Project: Investigate a Dataset of TMDb movie data

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Introduction

TMDB movies dataset has around more 10000 movies across different years, each movie has a set of data to use to come up with some insights. Such findings would give an overview and answers to the questions on many levels like monetary level, genre level, actor & director level, etc.

In [1]:
```
#import statements for all of the packages that you

import numpy as np
import pandas as pd
import os, fnmatch
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="darkgrid")
```

Data Wrangling

> **Tip**: In this section of the report, you will load in the data, check for cleanliness, and then trim and clean your dataset for analysis. Make sure that you document your steps carefully and justify your cleaning decisions.

General Properties

In [2]:
```
#Reading and Loading the data
df=pd.read_csv("tmdb-movies.csv")
df.sample(5)
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	...	ove
10525	9941	tt0090966	0.437451	14000000	62134225	Down and Out in Beverly Hills	Nick Nolte|Bette Midler|Richard Dreyfuss|Eliza...	NaN	Paul Mazursky	See what happens when a dirty bum meets the fi...	...	B Hills c Ba and Whiter
1155	266353	tt3347518	0.281505	0	0	In My Dreams	Katharine McPhee|Mike Vogel|JoBeth Williams|Je...	NaN	Kenny Leon	Close your eyes and fall in love.	...	Natali Ni frus witl
6873	10093	tt0433442	0.188603	15000000	11992014	The Return	Adam Scott|Kate Beahan|Sarah Michelle Gellar|P...	NaN	Asif Kapadia	The past never dies. It kills.	...	J Mills succ care f
7638	9703	tt0462396	0.320907	67000000	25303038	The Last Legion	Colin Firth|Ben Kingsley|Aishwarya Rai Bachcha...	NaN	Doug Lefler	The end of an empire...the beginning of a legend.	...	A R e crun Y Roi
2937	15373	tt0430922	1.103468	28000000	92380927	Role Models	Seann William Scott|Paul Rudd|Elizabeth Banks|...	NaN	David Wain	They're about to get more than they plea-barga...	...	sale tr con truck er

5 rows × 21 columns

In [3]:
```
#discovering the data structure
df.shape
```

Out[3]: (10866, 21)

In [4]:
```
#dicovering the data columns, its dtypes and their nulls if any
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 [5]:
```
#a brief of statistics to help us have an overview of the data and spot the errors of any
df.describe()
```

Out[5]:

	id	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_ad
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000	10866.000000	1.086600e+0
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922	2001.322658	1.755104e+0
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142	12.812941	3.430616e+0
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000	1960.000000	0.000000e+0
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000	1995.000000	0.000000e+0
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000	2006.000000	0.000000e+0
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000	2011.000000	2.085325e+0
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000	2015.000000	4.250000e+0

In [6]:
```
#figuring out if the data has any duplicates
df.duplicated().sum()
```

Out[6]: 1

In [7]:
```
#columns which have null values
df.isnull().sum()
```

Out[7]:
```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
homepage                7930
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

In [8]:
```
#figuring out the movies that have budget and revenus less than 6000 and 1000 respectively besides the movies of zero budget
df.query('budget < 6000' or df.query('revenue < 1000' or df.query('budget = 0')))
```

Out[8]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage
30	280996	tt3168230	3.927333	0	29355203	Mr. Holmes	Ian McKellen|Milo Parker|Laura Linney|Hattie M...	http://www.mrholmesfilm.com/
36	339527	tt1291570	3.358321	0	22354572	Solace	Abbie Cornish|Jeffrey Dean Morgan|Colin Farrel...	NaN
72	284289	tt2911668	2.272044	0	45895	Beyond the Reach	Michael Douglas|Jeremy Irvine|Hanna Mangan Law...	NaN
74	347096	tt3478232	2.165433	0	0	Mythica: The Darkspore	Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...	http://www.mythicamovie.com/#!blank/wufvh
75	308369	tt2582496	2.141506	0	0	Me and Earl and the Dying Girl	Thomas Mann|RJ Cyler|Olivia Cooke|Connie Britt...	http://www.foxsearchlight.com/meandearlandthed...
...	...	...	...	...	...	...	...	...
10860	5060	tt0060214	0.087034	0	0	Carry On Screaming!	Kenneth Williams|Jim Dale|Harry H. Corbett|Joa...	NaN
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson|Robert August|Lord 'Tally Ho' B...	NaN
10862	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner|Eva Marie Saint|Yves Montand|Tosh...	NaN
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...	NaN
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...	NaN

5760 rows × 21 columns

Tip: You should *not* perform too many operations in each cell. Create cells freely to explore your data. One option that you can take with this project is to do a lot of explorations in an initial notebook. These don't have to be organized, but make sure you use enough comments to understand the purpose of each code cell. Then, after you're done with your analysis, create a duplicate notebook where you will trim the excess and organize your steps so that you have a flowing, cohesive report.

Tip: Make sure that you keep your reader informed on the steps that you are taking in your investigation. Follow every code cell, or every set of related code cells, with a markdown cell to describe to the reader what was found in the preceding cell(s). Try to make it so that the reader can then understand what they will be seeing in the following cell(s).

Data Cleaning (Replace this with more specific notes!)

In [9]:
```
#Taking a copy from the original data to start cleaning it
df_clean = df.copy()
```

Define

Removing the duplicate rows

Code

In [10]:
```
df_clean.drop_duplicates(inplace=True)
```

Test

In [11]:
```
df_clean.duplicated().sum()
```

Out[11]:
```
0
```

Define

Converting Id column to string and release year column to a category

Code

In [12]:
```
df_clean['id'] = df_clean['id'].astype(str)
df_clean['release_year'] = df_clean['release_year'].astype('category')
```

Test

In [13]:
```
df_clean[['id', 'release_year']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   id            10865 non-null  object
 1   release_year  10865 non-null  category
dtypes: category(1), object(1)
memory usage: 183.3+ KB
```

Define

Converting release date to datetime

Code

In [14]:
```
df_clean ['release_date'] = pd.to_datetime(df_clean['release_date'])
```

Test

In [15]:
```
df_clean['release_date'].dtype
```

Out[15]:
```
dtype('<M8[ns]')
```

Define

Drop unneeded columns of text content

Code

In [16]:
```
df_clean.drop(['homepage', 'imdb_id', 'tagline','overview', 'keywords'], axis=1, inplace=True)
```

Test

In [17]:
```
list(df_clean)
```

Out[17]:
```
['id',
 'popularity',
 'budget',
 'revenue',
 'original_title',
 'cast',
 'director',
 'runtime',
 'genres',
 'production_companies',
 'release_date',
 'vote_count',
 'vote_average',
 'release_year',
 'budget_adj',
 'revenue_adj']
```

In [18]:
```
df_clean.isnull().sum()
```

Out[18]:
```
id                         0
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
director                  44
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

In [19]:
```
#Taking a copy from the cleaned data to start more cleaning to be ready for another set of analysis
df_clean_figures = df_clean.copy()
```

Define

Remving all the null data which does exist in cast, director, genres and production companies columns

Code

In [20]:
```
df_clean_figures = df_clean_figures[~(df_clean_figures.production_companies.isnull())]
```

In [21]:
```
df_clean_figures = df_clean_figures[~(df_clean_figures.director.isnull())]
```

In [22]:
```
df_clean_figures = df_clean_figures[~(df_clean_figures.genres.isnull())]
```

In [23]:
```
df_clean_figures = df_clean_figures[~(df_clean_figures.cast.isnull())]
```

Test

In [24]:
```
df_clean_figures.isnull().sum()
```

Out[24]:
```
id                      0
popularity              0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
runtime                 0
genres                  0
production_companies    0
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
revenue_adj             0
dtype: int64
```

Define

Removing all the movies of 0 budget, revenue, runtime in addition to movies with budget less 6000 and revenue less than 1000

Code

In [25]:
```
df_clean_figures = df_clean_figures[df_clean_figures['budget']!=0]
```

In [26]:
```
df_clean_figures = df_clean_figures[df_clean_figures['revenue']!=0]
```

In [27]:
```
df_clean_figures = df_clean_figures[df_clean_figures['runtime']!=0]
```

In [28]:
```
df_clean_figures =df_clean_figures[df_clean_figures['budget'] > 6000]
```

In [29]:
```
df_clean_figures =df_clean_figures[df_clean_figures['revenue'] > 1000]
```

Test

In [30]:
```
df_clean_figures.query('budget < 6000' or df_clean_figures.query('revenue < 1000' or df_clean_figures.query(
'budget = 0')))
```

Out[30]:

id	popularity	budget	revenue	original_title	cast	director	runtime	genres	production_companies	release_date	vote_count	vote_

Define

Editing this movie budget as it has an extra zero

Code

In [31]:
```
df_clean_figures.at[2244, 'budget'] = 42500000
df_clean_figures.at[2244, 'budget_adj'] = 42500000
```

