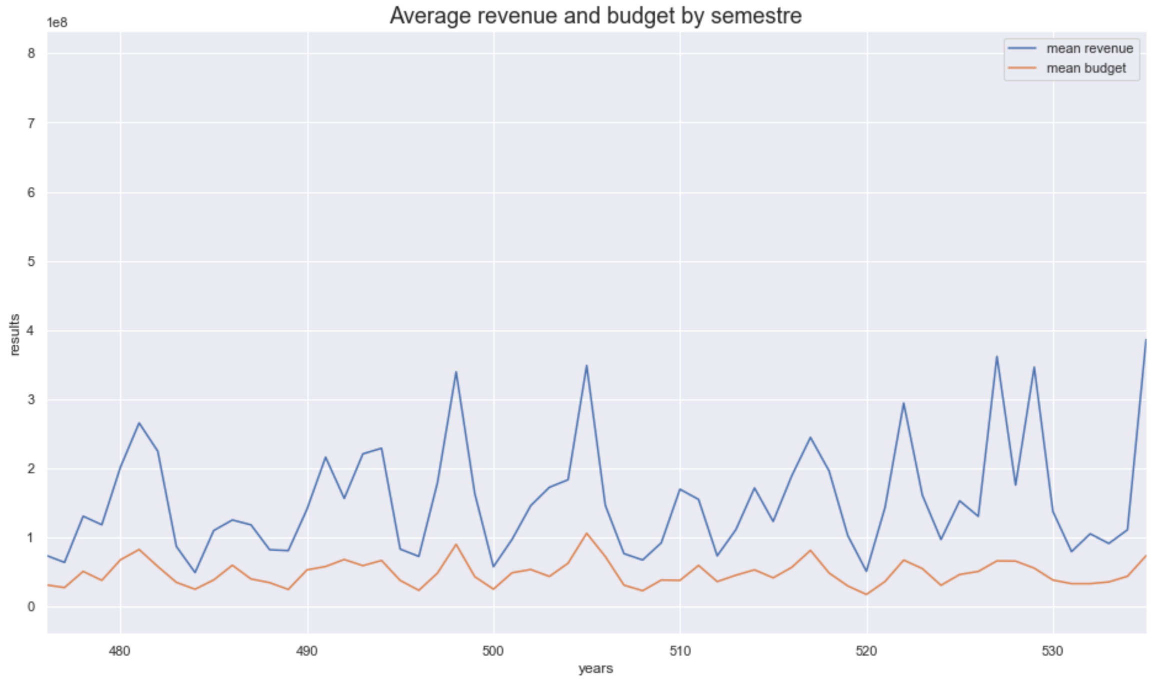
Out[35]:

	month_year	id	popularity	budget	revenue	vote_count	vote_
136	1982-04	601.000000	2.900556	1.050000e+07	7.929106e+08	1830.000000	7
114	1980-01	1891.000000	5.488441	1.800000e+07	5.384000e+08	3954.000000	8
80	1975-06	578.000000	2.563191	7.000000e+06	4.706540e+08	1415.000000	7
535	2015-12	264217.333333	4.516088	7.333333e+07	3.860243e+08	1765.222222	6
463	2009-12	17482.090909	1.680397	7.281818e+07	3.816423e+08	1114.454545	6
...	...	...	...	...	...	...	
91	1977-01	72277.000000	0.191541	8.100000e+05	1.258000e+06	12.000000	5
48	1970-02	2998.000000	0.279079	7.000000e+06	9.000000e+05	30.000000	6
44	1969-06	576.000000	0.615889	6.244087e+06	6.386410e+05	121.000000	7
134	1982-02	14373.000000	0.464188	2.000000e+00	1.600000e+01	27.000000	5
100	1978-04	28932.000000	0.439210	1.100000e+01	1.100000e+01	13.000000	6

536 rows × 12 columns

In [36]:

```
sns.set(style="darkgrid")
plt.figure(figsize=(16,9))
ax = sns.lineplot(x=df_y_m.index, y="revenue", label="mean revenue", data=df_y_m)
ax = sns.lineplot(x=df_y_m.index, y="budget", label="mean budget", data=df_y_m)
ax.set_title('Average revenue and budget by semestre', fontsize=18)
ax.set_xlabel('years')
ax.set_ylabel('results')
ax = plt.xlim(476, 535 )
```



en los ultmos 15 años, la curva del budget se mantine con oscilaciones moderadas. que impacatan exponecialmente al revenue. en el 2009, se presenta un maximo, que vulve a ser superado en 2012 y en 2015.

