

investigate-a-dataset-movie

March 24, 2019

1 Project: Investigate a Dataset The Movie

1.1 Table of Contents

Introduction

Question Researched

Data Wrangling

Exploratory Data Analysis

General Question

Associate Question

Trend Question

Conclusions

Introduction

In this project I use Movie Data. This dataset contains information about 10,000 movies collected from The Movie Database (TMDb). Contains data such as title, cast, director, runtime, budget, revenue, release year etc. - Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|) characters. - 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.

Research Question Questions in the projects are as follows:

1.1.1 Part 1: General

Which movie earns the highest and lowest profit?

Which movie have the highest and lowest revenue?

Which movie have the highest and lowest budget?

Which movie have the longest and shortest runtime?

How much movie released year by year?

How distribution of profit in different popularity levels in recent ten years?

How distribution of profit in different vote average levels in recent ten years?

1.1.2 Part 2: Find Associate Variable Movie Genre with Movie Metric

What movie genre that associated with high popularity?

What movie genre that associated with high revenue?

What movie genre that associated with high vote average?

What movie genre that associated with profit?

1.1.3 Part 3: Find Some Trend

What is the trend of the genre every 10 years

Data Wrangling

In this section I will load the data and print the example of data so I know the data sample value

```
In [1]: # import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
from collections import Counter
%matplotlib inline
```

```
In [2]: # Load data
df = pd.read_csv("tmdb-movies.csv")
# Print first row to see the example of data
df.head(1)
```

```
Out[2]:
```

	id	imdb_id	popularity	budget	revenue	original_title	\
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	
						cast	\
0	Chris Pratt	Bryce Dallas Howard	Irrfan Khan	Vi...			
		homepage	director	tagline	...	\	
0	http://www.jurassicworld.com/	Colin Trevorrow	The park is open.	...			
		overview	runtime	\			
0	Twenty-two years after the events of Jurassic ...	124					
		genres	\				
0	Action Adventure Science Fiction Thriller						
		production_companies	release_date	vote_count	\		
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	5562				
	vote_average	release_year	budget_adj	revenue_adj			
0	6.5	2015	1.379999e+08	1.392446e+09			

[1 rows x 21 columns]

```
In [3]: # find shape of data
r,c = df.shape
print("Dataset Movie contains %d rows and %d columns" % (r,c))
```

Dataset Movie contains 10866 rows and 21 columns

1.1.4 Data Cleaning

In this section I will find column that unnecessary for this research, find duplicate data, find missing data, and change some format data that can make this research easier.

1. Find Missing Value and Unnecessary Columns

```
In [4]: # print the information about count of not null data value and data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                10866 non-null int64
imdb_id           10856 non-null object
popularity        10866 non-null float64
budget            10866 non-null int64
revenue           10866 non-null int64
original_title    10866 non-null object
cast              10790 non-null object
homepage          2936 non-null object
director          10822 non-null object
tagline           8042 non-null object
keywords          9373 non-null object
overview          10862 non-null object
runtime           10866 non-null int64
genres            10843 non-null object
production_companies 9836 non-null object
release_date      10866 non-null object
vote_count        10866 non-null int64
vote_average      10866 non-null float64
release_year      10866 non-null int64
budget_adj        10866 non-null float64
revenue_adj       10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

From information above we know that column which missing values are: 1. imdb_id (object) 2. homepage (object) 3. tagline (object) 4. director (object) 5. overview (object) 6. keywords (object) 7. production_companies (object) 8. cast (object) 9. genres (object)

I don't need some columns such as imdb_id, homepage, tagline, and overview. So I will delete them.

1.1 Delete Unnecessary Columns

```
In [5]: # list of unnecessary columns
col = ['imdb_id', 'homepage', 'tagline', 'overview']
```

```
# delete unnecessary columns
df.drop(col,axis=1,inplace=True)
```

```
In [6]: # print statistical summary from numeric columns to find if any weird value
df.describe()
```

```
Out [6]:
```

	id	popularity	budget	revenue	runtime \
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

From summary above we found some weird data about budget, revenue, and runtime because the minimal value is zero. Lets output 1 sample of row that have zero number to check that is really zero or just another missing value.