Test

In [32]:
```
df_clean_figures.loc[2244]
```

Out[32]:
```
id                                                                   46528
popularity                                                         0.25054
budget                                                            42500000
revenue                                                           11087569
original_title                                             The Warrior's Way
cast                    Kate Bosworth|Jang Dong-gun|Geoffrey Rush|Dann...
director                                                       Sngmoo Lee
runtime                                                                100
genres                          Adventure|Fantasy|Action|Western|Thriller
production_companies                             Boram Entertainment Inc.
release_date                                          2010-12-02 00:00:00
vote_count                                                              74
vote_average                                                           6.4
release_year                                                          2010
budget_adj                                                        4.25e+07
revenue_adj                                                    1.10876e+07
Name: 2244, dtype: object
```

Define

Extracting the profit columns from the subtracting the revenue and the budget columns

Code

In [33]:
```
df_clean_figures['profit']= df_clean_figures['revenue'] - df_clean_figures['budget']
```

In [34]:
```
df_clean_figures['profit_adj']= df_clean_figures['revenue_adj'] - df_clean_figures['budget_adj']
```

Test

In [35]:
```
df_clean_figures['profit']
```

Out[35]:
```
0        1363528810
1         228436354
2         185238201
3        1868178225
4        1316249360
            ...    
10822      26236689
10828      10000000
10829       1347000
10835       8000000
10848       6885000
Name: profit, Length: 3772, dtype: int64
```

In [36]:
```
df_clean_figures['profit_adj']
```

Out[36]:
```
0        1.254446e+09
1        2.101614e+08
2        1.704191e+08
3        1.718723e+09
4        1.210949e+09
             ...     
10822    1.762585e+08
10828    6.718015e+07
10829    9.049166e+06
10835    5.374412e+07
10848    4.625353e+07
Name: profit_adj, Length: 3772, dtype: float64
```

In [37]:
```
df_clean_figures.head()
```

Out[37]:

	id	popularity	budget	revenue	original_title	cast	director	runtime	genres	production_c
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller	Universal Stuc Entertainment|
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller	Village Pictures|Ken
2	262500	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller	Entertainment| Films|R
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy	Lucasfilm Productions|
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller	Pictur Film|Medi

Store

Store the final datasets after cleaning them according to the needs of the project.

Code

In [38]:
```
df_clean.to_csv('tmdb-movies-clean.csv', index=False)
```

In [39]:
```
df_clean_figures.to_csv('tmdb-movies-clean-figures.csv', index=False)
```

Test

In [40]:
```
fnmatch.filter(os.listdir('.'), '*.csv')
```

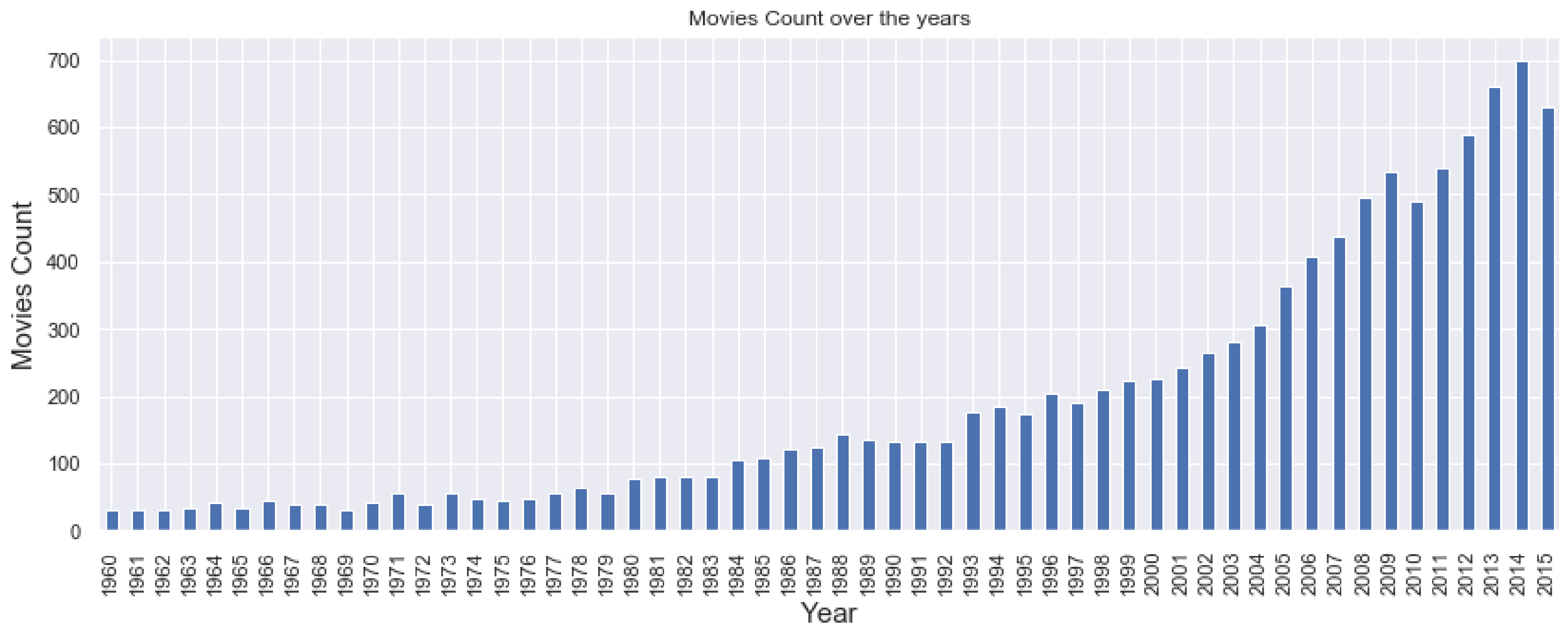
Out[40]:
```
['tmdb-movies-clean-figures.csv', 'tmdb-movies-clean.csv', 'tmdb-movies.csv']
```

Exploratory Data Analysis

df_clean dataset analysis

Q1: What is the distribution of the movies over the years of the dataset?

In [41]:
```
#Movies distribution over the years of the dataset
fig, (ax1) = plt.subplots(1, figsize=(12,5))
df_clean.groupby('release_year')['original_title'].count().plot(kind='bar', ax=ax1, title='Movies Count over
 the years')
ax1.set_xlabel('Year', size=15)
ax1.set_ylabel('Movies Count', size=15)
plt.tight_layout();
```

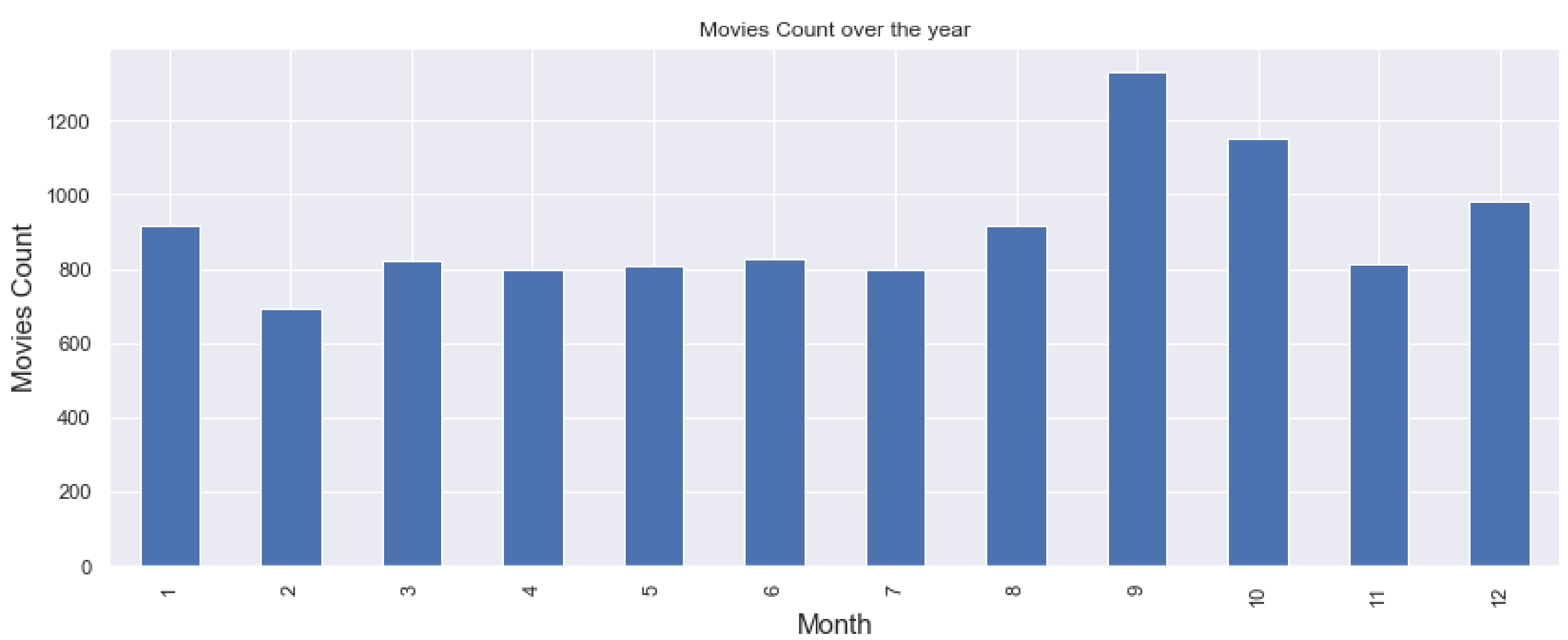


Feedback

It seeems that the movies number increases with years obviously. In addition, the number of movies over the first three decdes nearly belowe 100 movies a year since the sixties till the beginning of eighties. Besides, the number exceed the 100 ones starting from the mid eithties and took less time to reach the double in the late ninties. Then, it increased clearly since 2000s untill it increased dramatically from 2005 to 2015.