Budget & revenues by genre

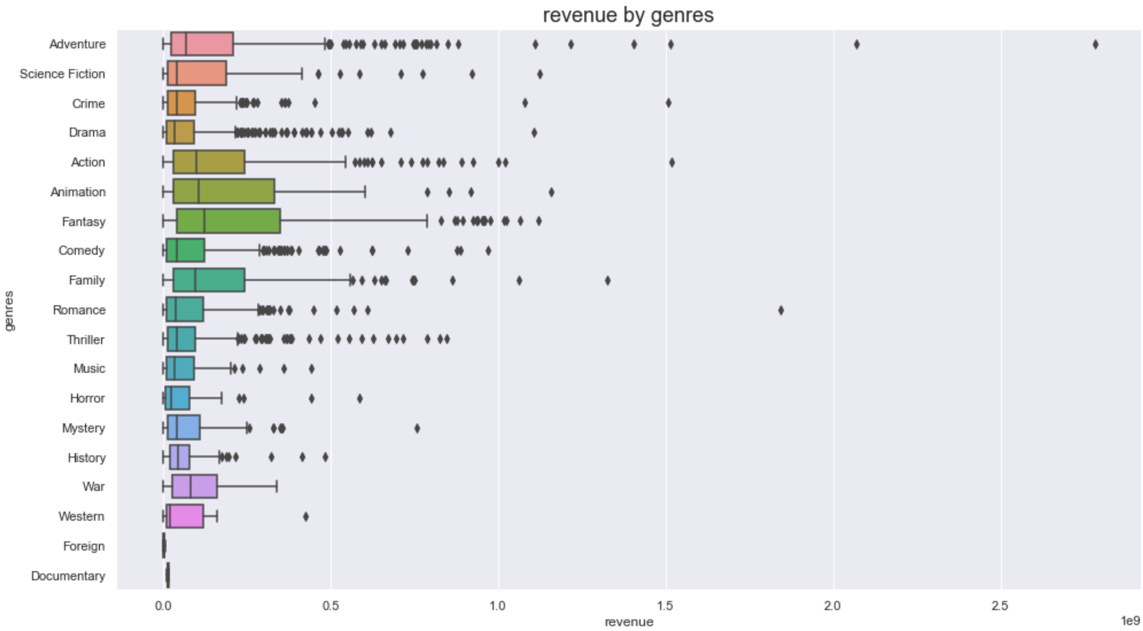
> - After having seen the evolution of the values generated by the industry over time, we decided to identify the results of each of the genres, to have a more complete perspective of the viewer's tastes and the companies invesments.
> - The group by allow done it before, allows us to make this plot using seaborn box plot

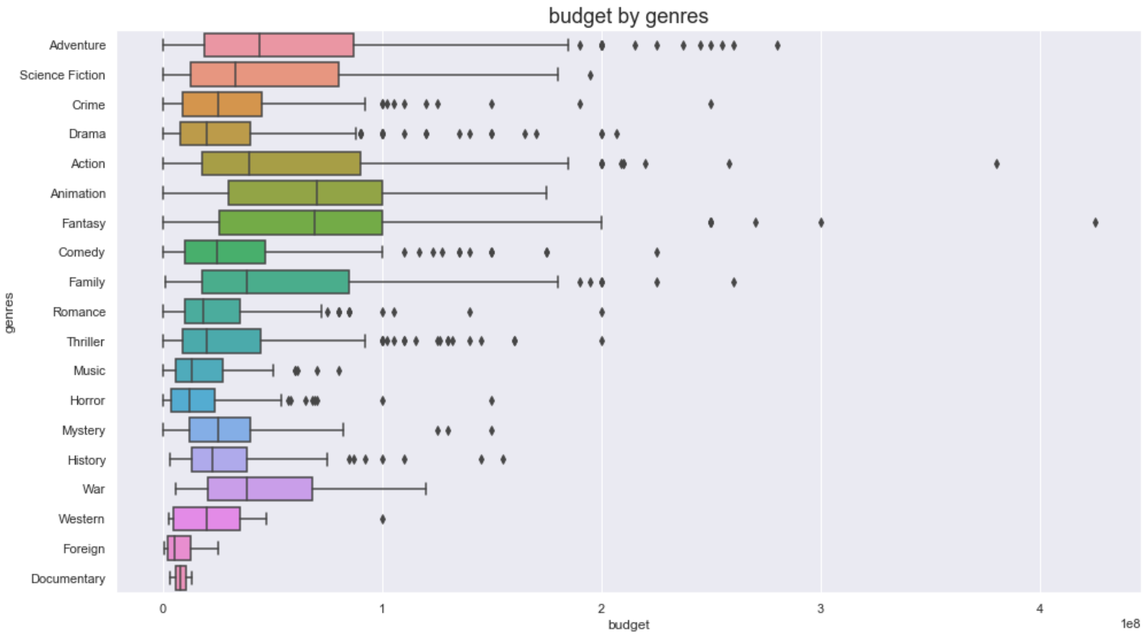
In [37]:

```
def boxplot(x_axes, y_axes, df):
    sns.set(style='darkgrid')
    plt.figure(figsize=(16,9))
    ax = sns.boxplot(x=x_axes, y=y_axes, orient= "h", data=df)
    ax.set_title(f'{x_axes} by {y_axes}', fontsize=18)
    ax.set_xlabel(f'{x_axes}')
    ax.set_ylabel(f'{y_axes}');
```

In [38]:

```
margins = ['revenue', 'budget']

for margin in margins:
    boxplot(margin, 'genres', df_2)
```





> in average, the profts of the film industries are exponencial.
> the genres that requires more budgets to make a production are Fantasy and animation, follows by adventure, At the same time, its revenues are the highest the foreign productions and the documentary are bellow the average.
>
> the diversity existing in the sector, has as a consequence a very large amplitude in monetary terms

Budget & Revenue relationship

> To understand the relationship between revenue and budget we can use the scatterplot.