```
In [7]: # print sample that have budget zero to know is this real zero or not
df.query('budget == 0').head(1)
```

```
Out [7]:
```

	id	popularity	budget	revenue	original_title \
30	280996	3.927333	0	29355203	Mr. Holmes

	cast	director \
30	Ian McKellen Milo Parker Laura Linney Hattie M...	Bill Condon

	keywords	runtime	genres \
30	london detective sherlock holmes	103	Mystery Drama

	production_companies	release_date \
30	BBC Films See-Saw Films FilmNation Entertainme...	6/19/15

	vote_count	vote_average	release_year	budget_adj	revenue_adj
30	425	6.4	2015	0.0	2.700677e+07

I found from google that Mr.Holmes budget is 10 million USD, so in that data I assumed zero number is mean missing value. Because of that I will change zero to NA so we can know there is some missing value from function 'info'

1.2 Change Zero Value to NA

```
In [8]: # change zero number to NA
        zero_col = ['budget', 'revenue', 'runtime','budget_adj', 'revenue_adj']

        # replace all zero value from to NAN in the list
        df[zero_col] = df[zero_col].replace(0, np.NAN)
```

```
In [9]: # see the update info
        df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 17 columns):
id                10866 non-null int64
popularity        10866 non-null float64
budget            5170 non-null float64
revenue           4850 non-null float64
original_title    10866 non-null object
cast              10790 non-null object
director          10822 non-null object
keywords          9373 non-null object
runtime           10835 non-null float64
genres            10843 non-null object
production_companies 9836 non-null object
release_date      10866 non-null object
vote_count        10866 non-null int64
vote_average      10866 non-null float64
release_year      10866 non-null int64
budget_adj        5170 non-null float64
revenue_adj       4850 non-null float64
dtypes: float64(7), int64(3), object(7)
memory usage: 1.4+ MB
```

From updated info we find some columns with small missing value ($\geq 95\%$ from all row or ≥ 10322 data) they are cast, director, runtime, and genres. I choose 95% as threshold because I didn't want to delete too much data

1.3 Remove Missing Value

```
In [10]: # list the column that we want to remove missing value
         col_mv = ['cast', 'director', 'runtime', 'genres']

         # remove missing value
```

```

df.dropna(subset=col_mv, inplace=True)

# see the update information
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10704 entries, 0 to 10865
Data columns (total 17 columns):
id                10704 non-null int64
popularity        10704 non-null float64
budget            5151 non-null float64
revenue           4844 non-null float64
original_title    10704 non-null object
cast              10704 non-null object
director          10704 non-null object
keywords          9294 non-null object
runtime           10704 non-null float64
genres            10704 non-null object
production_companies 9760 non-null object
release_date      10704 non-null object
vote_count        10704 non-null int64
vote_average      10704 non-null float64
release_year      10704 non-null int64
budget_adj        5151 non-null float64
revenue_adj       4844 non-null float64
dtypes: float64(7), int64(3), object(7)
memory usage: 1.5+ MB

```

2. Drop Duplicated

```

In [11]: # drop duplicate row in data
df.drop_duplicates(inplace=True)

# see the update info
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10703 entries, 0 to 10865
Data columns (total 17 columns):
id                10703 non-null int64
popularity        10703 non-null float64
budget            5150 non-null float64
revenue           4843 non-null float64
original_title    10703 non-null object
cast              10703 non-null object
director          10703 non-null object
keywords          9293 non-null object

```

```

runtime                10703 non-null float64
genres                 10703 non-null object
production_companies   9759 non-null object
release_date           10703 non-null object
vote_count             10703 non-null int64
vote_average           10703 non-null float64
release_year           10703 non-null int64
budget_adj             5150 non-null float64
revenue_adj            4843 non-null float64
dtypes: float64(7), int64(3), object(7)
memory usage: 1.5+ MB

```

3. Change Data Type

from the update info we can see that columns `release_date` have type as object, so I will change it in type date.