Q2: Which are the months that have the highest numbers of movies released over the year?

In [42]:
```
#Movies distribution over the months of the years
fig, (ax1) = plt.subplots(1, figsize=(12,5))
h= df_clean['release_date'].dt.month
df_clean.groupby(h)['original_title'].count().plot(kind='bar', ax=ax1, title='Movies Count over the year')
ax1.set_xlabel('Month', size=15)
ax1.set_ylabel('Movies Count', size=15)
plt.tight_layout();
```



Feedback

The data demonstrates a fluctuation regarding the number of released movies over the year, however, September, October, December and January showcase that they witnessed a high number of released movies. Consequently, these months might be a season to release the movies.

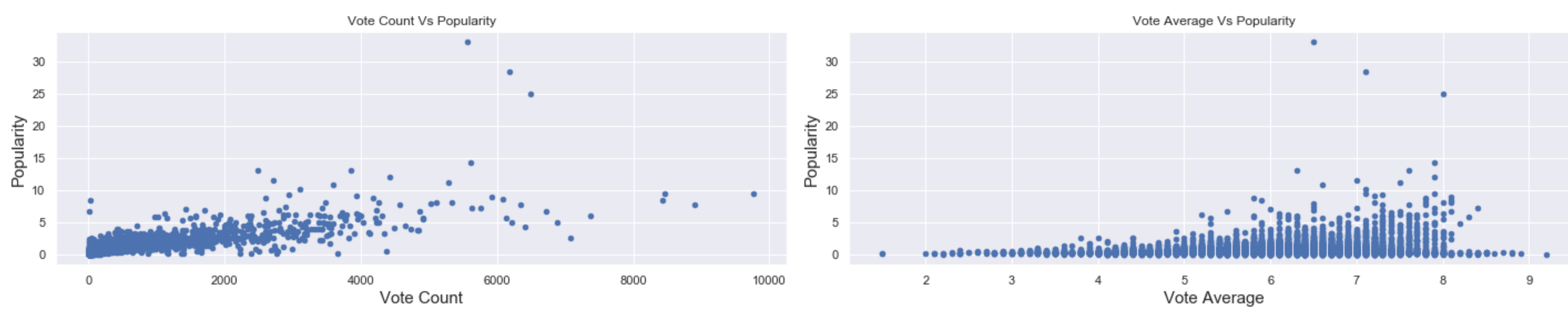
Q3: What does the populairty seem in comparison with both vote average and count?

In [43]:
```
#popularity vs vote count and vote average
fig, (ax1,ax2) = plt.subplots(1,2, figsize=(20,4))
df_clean.plot(x='vote_count',y='popularity', kind='scatter', ax=ax1, title= 'Vote Count Vs Popularity')
ax1.set_xlabel('Vote Count', size=15)
ax1.set_ylabel('Popularity', size=15)

df_clean.plot(x='vote_average',y='popularity', kind='scatter', ax=ax2, title="Vote Average Vs Popularity")
ax2.set_xlabel('Vote Average', size=15)
ax2.set_ylabel('Popularity', size=15)

plt.tight_layout();
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will
have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you r
eally want to specify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will
have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you r
eally want to specify the same RGB or RGBA value for all points.
```

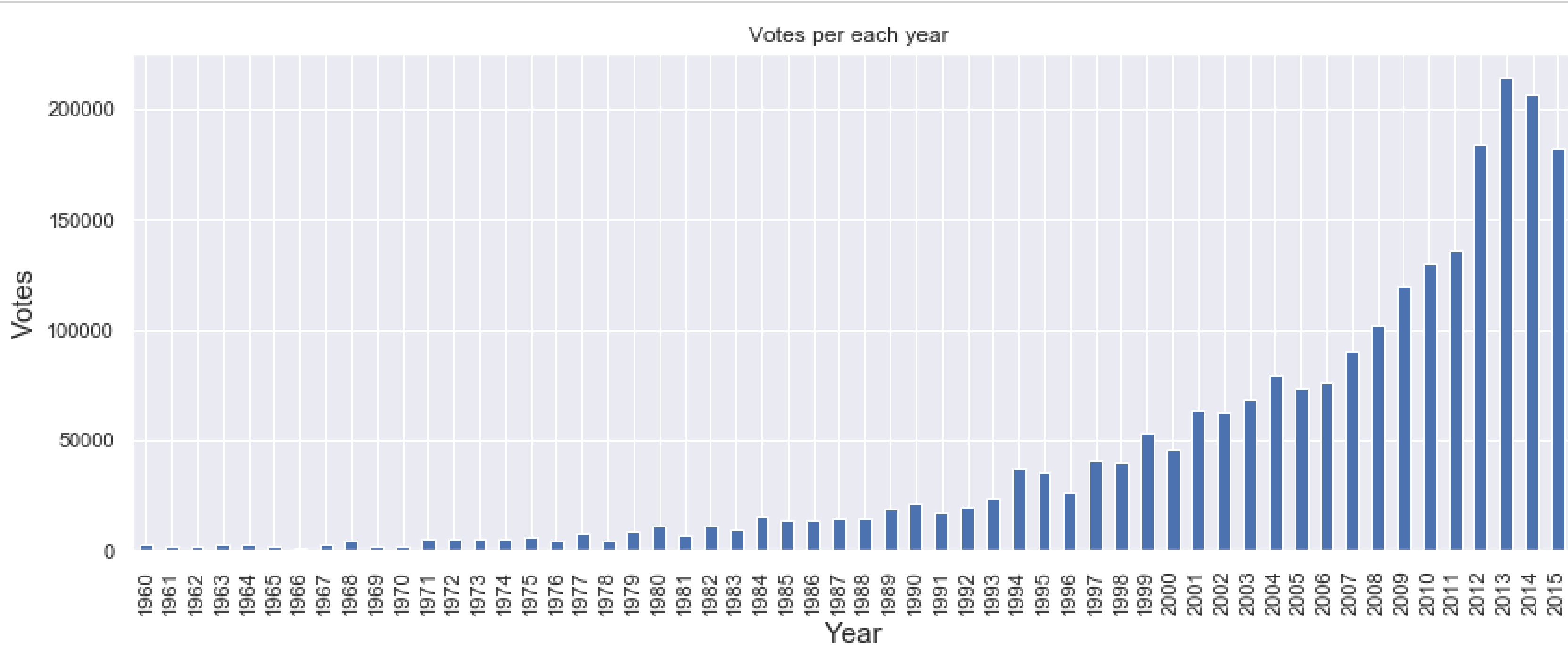


Feedback

A popularity metric is calculated based on a set of factors such as votes, views, being in favorite, watchlist, etc based on the TMDB website. According to the left chart, the votes seem to contribute to the popularity of the movie slightly no matter how large the count is. Besides, the movies with an average score between 6 and 8 are more popular than the rest. Over and above, the majority of movies have less than 10 in popularity. So, it means that the highest values could be outliers.

Q4: In which year do its movies have the highest votes?

In [44]:
```
#which year, its movies have the most vote counts
fig, (ax1) = plt.subplots(1, figsize=(12,5))
df_clean.groupby('release_year')['vote_count'].sum().plot(kind='bar', ax=ax1, title='Votes per each year ')
ax1.set_xlabel('Year', size=15)
ax1.set_ylabel('Votes', size=15)
plt.tight_layout();
```