In [39]:

```
def scatterplot(x_axes, y_axes, hue, df):
    sns.set(style='darkgrid')
    plt.figure(figsize=(16,9))

    ax = sns.scatterplot(x=x_axes, y=y_axes, hue=hue, data=df)
    ax.set_title(f'{x_axes} & {y_axes} by {hue}', fontsize=18)
    ax.set_xlabel(f'{x_axes}')
    ax.set_ylabel(f'{y_axes}');
```

In [40]:

```
scatterplot('budget', 'revenue', 'genres', df_2)
```

There is a moderate positive correlation betwen budget and revenue.

Budget & Revenue by production companie

> after having studied the behavior of the industry. we propose to focus on the main companies and observe their results. We know that he manages 22% of the profits, so his behaviors define the general results.

In [41]:

```
df_companies = df_2.groupby(by=['production_companies'], as_index=False).sum()
df_companies.sort_values(by='revenue', ascending=False).head(10)
```

Out[41]:

	production_companies	id	popularity	budget	revenue	vote_count	vo
1196	Warner Bros	4366930	200.362563	6819177000	18901681612	97912	
1151	Twentieth Century Fox Film Corporation	2042835	124.332429	3781350000	18724840150	71654	
862	Pixar Animation Studios	489436	56.476804	2301000000	9698819254	45111	
55	Amblin Entertainment	779493	84.065109	1834800000	9053944857	38989	
1168	Universal Pictures	880892	52.005811	2564777025	6587816806	20459	
780	New Line Cinema	238946	43.772675	1067000000	5988101890	29690	
821	Original Film	1152462	36.146177	1725000000	5962013012	29108	
1193	Walt Disney Production	1018681	49.080999	2303431000	5648410737	20170	
565	Jerry Bruckheimer Films	128277	31.591672	1855000000	5120058749	19287	
633	Legendary Pictures	665497	55.847220	1410000000	4216538498	30711	

In [42]:

```
profit_ten = df_companies.sort_values(by='revenue', ascending=False).head(10).iloc[:,4]
.sum() / df_2.iloc[:,3].sum()*100

print(f' the total revenue generated by the film industry ascends to {df_2.iloc[:,3].su
m()}, of witch {profit_ten} % is controled by the 10 mayor companies in the industry ')
```

```
 the total revenue generated by the film industry ascends to 406544127181,
of witch 22.11376811378069 % is controled by the 10 mayor companies in the
industry
```

In [43]:

```
prin_comp = list(df_companies.sort_values(by='revenue', ascending=False).head(10).iloc
[:,0])
```

In [44]:

```
df_prin_comp = df_2.loc[df_2['production_companies'].isin(prin_comp)]
```

In [45]:

```
df_time_comp = df_prin_comp.groupby(['release_year','production_companies'],axis=0,as_i
ndex=False).sum()
df_time_comp.sort_values('revenue',ascending=False).head(10)
```

Out[45]:

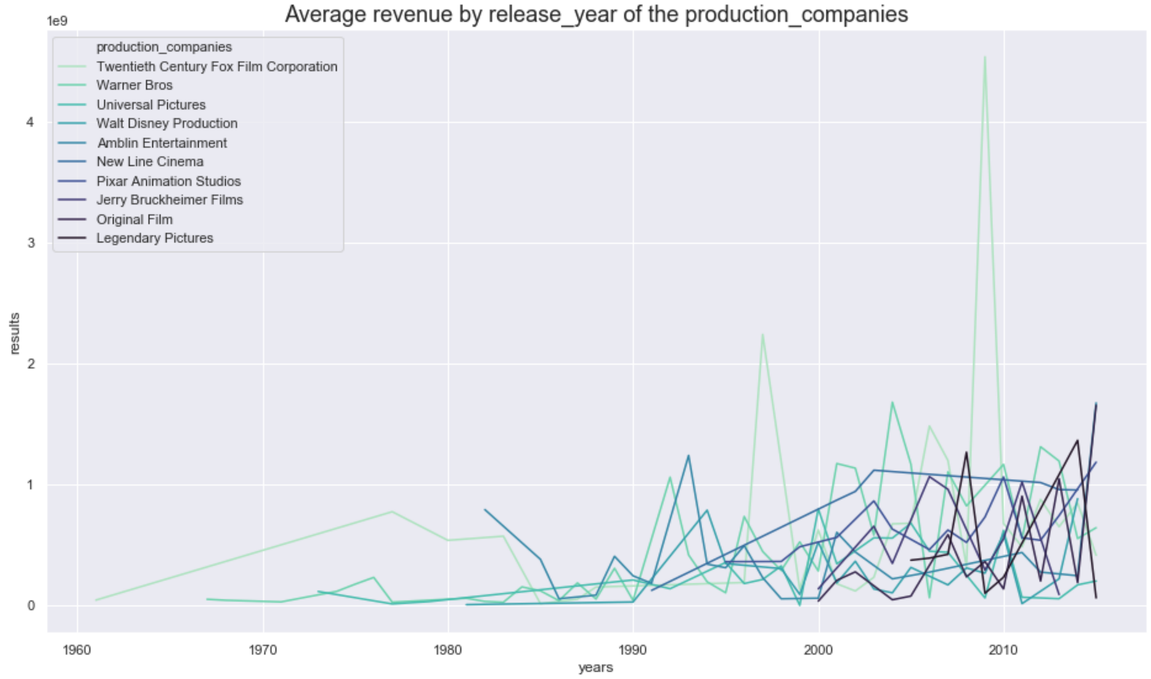
	release_year	production_companies	id	popularity	budget	revenue	vote_c
135	2009	Twentieth Century Fox Film Corporation	114662	17.075648	603000000	4541406391	1
55	1997	Twentieth Century Fox Film Corporation	19468	7.697376	256500000	2242688658	
103	2004	Warner Bros	31789	11.683866	454000000	1682199952	
176	2015	Amblin Entertainment	431495	36.633973	190000000	1676139283	
178	2015	Original Film	425704	12.979555	248000000	1656420175	
114	2006	Twentieth Century Fox Film Corporation	5029	6.755179	290000000	1484709726	
169	2014	Legendary Pictures	331258	31.667504	395000000	1366357750	1
159	2012	Warner Bros	117760	8.594509	294500000	1313365415	
125	2008	Legendary Pictures	7995	10.308507	290000000	1267921825	
40	1993	Amblin Entertainment	753	4.582214	85000000	1241365768	