```

In [12]: # change string to date format
         df.release_date = pd.to_datetime(df['release_date'])

         # see the update info
         df.info()

```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10703 entries, 0 to 10865
Data columns (total 17 columns):
id                10703 non-null int64
popularity         10703 non-null float64
budget            5150 non-null float64
revenue           4843 non-null float64
original_title     10703 non-null object
cast              10703 non-null object
director          10703 non-null object
keywords          9293 non-null object
runtime           10703 non-null float64
genres            10703 non-null object
production_companies 9759 non-null object
release_date       10703 non-null datetime64[ns]
vote_count        10703 non-null int64
vote_average       10703 non-null float64
release_year       10703 non-null int64
budget_adj         5150 non-null float64
revenue_adj        4843 non-null float64
dtypes: datetime64[ns](1), float64(7), int64(3), object(6)
memory usage: 1.5+ MB

```

Clean Data Information

```
In [13]: # the last data info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10703 entries, 0 to 10865
Data columns (total 17 columns):
id                10703 non-null int64
popularity        10703 non-null float64
budget            5150 non-null float64
revenue           4843 non-null float64
original_title    10703 non-null object
cast              10703 non-null object
director          10703 non-null object
keywords          9293 non-null object
runtime           10703 non-null float64
genres            10703 non-null object
production_companies 9759 non-null object
release_date      10703 non-null datetime64[ns]
vote_count        10703 non-null int64
vote_average      10703 non-null float64
release_year      10703 non-null int64
budget_adj        5150 non-null float64
revenue_adj       4843 non-null float64
dtypes: datetime64[ns](1), float64(7), int64(3), object(6)
memory usage: 1.5+ MB
```

```
In [14]: # the last statistica summary from data
df.describe()
```

```
Out[14]:
```

	id	popularity	budget	revenue	runtime \
count	10703.000000	10703.000000	5.150000e+03	4.843000e+03	10703.000000
mean	64904.988321	0.653818	3.084401e+07	8.933981e+07	102.736896
std	91161.996308	1.005687	3.893782e+07	1.621546e+08	30.079331
min	5.000000	0.000188	1.000000e+00	2.000000e+00	3.000000
25%	10538.500000	0.211533	6.000000e+06	7.779664e+06	90.000000
50%	20235.000000	0.388036	1.750000e+07	3.191160e+07	99.000000
75%	73637.000000	0.722438	4.000000e+07	1.000000e+08	112.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10703.000000	10703.000000	10703.000000	5.150000e+03	4.843000e+03
mean	220.333178	5.966112	2001.235355	3.701495e+07	1.152341e+08
std	579.481969	0.930155	12.825920	4.198674e+07	1.989424e+08
min	10.000000	1.500000	1960.000000	9.210911e-01	2.370705e+00
25%	17.000000	5.400000	1995.000000	8.210996e+06	1.048057e+07
50%	39.000000	6.000000	2006.000000	2.294283e+07	4.402879e+07
75%	149.000000	6.600000	2011.000000	5.024535e+07	1.317599e+08
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

Exploratory Data Analysis

in this section I will answer the question was declare in introduction

I define some function that can help to answer the question

list function name: Function as_currency Function get_movie_info Function get_hi_low

```
In [15]: # change numeric format to dollar format
```

```
def as_currency(amount):
    if amount >= 0:
        return '${:, .2f}'.format(amount)
    else:
        return '-${:, .2f}'.format(-amount)
```

```
In [16]: # get movie information
```

```
def get_movie_info(index, title):
    info = pd.DataFrame(df.loc[index])

    currency_col = ['budget', 'revenue', 'profit', 'budget_adj', 'revenue_adj', 'profit_adj']
    for idx in currency_col:
        info.loc[idx] = as_currency(info.loc[idx].item())

    info.columns = [title]
    return info
```

```
In [17]: # get hihgest and lowes data information
```

```
def get_hi_low(column):
    # highest
    ## get the index value of the highest number
    highest_idx = df[column].idxmax(skipna=True)
    ## get data from index before
    title = "Highest " + column
    highest_data = get_movie_info(highest_idx, title)

    # lowest
    ## get the index value of the highest number
    lowest_idx = df[column].idxmin(skipna=True)
    ## get data from index before
    title = "Lowest " + column
    lowest_data = get_movie_info(lowest_idx, title)

    #concatenating two dataframes
    hi_low_data = pd.concat([highest_data, lowest_data], axis = 1)

    return hi_low_data
```