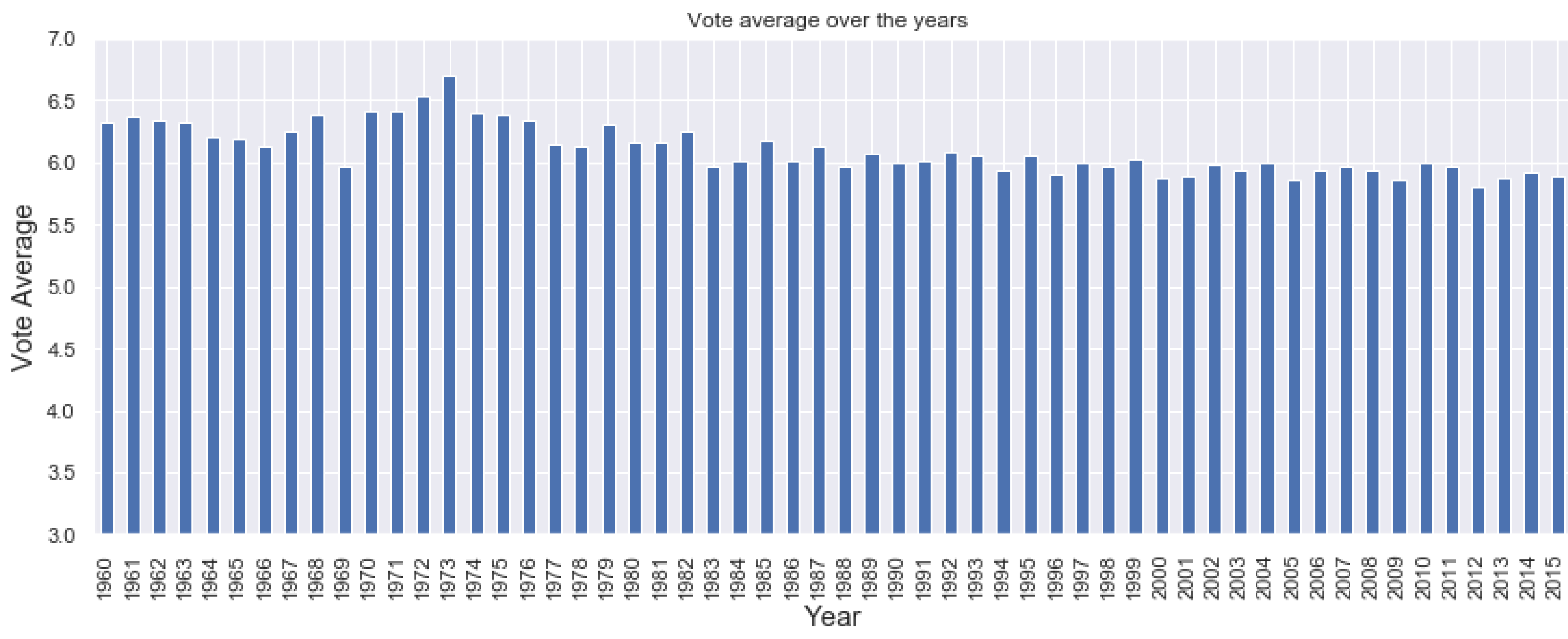


Feedback

It seems that the movies' fans are more fond of the recent movies other than the older ones to give such big amount of votes to the last years' movies and it turns out from other side that the recent movies are more seen than the older ones.

Q5: In which year do its movies have the highest vote average?

In [45]:
```
#which year, its movies have the most highest vote average
fig, (ax1) = plt.subplots(1, figsize=(12,5))
df_clean.groupby('release_year')['vote_average'].mean().plot(kind='bar', ylim=(3,7), ax=ax1, title='Vote aver
age over the years ')
ax1.set_xlabel('Year', size=15)
ax1.set_ylabel('Vote Average', size=15)
plt.tight_layout();
```



Feedback

In contract with the previous chart, the older movies got higher scoring average than the recent ones and it could be in this way as there are less amount of votes. But, it doesn't overlook how much good such old movies.

Q6: Do the movies with the highest votes having the highest vote average and vice versa?

In [46]:
```
#the highest vote counts
df_clean[['original_title', 'vote_count', 'vote_average']].sort_values(ascending=False, by = 'vote_count').il
oc[:10,0:]
```

Out[46]:

	original_title	vote_count	vote_average
1919	Inception	9767	7.9
4361	The Avengers	8903	7.3
1386	Avatar	8458	7.1
2875	The Dark Knight	8432	8.1
4364	Django Unchained	7375	7.7
4382	The Hunger Games	7080	6.7
5425	Iron Man 3	6882	6.9
4363	The Dark Knight Rises	6723	7.5
629	Interstellar	6498	8.0
4367	The Hobbit: An Unexpected Journey	6417	6.9

In [47]:
```
#the highest vote average
df_clean[['original_title', 'vote_count', 'vote_average']].sort_values(ascending=False, by = 'vote_average').
iloc[:10,0:]
```

Out[47]:

	original_title	vote_count	vote_average
3894	The Story of Film: An Odyssey	14	9.2
538	The Mask You Live In	11	8.9
1200	Black Mirror: White Christmas	41	8.8
2269	Life Cycles	27	8.8
6911	Pink Floyd: Pulse	23	8.7
2401	Opeth: In Live Concert At The Royal Albert Hall	10	8.6
3690	The Art of Flight	60	8.5
8411	Queen - Rock Montreal	14	8.5
8221	A Personal Journey with Martin Scorsese Throug...	11	8.5
8839	Dave Chappelle: Killin' Them Softly	17	8.5

Feedback

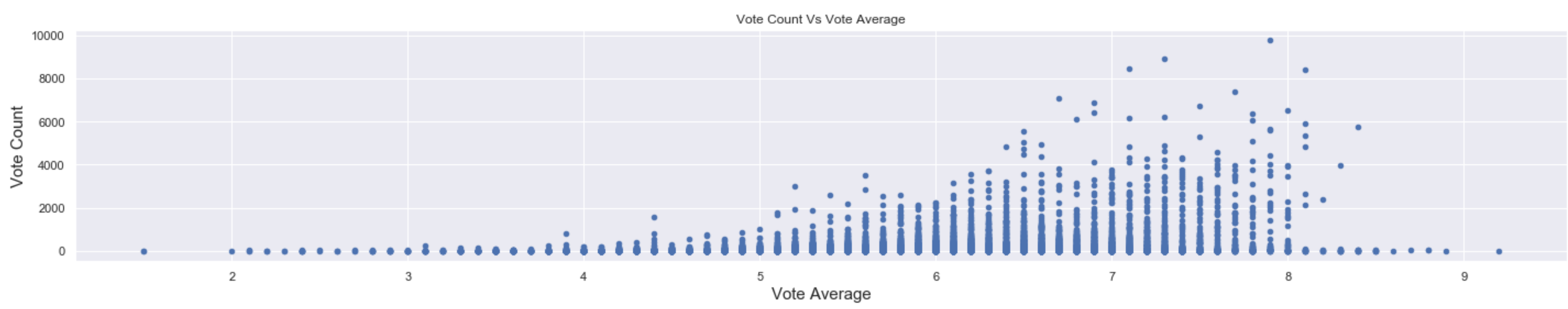
Movies with the highest vote average have very low vote counts, unlike the movies with the highest vote counts which have a fine score average. So, the vote average of the movies with the highest vote counts is more than authentic due to such a significant amount of votes which may give an indication of how such movies really look like to the movies' fans.

Q7: Does the highest vote average mean high vote count?

In [48]:
```
fig, (ax1) = plt.subplots(1, figsize=(20,4))
df_clean.plot(x='vote_average',y='vote_count', kind='scatter', ax=ax1, title= 'Vote Count Vs Vote Average')
ax1.set_xlabel('Vote Average', size=15)
ax1.set_ylabel('Vote Count', size=15)


plt.tight_layout();
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will
have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you r
eally want to specify the same RGB or RGBA value for all points.
```



Feedback

The movies' average vote increases with the vote counts as there is a gradual increase starting from average score 5 until we reach average score 8. While the movies with average score more than 8 have low amount of votes.

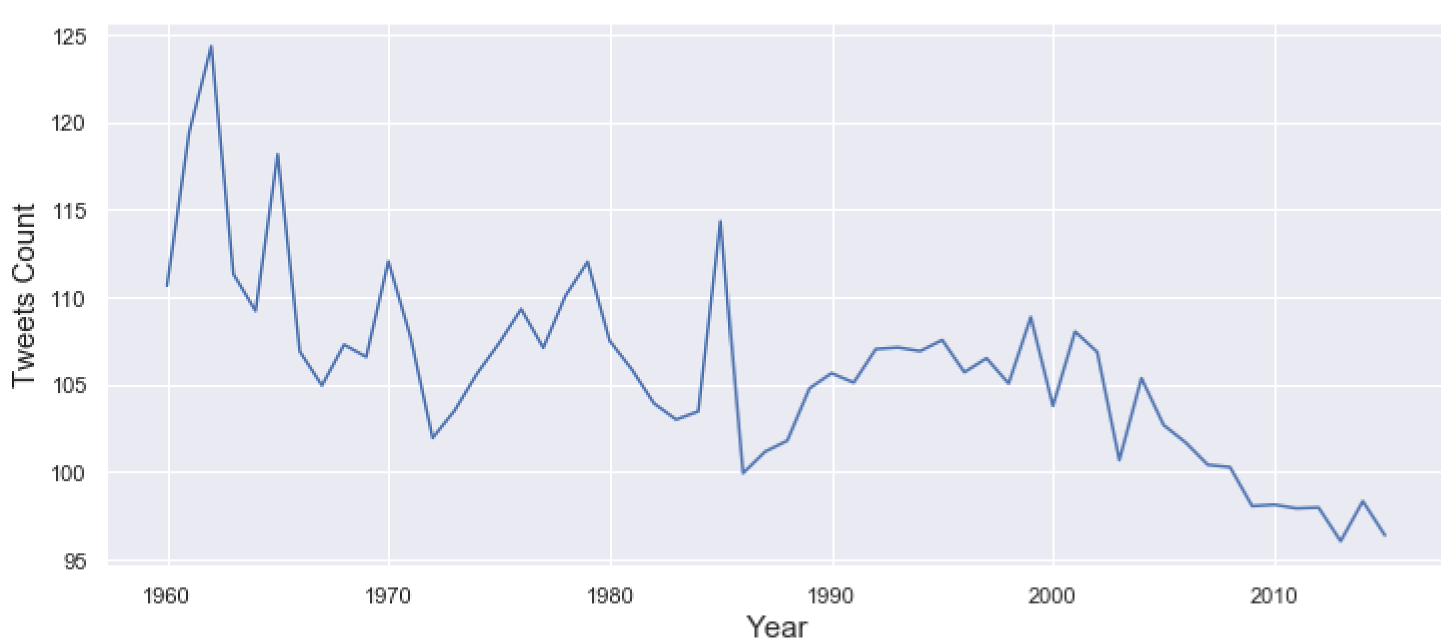
Q8: Did the movies runtime change over the years?