In [46]:

```
def lineplot_x_1(x_axes, y_axes, hue, df):
    sns.set(style="darkgrid")
    plt.figure(figsize=(16,9))
    palette = sns.color_palette("mako_r", df[f'{hue}'].nunique())
    ax = sns.lineplot(x=x_axes, y=y_axes, hue=hue, palette=palette, data=df)

    ax.set_title(f'Average {y_axes} by {x_axes} of the {hue}', fontsize=18)
    ax.set_xlabel('years')
    ax.set_ylabel('results');
```

In [47]:

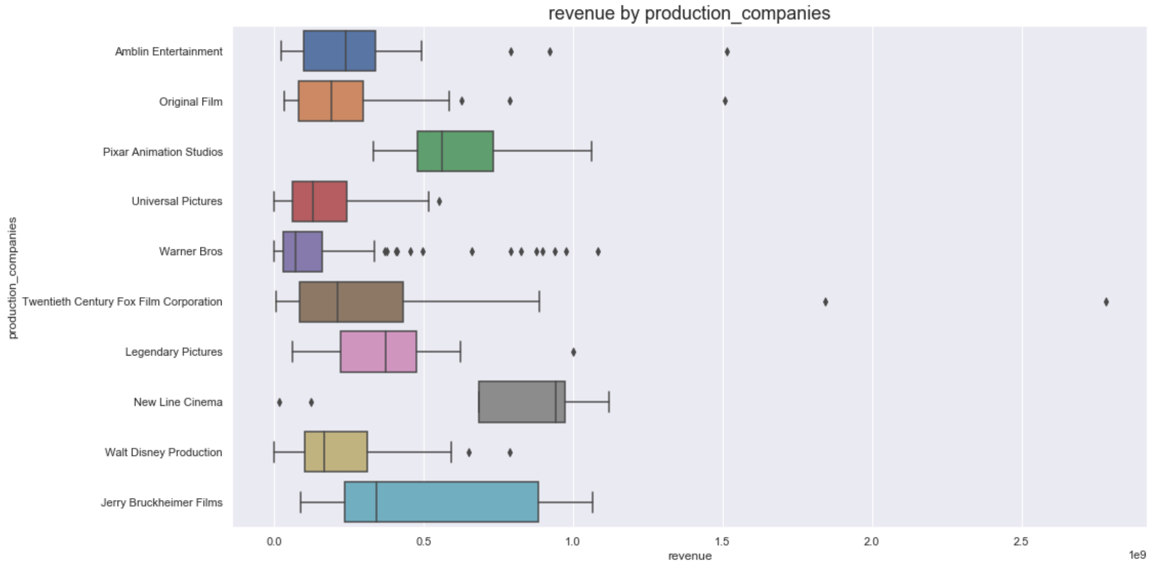
```
lineplot_x_1('release_year', 'revenue', 'production_companies', df_time_comp)
```