General Question

1. Which movie earns the highest and lowest profit?

```

In [18]: # add column profit in data
df['profit'] = df['revenue']-df['budget']
df['profit_adj'] = df['revenue_adj']-df['budget_adj']

# previewing the changes in the dataset
df.head(3)

Out[18]:
```

	id	popularity	budget	revenue	original_title
0	135397	32.985763	150000000.0	1.513529e+09	Jurassic World
1	76341	28.419936	150000000.0	3.784364e+08	Mad Max: Fury Road
2	262500	13.112507	110000000.0	2.952382e+08	Insurgent

	cast	director
0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...	Colin Trevorrow
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...	George Miller
2	Shailene Woodley Theo James Kate Winslet Ansel...	Robert Schwentke

	keywords	runtime
0	monster dna tyrannosaurus rex velociraptor island	124.0
1	future chase post-apocalyptic dystopia australia	120.0
2	based on novel revolution dystopia sequel dyst...	119.0

	genres
0	Action Adventure Science Fiction Thriller
1	Action Adventure Science Fiction Thriller
2	Adventure Science Fiction Thriller

	production_companies	release_date	vote_count
0	Universal Studios Amblin Entertainment Legenda...	2015-06-09	5562
1	Village Roadshow Pictures Kennedy Miller Produ...	2015-05-13	6185
2	Summit Entertainment Mandeville Films Red Wago...	2015-03-18	2480

	vote_average	release_year	budget_adj	revenue_adj	profit
0	6.5	2015	1.379999e+08	1.392446e+09	1.363529e+09
1	7.1	2015	1.379999e+08	3.481613e+08	2.284364e+08
2	6.3	2015	1.012000e+08	2.716190e+08	1.852382e+08

	profit_adj
0	1.254446e+09
1	2.101614e+08
2	1.704191e+08

```

In [19]: # check the update data, kolom profit and profit_adj will have na value because some re
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 10703 entries, 0 to 10865
Data columns (total 19 columns):

```

```

id                10703 non-null int64
popularity        10703 non-null float64
budget           5150 non-null float64
revenue          4843 non-null float64
original_title    10703 non-null object
cast             10703 non-null object
director         10703 non-null object
keywords         9293 non-null object
runtime          10703 non-null float64
genres           10703 non-null object
production_companies 9759 non-null object
release_date      10703 non-null datetime64[ns]
vote_count       10703 non-null int64
vote_average     10703 non-null float64
release_year     10703 non-null int64
budget_adj       5150 non-null float64
revenue_adj      4843 non-null float64
profit           3849 non-null float64
profit_adj       3849 non-null float64
dtypes: datetime64[ns](1), float64(9), int64(3), object(6)
memory usage: 1.6+ MB

```

list used function: Function get_hi_low

```

In [20]: # Find highest and lowest profit
         get_hi_low('profit')

```

```

Out[20]:

```

	Highest profit \
id	19995
popularity	9.43277
budget	\$237,000,000.00
revenue	\$2,781,505,847.00
original_title	Avatar
cast	Sam Worthington Zoe Saldana Sigourney Weaver S...
director	James Cameron
keywords	culture clash future space war space colony so...
runtime	162
genres	Action Adventure Fantasy Science Fiction
production_companies	Ingenious Film Partners Twentieth Century Fox ...
release_date	2009-12-10 00:00:00
vote_count	8458
vote_average	7.1
release_year	2009
budget_adj	\$240,886,902.89
revenue_adj	\$2,827,123,750.41
profit	\$2,544,505,847.00
profit_adj	\$2,586,236,847.52