In [49]:
```
fig, ax1 = plt.subplots(1, figsize=(12,5))

runtime = df_clean.groupby('release_year')['runtime'].mean()

plt.plot(runtime)
plt.xlabel('Year', size=15)
plt.ylabel('Tweets Count', size=15)

plt.show()
```



Feedback

It seems the movies' runtime really decreases with years and it might be due to the obvious emergence of the various kinds of movies recently such as documentary, short movies, etc which has less runtime.

Q9: Who has directed the highest number of movies?

In [50]:
```
df_clean['director'].value_counts().iloc[:10, ]
```

Out[50]:
```
Woody Allen          45
Clint Eastwood       34
Steven Spielberg     29
Martin Scorsese      29
Ridley Scott         23
Steven Soderbergh    22
Ron Howard           22
Joel Schumacher      21
Brian De Palma       20
Wes Craven           19
Name: director, dtype: int64
```

Q10: What are the most popular movies?

In [51]:
```
df_clean[['original_title', 'popularity', 'release_year']].sort_values(ascending = False, by = 'popularity').
iloc[:10,]
```

Out[51]:

	original_title	popularity	release_year
0	Jurassic World	32.985763	2015
1	Mad Max: Fury Road	28.419936	2015
629	Interstellar	24.949134	2014
630	Guardians of the Galaxy	14.311205	2014
2	Insurgent	13.112507	2015
631	Captain America: The Winter Soldier	12.971027	2014
1329	Star Wars	12.037933	1977
632	John Wick	11.422751	2014
3	Star Wars: The Force Awakens	11.173104	2015
633	The Hunger Games: Mockingjay - Part 1	10.739009	2014

df_genres dataset analysis

Q1: What are the most popular genres across the dataset?

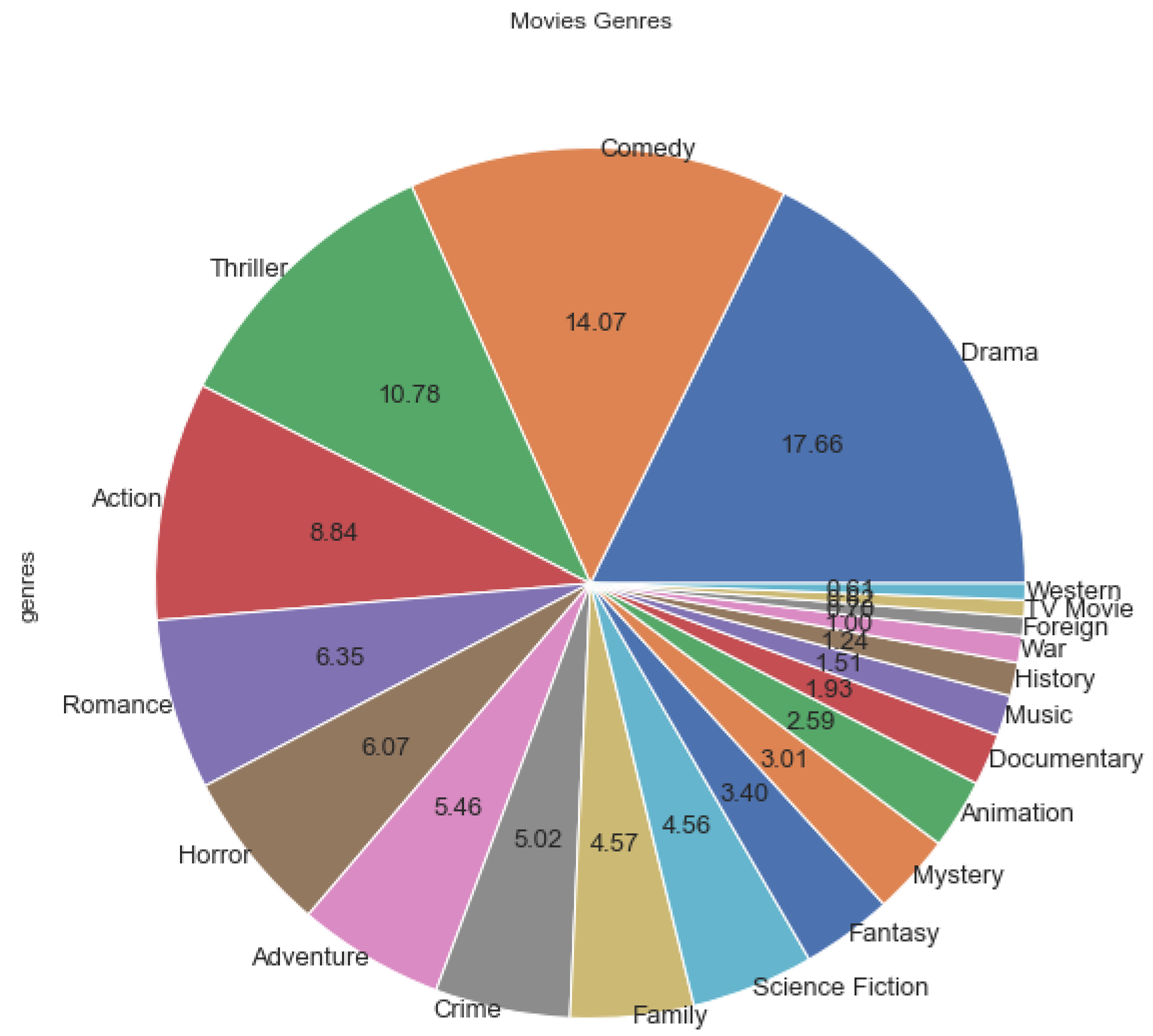
In [52]:
```
#copying from df_clean to split the genres to find the movies' genres over the years
#Approach to follow from https://programmer.ink/think/pandas-how-do-i-split-text-in-a-column-into-multiple-li
nes-python.html
df_genres = df_clean.copy()
```

In [53]:
```
df_genres = df_genres['genres'].str.split('|', expand=True).stack()
```

In [54]:
```
df_genres = df_genres.reset_index(level=0, drop=True)
```

In [55]:
```
df_genres = df_genres.rename('genres')
```

In [56]:
```
df_genres.value_counts().plot(kind= 'pie', autopct='%.2f', fontsize=13, figsize=(10, 10),
                                                title="Movies Genres",labeldistance=1);
```



Feedback

Drama comes first as a genre, for the movies included in the dataset, then comedy and third comes thriller. These three genres only make 40% of the total genres found in the dataset.

df_cast dataset analysis

Q1: Who has participated the most in the movies across the dataset?

In [57]:
```
#copying from df_clean to split the cast to find most participating actor in these movies
df_cast = df_clean.copy()
```

In [58]:
```
df_cast = df_cast['cast'].str.split('|', expand=True).stack()
```

In [59]:
```
df_cast = df_cast.reset_index(level=0, drop=True)
```

In [60]:
```
df_cast = df_cast.rename('cast')
```

In [61]:
```
df_cast.value_counts().iloc[:10, ]
```

Out[61]:
```
Robert De Niro       72
Samuel L. Jackson    71
Bruce Willis         62
Nicolas Cage         61
Michael Caine        53
Robin Williams       51
John Cusack          50
Morgan Freeman       49
John Goodman         49
Liam Neeson          48
Name: cast, dtype: int64
```

df_production dataset analysis

Q1: Which companies produced the highest number of movies?