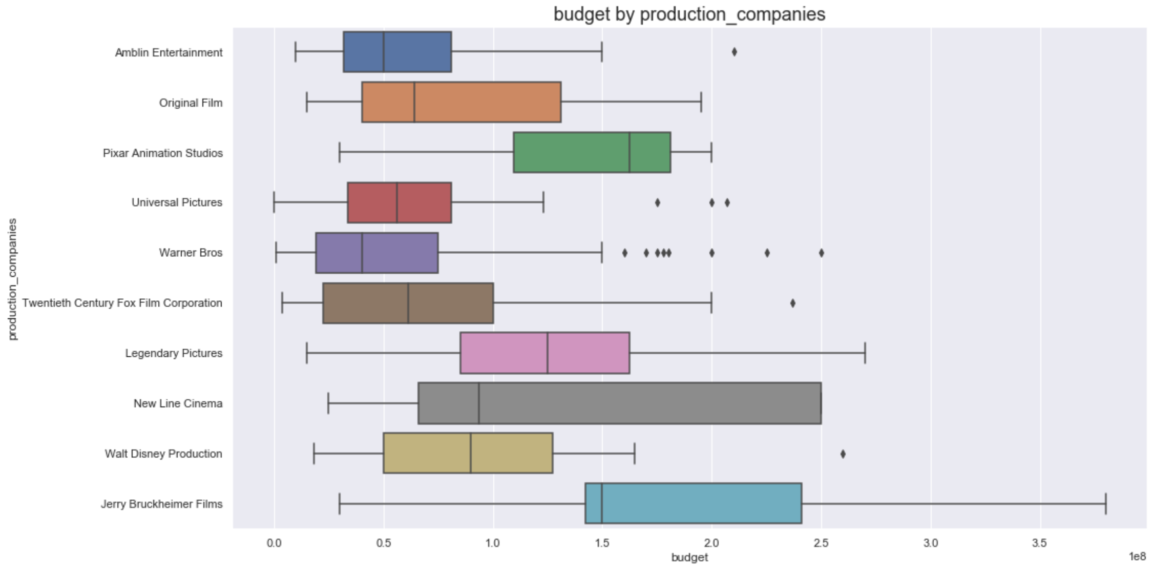


twenty century fox is the longest-running production company on the mayors 10 list. company profit curves show 2 extreme outlier. both belonging to twenty century fox and directed by the same director James Cameron: Titanic and avatar
Pixar animations is the cmost stable of the mayor ten.

In [48]:

```
for margin in margins:
    boxplot(margin, 'production_companies', df_prin_comp)
```





in average Pixar Animations is the company with most budgets investissements, clossely followed by Jerry Bruckheimer Films, but with a wider dsitribution. in fact, this company spended the bigger budget for a film production on another hand, Warner Bros has the smaller average budget but with the biggest number of possitives outliers
regarding the revenues, new line cinema leads the table. followed by Pixar animations, which has no adversaries in its genre
the films that collected the most belong in first and second place to 20 century fox, and in third place to amban films

What is the most popular genre?

> the values related to the popularity and rating of the viewers was complete in the kaggle dataset, to answer this question then we use that dataset again as the largest number of values

In [49]:

```
df.head()
```

Out[49]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http:/
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	

5 rows × 21 columns

In [50]:

```
#table = pd.pivot_table(df, values='D', index=['A', 'B'],columns=['C'], aggfunc=np.sum)
df.pivot_table(values='popularity', index=['genres'], columns=['release_year'], aggfunc
=np.mean)
```

Out[50]:

release_year	1960	1961	1962	1963	1964	1965	1966	196
genres								
Action	NaN	0.275009	1.391843	NaN	1.185667	1.910465	0.291704	0.43831
Adventure	1.872132	0.657446	0.468481	0.781120	NaN	0.312067	0.297781	0.28557
Animation	NaN	2.631987	NaN	NaN	NaN	NaN	0.276133	Na
Comedy	NaN	NaN	0.153654	0.203298	0.544644	NaN	0.223819	0.10172
Crime	NaN	0.806519	NaN	NaN	0.626005	0.289649	0.737730	Na
Documentary	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Drama	0.412792	0.390316	0.453233	0.324263	0.231447	0.213986	0.263784	0.58221
Family	0.278064	0.280829	NaN	1.179561	0.665686	0.957326	0.540682	Na
Fantasy	NaN	NaN	NaN	NaN	0.160098	NaN	NaN	Na
Foreign	NaN	NaN	NaN	0.201754	0.152209	NaN	NaN	Na
History	0.162753	0.538364	NaN	0.804533	0.321129	0.153438	0.418900	Na
Horror	NaN	NaN	NaN	0.045417	0.349468	0.086219	0.034555	0.56478
Music	NaN	0.229252	0.323933	NaN	1.400006	0.624024	NaN	0.09454
Mystery	NaN	NaN	0.126140	0.408031	NaN	0.071354	0.509263	Na
Romance	0.465497	0.200269	0.124418	0.331643	0.162341	0.209034	0.239435	0.27515
Science Fiction	NaN	0.194495	0.179212	0.467836	0.237514	0.199141	0.408574	0.24283
TV Movie	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Thriller	0.446302	NaN	0.308033	1.113477	0.371976	0.213382	0.402730	1.55480
War	NaN	NaN	NaN	NaN	NaN	0.246816	0.317824	Na
Western	0.268273	NaN	0.209355	NaN	NaN	0.141221	0.267152	Na