	Lowest profit
id	46528
popularity	0.25054
budget	\$425,000,000.00
revenue	\$11,087,569.00
original_title	The Warrior's Way
cast	Kate Bosworth Jang Dong-gun Geoffrey Rush Dann...
director	Sngmoo Lee
keywords	assassin small town revenge deception super speed
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	\$425,000,000.00
revenue_adj	\$11,087,569.00
profit	-\$413,912,431.00
profit_adj	-\$413,912,431.00

from information above we know that the highest profit movie is Avatar(2009) which is \ \$2,544,505,847 and the lowest profit is The Warrior's Way(2010) which is - \ \$413,912,431.00, so that movie was loss money. from the information movie we know that columns ending with "_adj" show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time. So I also want to check the highest and lowest profit movie if we accounting for inflation over time

list used function: Function get_hi_low

```
In [21]: # Find highest and lowest profit_adj
         get_hi_low('profit_adj')
```

Out[21]:	Highest profit_adj \
id	11
popularity	12.0379
budget	\$11,000,000.00
revenue	\$775,398,007.00
original_title	Star Wars
cast	Mark Hamill Harrison Ford Carrie Fisher Peter ...
director	George Lucas
keywords	android galaxy hermit death star lightsaber
runtime	121
genres	Adventure Action Science Fiction
production_companies	Lucasfilm Twentieth Century Fox Film Corporation
release_date	1977-03-20 00:00:00
vote_count	4428
vote_average	7.9

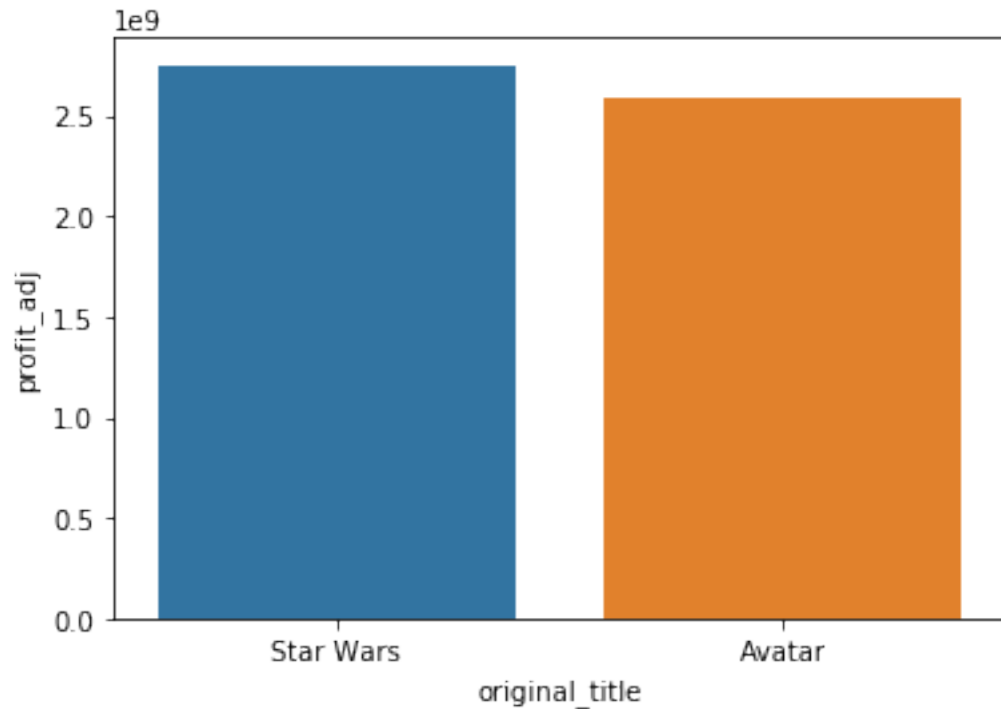
release_year	1977
budget_adj	\$39,575,591.36
revenue_adj	\$2,789,712,242.28
profit	\$764,398,007.00
profit_adj	\$2,750,136,650.92
	Lowest profit_adj
id	46528
popularity	0.25054
budget	\$425,000,000.00
revenue	\$11,087,569.00
original_title	The Warrior's Way
cast	Kate Bosworth Jang Dong-gun Geoffrey Rush Dann...
director	Sngmoo Lee
keywords	assassin small town revenge deception super speed
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	\$425,000,000.00
revenue_adj	\$11,087,569.00
profit	-\$413,912,431.00
profit_adj	-\$413,912,431.00

from information above we know that the highest profit movie from all movie in our data is Star Wars(1977) which is \ \$2,750,136,650.92 that is the highest profit if we accounting for inflation over time. The profit from Start Wars is \ \$163,899,803.4 more than Avatar. The lowest movie profit is still The Warrior's Way(2010) which is -\ \$413,912,431.00