In [62]:
```
#copying from df_clean to split the cast to find most participating actor in these movies
df_production = df_clean.copy()
```

In [63]:
```
df_production = df_production['production_companies'].str.split('|', expand=True).stack()
```

In [64]:
```
df_production = df_production.reset_index(level=0, drop=True)
```

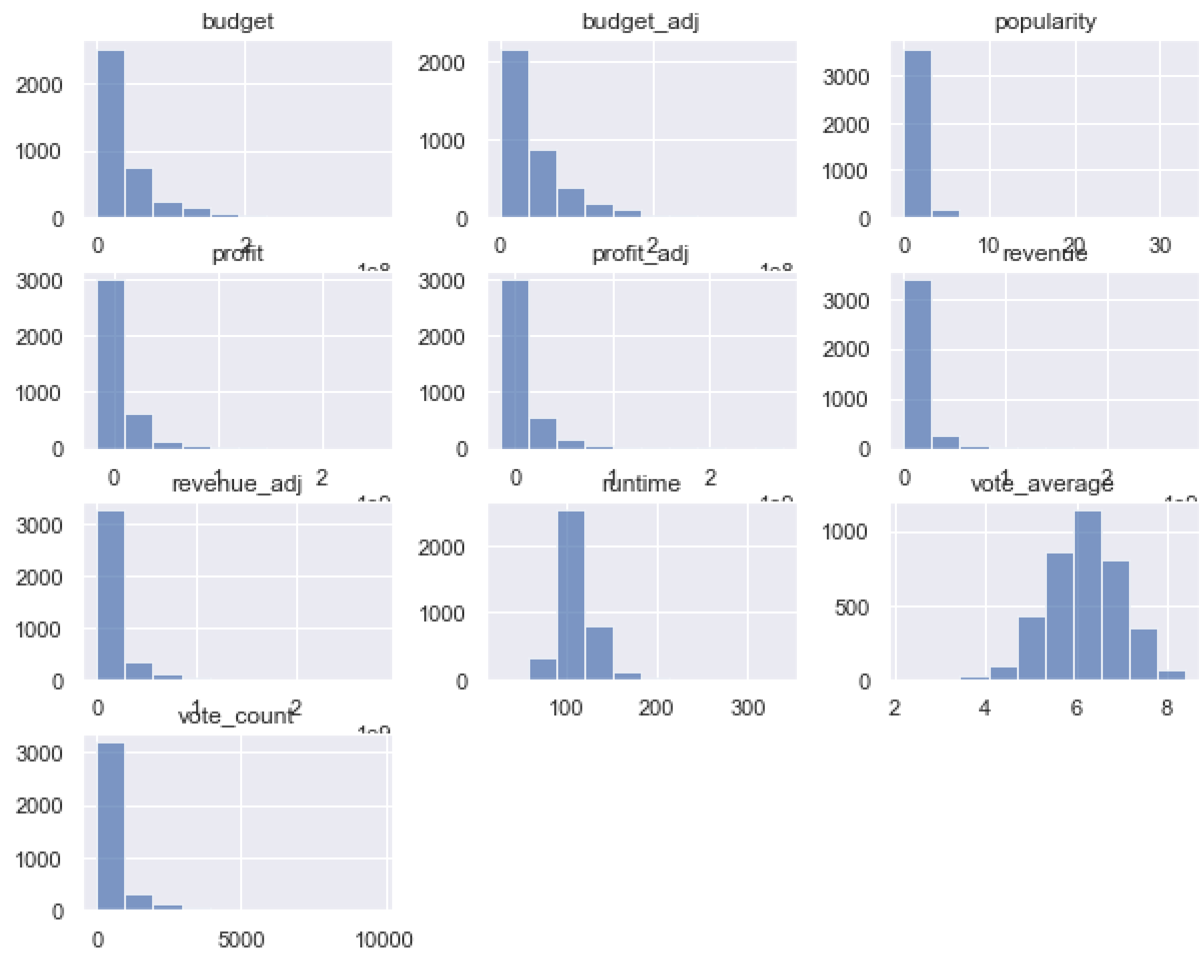
In [65]:
```
df_production = df_production.rename('production_companies')
```

In [66]:
```
df_production.value_counts().iloc[:10, ]
```

Out[66]:
```
Universal Pictures                        522
Warner Bros.                              509
Paramount Pictures                        431
Twentieth Century Fox Film Corporation    282
Columbia Pictures                         272
New Line Cinema                           219
Metro-Goldwyn-Mayer (MGM)                 218
Walt Disney Pictures                      214
Touchstone Pictures                       178
Columbia Pictures Corporation             160
Name: production_companies, dtype: int64
```

df_clean_figures dataset analysis

In [67]:
```
#A glimpse how the data distribution seem:
df_clean_figures.hist(figsize = (10,8), alpha=0.7);
```



In [68]:
```
df_clean_figures.head()
```

Out[68]:

	id	popularity	budget	revenue	original_title	cast	director	runtime	genres	production_c
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller	Universal Stuc Entertainment|
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller	Village Pictures|Ken
2	262500	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller	Entertainment| Films|R
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy	Lucasfilm Productions|
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller	Pictur Film|Medi

Q1: What are the biggest money-losing and most profitable movies?

In [69]:
```
df_clean_figures[['original_title', 'profit','profit_adj', 'release_year']].sort_values(ascending=False, by=
'profit').iloc[:10,:]
```

Out[69]:

	original_title	profit	profit_adj	release_year
1386	Avatar	2544505847	2.586237e+09	2009
3	Star Wars: The Force Awakens	1868178225	1.718723e+09	2015
5231	Titanic	1645034188	2.234714e+09	1997
0	Jurassic World	1363528810	1.254446e+09	2015
4	Furious 7	1316249360	1.210949e+09	2015
4361	The Avengers	1299557910	1.234248e+09	2012
3374	Harry Potter and the Deathly Hallows: Part 2	1202817822	1.166009e+09	2011
14	Avengers: Age of Ultron	1125035767	1.035032e+09	2015
5422	Frozen	1124219009	1.052306e+09	2013
8094	The Net	1084279658	1.551568e+09	1995

In [70]:
```
df_clean_figures[['original_title', 'profit','profit_adj', 'release_year']].sort_values(ascending=True, by='p
rofit').iloc[:10,:]
```

Out[70]:

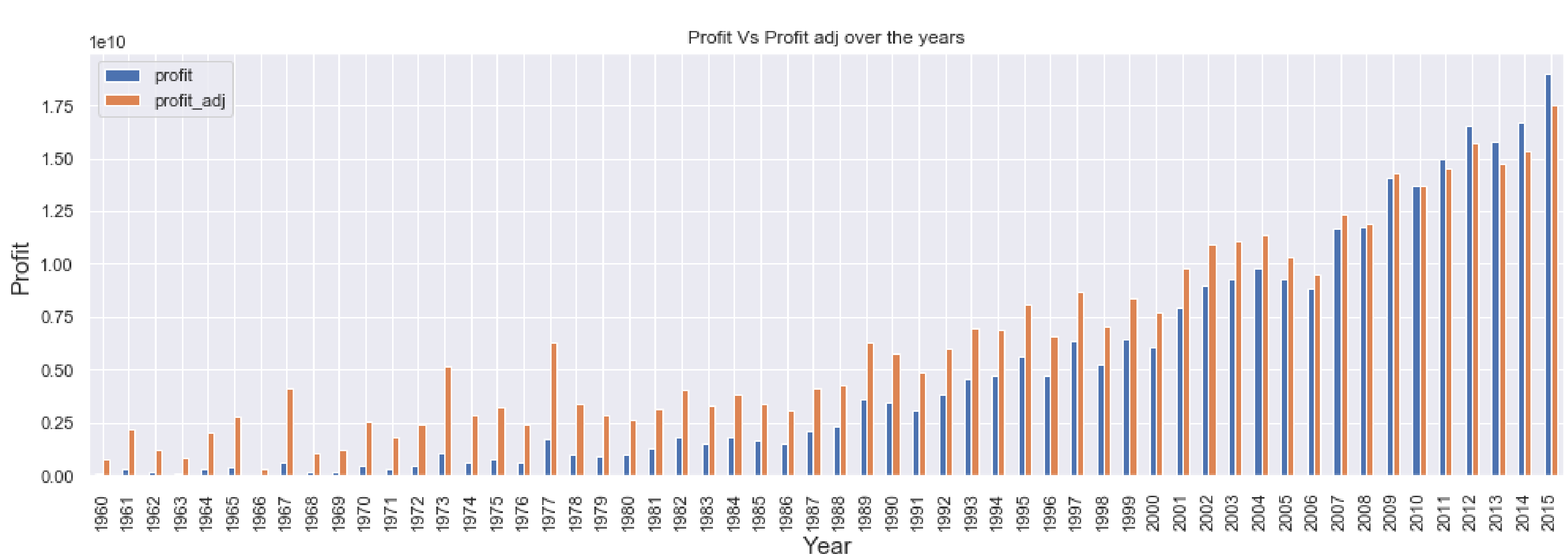
	original_title	profit	profit_adj	release_year
5508	The Lone Ranger	-165710090	-1.551102e+08	2013
7031	The Alamo	-119180039	-1.375868e+08	2004
3484	Mars Needs Moms	-111007242	-1.076102e+08	2011
2435	The 13th Warrior	-98301101	-1.286813e+08	1999
4078	The Adventures of Pluto Nash	-92896027	-1.126143e+08	2002
6590	Flushed Away	-84540684	-9.144505e+07	2006
2915	Australia	-80445998	-8.147463e+07	2008
8102	Cutthroat Island	-79482678	-1.137371e+08	1995
8765	Supernova	-75171919	-9.518961e+07	2000
6309	A Sound of Thunder	-74010360	-8.263725e+07	2005

Q2: Does the inflation have that remarkable impact on movies profit over the years?