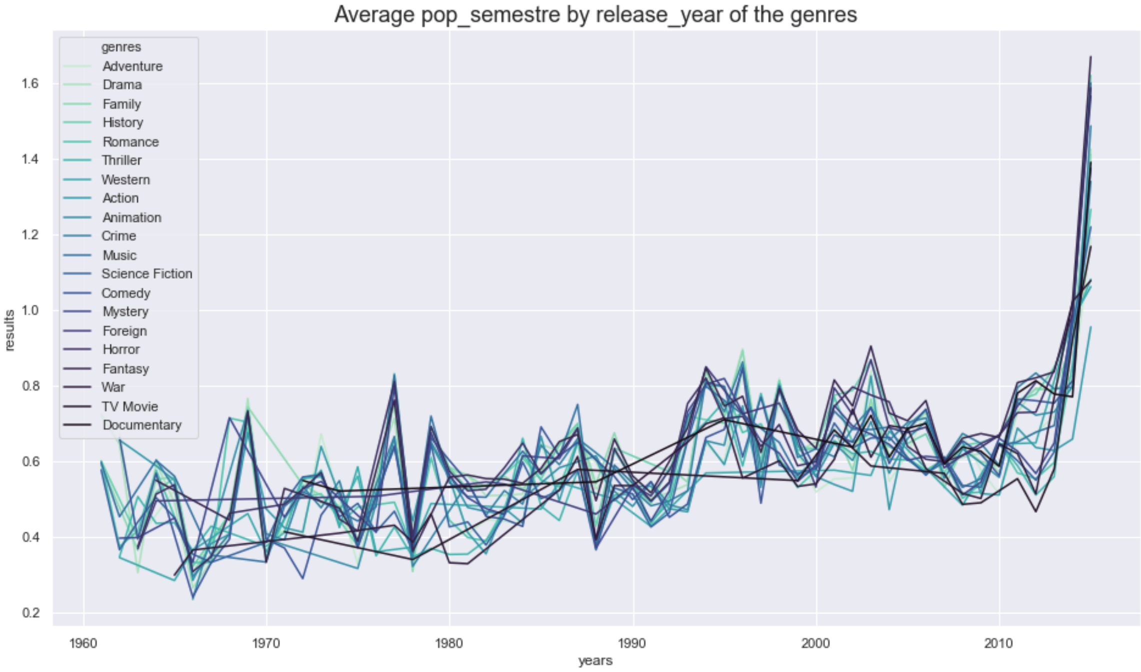
20 rows × 56 columns

In [51]:

```
df_popularity = df.groupby(['release_year', 'genres'],as_index=False).mean()
df_popularity['pop_semestre'] = df_popularity['popularity'].rolling(12).mean()
```

In [52]:

```
lineplot_x_1('release_year', 'pop_semestre', 'genres', df_popularity)
```



Against the first impressions, the audience popularity increase exponnentialy. The last 5 years of the reccord registred have been the most attractives to genelar audiences

In [61]:

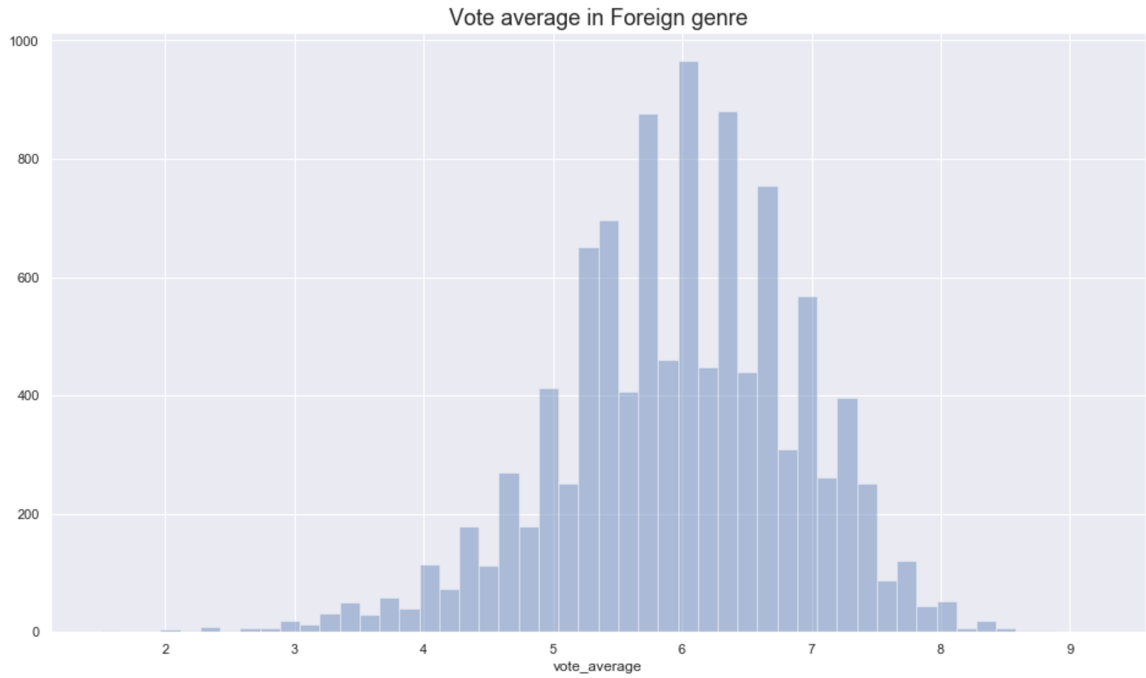
```
df_popularity.loc[df_popularity['release_year']==2015].sort_values(by='popularity',asce
nding=False)
```

Out[61]:

	release_year	genres	id	popularity	budget	revenue	ru
854	2015	Adventure	251646.200000	4.665070	6.216000e+07	3.140688e+08	101.
861	2015	Fantasy	209785.500000	3.533745	7.075000e+07	1.815848e+08	116.
857	2015	Crime	287416.125000	1.906528	3.525000e+07	1.218250e+08	116.
855	2015	Animation	274308.687500	1.903577	4.131250e+07	2.065514e+08	80.
860	2015	Family	289652.800000	1.808794	6.800000e+07	6.748480e+07	84.
867	2015	Science Fiction	289027.346154	1.344678	1.025000e+07	2.626538e+07	92.
853	2015	Action	297687.289474	1.315581	1.685921e+07	4.569690e+07	92.
859	2015	Drama	294297.709302	1.189173	1.160814e+07	3.243085e+07	104.
866	2015	Romance	279791.785714	1.065802	4.714286e+06	4.568167e+07	106.
871	2015	Western	321466.000000	0.993217	3.090000e+07	0.000000e+00	125.
865	2015	Mystery	294790.461538	0.904213	5.346154e+06	1.483834e+07	100.
869	2015	Thriller	287017.693878	0.865156	5.869388e+06	1.641517e+07	94.
856	2015	Comedy	290402.210526	0.842056	1.226276e+07	3.974254e+07	88.
864	2015	Music	302290.944444	0.739470	5.522222e+06	2.869487e+07	107.
863	2015	Horror	309882.590909	0.529663	2.834091e+06	8.733089e+06	89.
862	2015	History	289493.400000	0.491164	6.260000e+06	3.200484e+06	103.
858	2015	Documentary	327465.909091	0.279312	0.000000e+00	1.729417e+06	90.
870	2015	War	325258.000000	0.238515	3.000000e+06	4.538850e+04	83.
868	2015	TV Movie	358140.545455	0.221470	2.727273e+05	0.000000e+00	96.

In [70]:

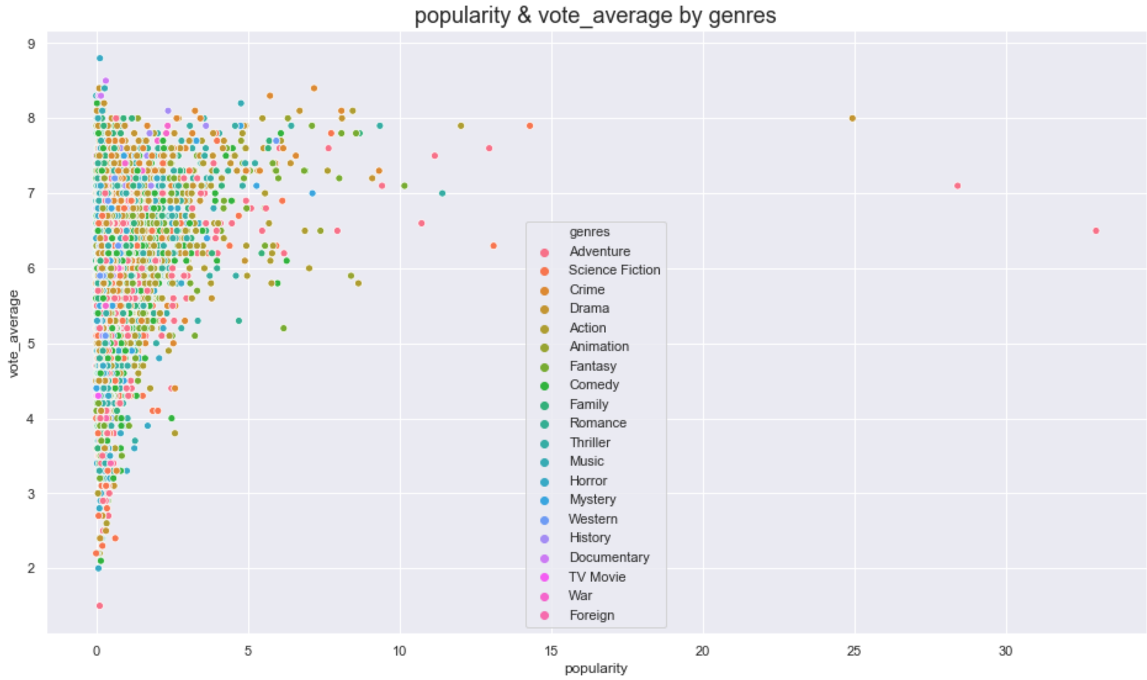
```
#genres = [i for i in df.genres.unique().tolist() if type(i) == str]
#for genre in genres:

sns.set(style='darkgrid')
plt.figure(figsize=(16,9))
plot=df['vote_average']
ax = sns.distplot(plot,kde=False,hist=True)
ax.set_title(f'Vote average in {genre} genre', fontsize=18);
```



less than 1000 movies have been rates with more than 7 points
over 1500 have been rated with 5 or less. over 4500 have been rated between 5.5 and 6.5

In [55]:

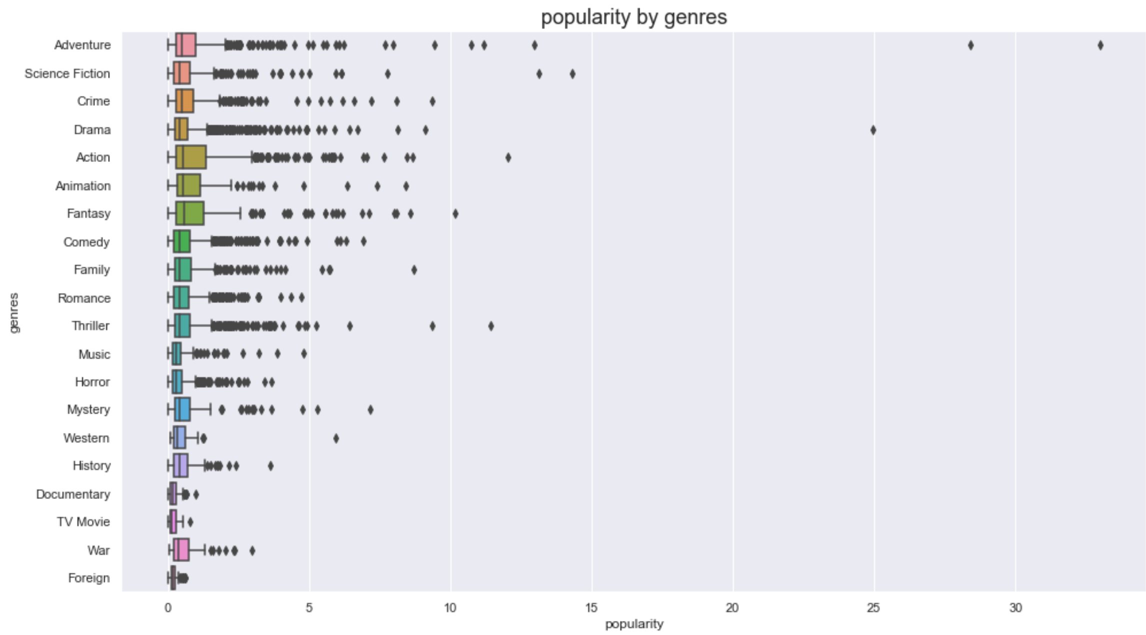
```
scatterplot('popularity', 'vote_average', 'genres', df)
```