In [71]:
```
fig, (ax1) = plt.subplots(1, figsize=(14,5))
df_clean_figures.groupby('release_year')['profit', 'profit_adj'].sum().plot(kind='bar', ax=ax1, title='Profit
Vs Profit adj over the years')
ax1.set_xlabel('Year', size=15)
ax1.set_ylabel('Profit', size=15)

plt.tight_layout();
```

```
C:\Users\Ahmed Nasser\anaconda3\lib\site-packages\ipykernel_launcher.py:2: FutureWarning: Indexing with multi
ple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
```



Feedback

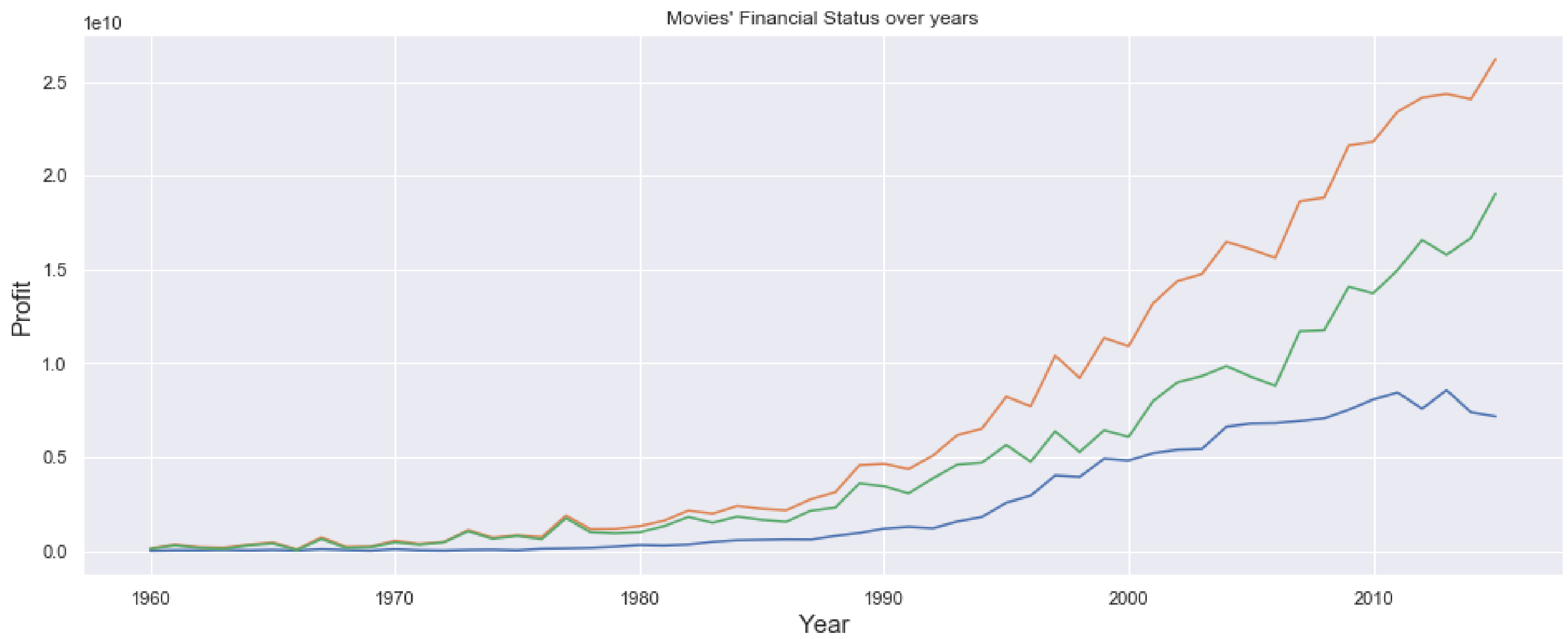
As expected that the older movies' profit seem to be good in terms of 2010 dollars besides elucidating really remarkable profit across the seventies.

Q3: How would the budgets, revenues and profits change over the years?

In [72]:
```
fig, (ax1) = plt.subplots(1, figsize=(16,6))

monetary = df_clean_figures.groupby('release_year')['budget','revenue','profit'].sum()
plt.plot(monetary)
plt.xlabel('Year', size=15)
plt.ylabel('Profit', size=15)
plt.title('Movies\' Financial Status over years')
plt.show()
```

```
C:\Users\Ahmed Nasser\anaconda3\lib\site-packages\ipykernel_launcher.py:3: FutureWarning: Indexing with multi
ple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```

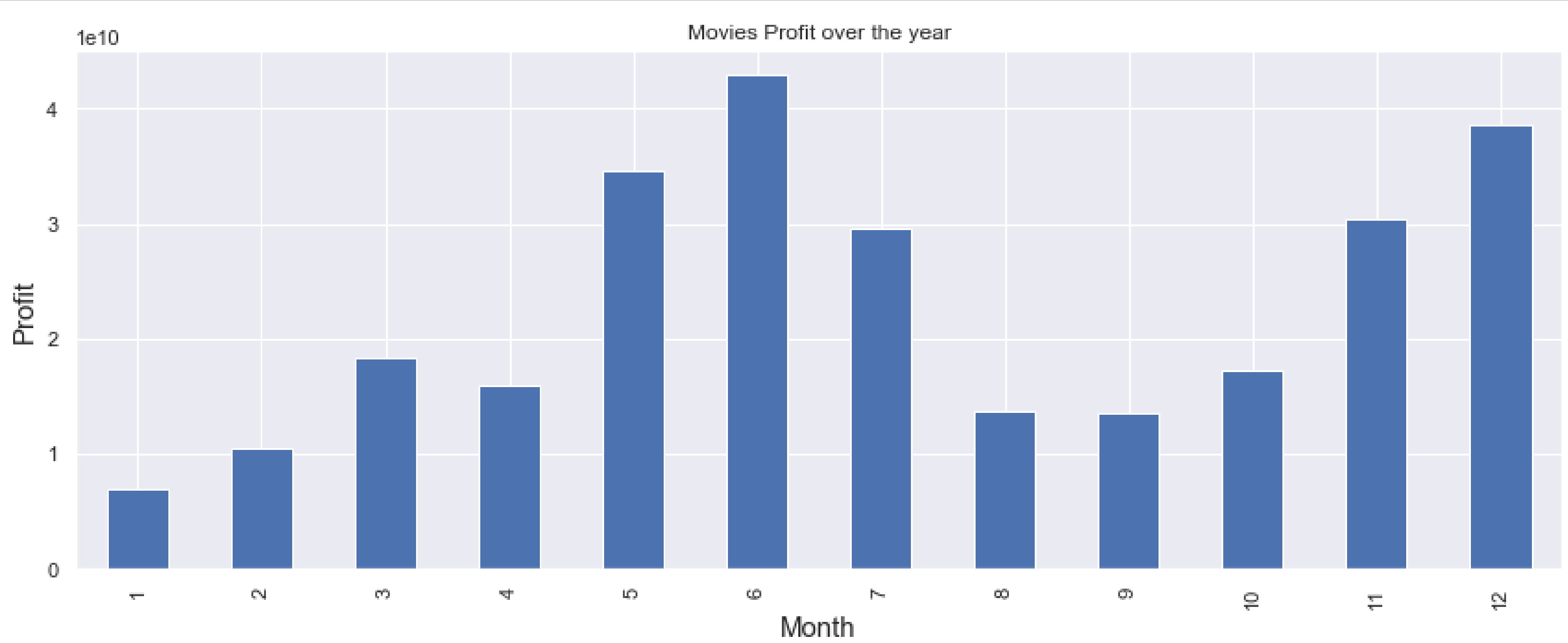


Feedback

Such a graph shows a very increase in movies' budget with years especially starting from the 2000s. In addition, there is a kind of rapprochement between the budget and revenue in the sixties, seventies and eighties till almost the nineties. Then, both the revenue and budget had increased very remarkably, however, the difference between them got bigger unlike the previous decades.

Q4: Which months witness the highest profit over the year?

In [73]:
```
fig, (ax1) = plt.subplots(1, figsize=(12,5))
h= df_clean_figures['release_date'].dt.month
df_clean_figures.groupby(h)['profit'].sum().plot(kind='bar', ax=ax1, title='Movies Profit over the year')
ax1.set_xlabel('Month', size=15)
ax1.set_ylabel('Profit', size=15)
plt.tight_layout();
```



Feedback

As per the graph, it demonstrates that the highest profit across five months a year and they could be the months where a lot of people have a plenty of time to go to the cinemas. So, it can be taken into consideration to release a movie in such times to gurantee a good turnout

Q5: Which directors do whose movies make the highest and least profit?

In [74]:
```
#the directors whose movies made the highest profit
df_clean_figures.groupby('director')['profit'].sum().sort_values(ascending= False).iloc[:10, ]
```

Out[74]:
```
director
Steven Spielberg     7467063772
Peter Jackson        5197244659
James Cameron        5081994863
Michael Bay          3557208171
David Yates          3379295625
Christopher Nolan    3162548502
Chris Columbus       3116631503
George Lucas         2955996893
Robert Zemeckis      2846690869
J.J. Abrams          2839169916
Name: profit, dtype: int64
```

In [75]:
```
#the directors whose movies made the least profit
df_clean_figures.groupby('director')['profit'].sum().sort_values(ascending= True).iloc[:10, ]
```

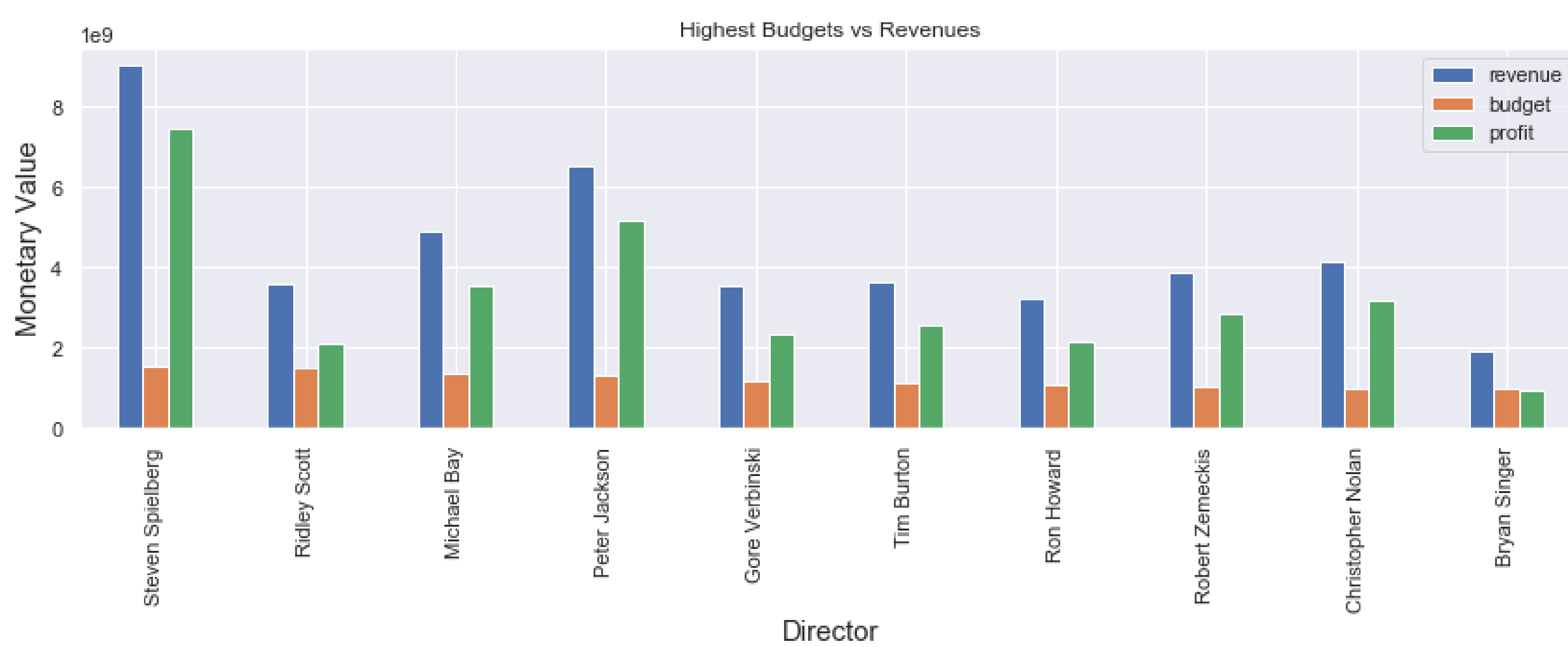
Out[75]:
```
director
David Bowers|Sam Fell                -84540684
Walter Hill|Jack Sholder             -75171919
Andrei Konchalovsky                  -74885029
Joby Harold                          -71626175
Rod Lurie                            -70346150
Simon Wells                          -67278066
Oliver Hirschbiegel|James McTeigue   -64928486
Lawrence Kasanoff                    -64926294
John Bruno                           -60989310
Steven Zaillian                      -58846202
Name: profit, dtype: int64
```

Q6: Do the directors that use the highest budgets get the highest revenue in return?

In [76]:
```
fig, (ax1) = plt.subplots(1, figsize=(12,5))