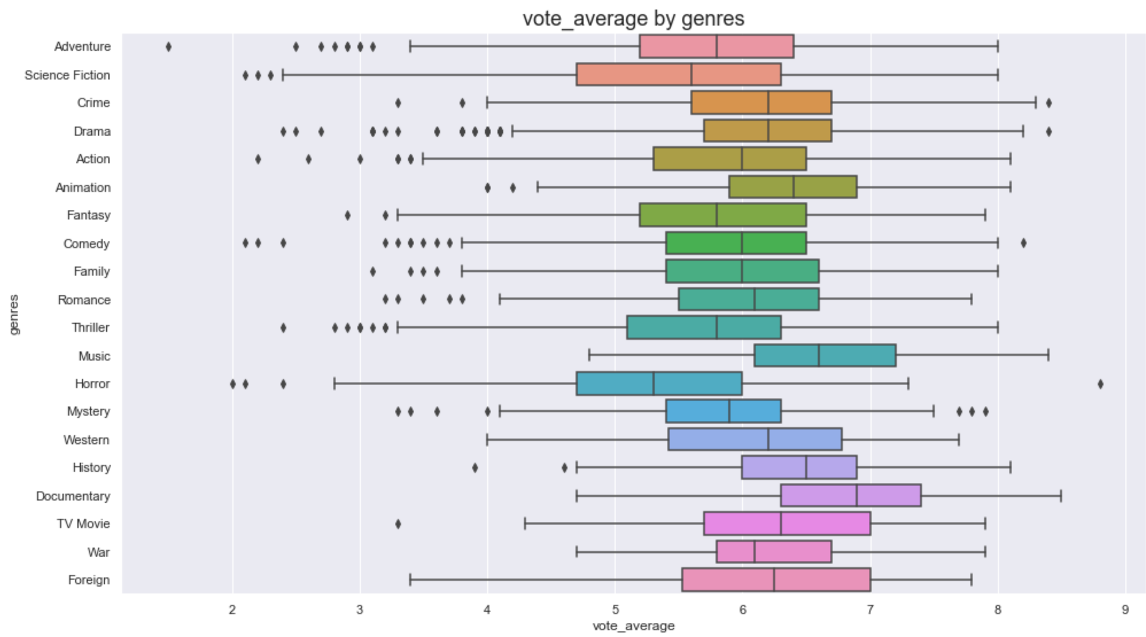


Dispite the blockbuster outliers. A strong positive correlation exists between the popularity and the average votes of a movie

In [56]:

```
people_choice = ['popularity', 'vote_average']

for choice in people_choice:
    boxplot(choice, 'genres', df)
```





the genre most popular is action, but the most populars movies are in the adventure genre.
the amound of outliers affects the visualization of this variable
the votes average is the result of what it seems an online survey. the volumen of vots registers is significantly small in comparation with the audience popularity. so this results can be bias.
The big mayority of genres has the average vots between 6 and 7.

Conclusions

- despite the new competitors that have emerged in recent years and the increase in illegal online download and playback platforms. The profits of the great companies in the film industry are exceeded year by year, with the virtue of having leveled expenses on average.
- the volatility of the benefits is directly related to the budgets invested in that period. movements in the budget curve have an exponential impact on the profit curve
- the total revenue generated by the film industry ascends to 406.544.127.181,00 us, of witch 22.11 % is controled by the 10 mayor companies.
- The adventure genre presents two big hits but in general terms the audiences preferes action or fantasy. Also comedy over drama
- in valoration termes, the betters are music film or documentary boths requiered a slow budget but they don't appeal to the big audiences. this cases can presents a bias in the votes

limitations:

Related to the monetary values of the film industry we find certain limitations.

- Budgets and revenues do not have currency units, we must assume that they are in it to perform the analysis.
- The time factor in the budgets was not taken into account, inflation coefficients from different periods were not considered. So the values at the temporal level can have partial results.
- Within the monetary variables we find both budgets and benefits with values equal to zero (almost half of the datset). To do the study, we discarded them from the sample and considerably reduced the number of elements.

Regarding the ratings and ratings of the films

- Absence of spatial information. The lack of information in this regard prevents us from clustering or generating a diagnosis about any spatial unit. They are absolute values without spatial reference.
- Very uneven relationship between popularity and number of votes. The opinion of the voters is much lower in scale than the number of spectators, the values are at risk of being partial

In [57]:

```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[57]:

4294967295