df_clean_figures.groupby('director')['revenue','budget', 'profit'].sum().sort_values(ascending= False, by='budget').iloc[:10,:].plot(kind='bar',ax=ax1, title='Highest Budgets vs Revenues')
ax1.set_xlabel('Director', size=15)
ax1.set_ylabel('Monetary Value', size=15)
plt.tight_layout();
```

```
C:\Users\Ahmed Nasser\anaconda3\lib\site-packages\ipykernel_launcher.py:3: FutureWarning: Indexing with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```



Feedback

It seems that using high budgets would be a favor as it gets a high revenue in return as mentioned

Q7: Which production companies making the highest revenue and profit?

In [77]:
```
df_clean_figures.groupby('production_companies')['profit'].sum().sort_values(ascending= False).iloc[:10, ]
```

Out[77]:
```
production_companies
Walt Disney Pictures|Pixar Animation Studios
5791558520
Paramount Pictures
5126632638
DreamWorks Animation
4689741096
Marvel Studios
4657808966
Blue Sky Studios|Twentieth Century Fox Animation
3305820202
Columbia Pictures
3232619748
Universal Pictures|Illumination Entertainment
2851800871
Ingenious Film Partners|Twentieth Century Fox Film Corporation|Dune Entertainment|Lightstorm Entertainment
2544505847
Walt Disney Pictures|Walt Disney Animation Studios
2438726837
Eon Productions
2258131033
Name: profit, dtype: int64
```

In [78]:
```
df_clean_figures.groupby('production_companies')['revenue'].sum().sort_values(ascending= False).iloc[:10, ]
```

Out[78]:
```
production_companies
Walt Disney Pictures|Pixar Animation Studios          7648558520
Paramount Pictures                                    7040937553
DreamWorks Animation                                  6676741096
Marvel Studios                                        6027808966
Columbia Pictures                                     4621239748
Blue Sky Studios|Twentieth Century Fox Animation      3938820202
Walt Disney Pictures|Walt Disney Animation Studios    3498726837
Universal Pictures|Illumination Entertainment         3203800871
Universal Pictures                                    3139395421
Eon Productions                                       3126131033
Name: revenue, dtype: int64
```

An overview of Data Assessing and wrangling steps

In beginning, after assessing the data, there have been 10866 rows and 21 columns of various data and dtypes. Besides, there are null values in 9 columns, one duplicate row and the monetary-related columns have very low values which don't make any sense. Moreover, there are some other columns of only text content with no benefit to working on and some other columns to be transformed into a specific dtype to use.

So, a first copy has been made to perform such operations starting from dropping the null values, unneeded columns and transforming some columns.

Then, a second copy has been made to perform extra operations such as dropping all the null values and all the budget and revenue columns of zero values. Then, after some research about the movies with a very low budget and revenue values, they have been dropped as they represent fake data. Over and above, a profit column has been created by subtracting the revenue and budget columns to find some trends regarding profitability.

Conclusions

Speaking of the data analysis, here are the findings:

Popularity ranges from 0 to 32 approximately. Votes range from 1.5 to 9.2 (on a scale-out of 10), with an average of 5.97. The budget ranges from approx. 0 - 425 million (average 14.6 million) in USD dollars. Revenue (USD) ranges from approx. 0 - 2.78 billion (average 39.8 million) in USD dollars. Release years range from 1960 - 2015.

-The movie's release increases with time clearly where it was below 100 movies in the first three decades. Then, it broke the 100s barrier from the mid-eighties and took less time to reach the highest number in the late nineties. Then, it a dramatic upsurge in the 2000s especially the last years.

-These months "September, October, December, and January" have a high number of movies released compared to the others across the year.

-There is a slight positive correlation between the popularity and both vote average and vote count.

-The most recent years' movies have the highest vote count while the older years' movies have the highest vote average.

-The highest vote average movies have very low vote count while the highest vote count movies have fine to considerable vote average.

-There is a positive correlation between vote average and vote count to an average score of 8, then there isn't after that.

-Movies runtime average changes drastically over time from nearly 120 minutes to less than 100 minutes.

-Woody Allen has more than 40 movies on the list and Clint Eastwood has more than 30 movies.

-9 out of the top 10 popular movies are last decades movies.

-Drama, comedy, and thriller are the top three genres across the dataset with nearly 40% of the total genres.

-Robert De Niro and Samuel L. Jackson have starred in more than 70 movies on the list.

-Universal Pictures, Warner Bros, Paramount Pictures have the highest number of produced movies over 400 movies.

-Most of the top ten of the biggest money-losing and most profitable movies are the last two decades' movies while the rest are the late nineties.

-Inflation has a very obvious impact, especially when the profit of the older decades' movies got translated into the 2010 USD dollar.

-Budget, revenue and profit have been increased dramatically with time. Besides, there is a considerable profit over the last decades in comparison with older ones.

-May, June, July, November, and December witnessed the movies with the highest profit.

-Steven Spielberg, Peter Jackson, and James Cameron are top directors whose movies make a lot of profit of more than 5 billion dollars.

-Directors who spent a lot of money "highest movie budgets" got a very high revenue in return.

-Walt Disney Pictures, Pixar Animation Studios, and Paramount Pictures made the highest profit and revenue over 7 and 5 billion dollars respectively.

In [ ]:

```

```