In [22]: # visualize different profit_adj from Star Wars and Avatar

```
highest_profit = df[['original_title','profit_adj']].query("original_title in ['Star Wars']")
sns.barplot(x="original_title", y="profit_adj", data=highest_profit)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff0b73b05c0>



Answer Question General 1

- The highest profit movie is Avatar(2009), but if we check the inflation over time so the highest profit movie is Star Wars(1977)
- The lowest profit movie is The Warrior's Way(2010)

Go To List Question

2. Which movie have the highest and lowest revenue?

list used function: Function get_hi_low

```
In [23]: # Highest and lowest revenue
         get_hi_low('revenue')
```

```
Out[23]:
```

	Highest revenue \
id	1995
popularity	9.43277
budget	\$237,000,000.00
revenue	\$2,781,505,847.00
original_title	Avatar
cast	Sam Worthington Zoe Saldana Sigourney Weaver S...
director	James Cameron
keywords	culture clash future space war space colony so...
runtime	162
genres	Action Adventure Fantasy Science Fiction
production_companies	Ingenious Film Partners Twentieth Century Fox ...

release_date	2009-12-10 00:00:00
vote_count	8458
vote_average	7.1
release_year	2009
budget_adj	\$240,886,902.89
revenue_adj	\$2,827,123,750.41
profit	\$2,544,505,847.00
profit_adj	\$2,586,236,847.52

	Lowest revenue
id	13537
popularity	0.462609
budget	\$6,000,000.00
revenue	\$2.00
original_title	Shattered Glass
cast	Hayden Christensen Peter Sarsgaard Chloë Sevini...
director	Billy Ray
keywords	NaN
runtime	94
genres	Drama History
production_companies	Lions Gate Films Cruise/Wagner Productions Bau...
release_date	2003-11-14 00:00:00
vote_count	46
vote_average	6.4
release_year	2003
budget_adj	\$7,112,115.87
revenue_adj	\$2.37
profit	-\$5,999,998.00
profit_adj	-\$7,112,113.50

from information above we know that the highest revenue movie is Avatar(2009) which is \\$2,781,505,847. The lowest movie revenue is Shattered Glass(2003) which is \\$2

list used function: Function get_hi_low

```
In [24]: # Highest and lowest revenue_adj
         get_hi_low('revenue_adj')
```

```
Out[24]: Highest revenue_adj \
id 19995
popularity 9.43277
budget $237,000,000.00
revenue $2,781,505,847.00
original_title Avatar
cast Sam Worthington|Zoe Saldana|Sigourney Weaver|S...
director James Cameron
keywords culture clash|future|space war|space colony|so...
runtime 162
```

genres	Action Adventure Fantasy Science Fiction
production_companies	Ingenious Film Partners Twentieth Century Fox ...
release_date	2009-12-10 00:00:00
vote_count	8458
vote_average	7.1
release_year	2009
budget_adj	\$240,886,902.89
revenue_adj	\$2,827,123,750.41
profit	\$2,544,505,847.00
profit_adj	\$2,586,236,847.52
	Lowest revenue_adj
id	13537
popularity	0.462609
budget	\$6,000,000.00
revenue	\$2.00
original_title	Shattered Glass
cast	Hayden Christensen Peter Sarsgaard Chloë Sevi...
director	Billy Ray
keywords	NaN
runtime	94
genres	Drama History
production_companies	Lions Gate Films Cruise/Wagner Productions Bau...
release_date	2003-11-14 00:00:00
vote_count	46
vote_average	6.4
release_year	2003
budget_adj	\$7,112,115.87
revenue_adj	\$2.37
profit	-\$5,999,998.00
profit_adj	-\$7,112,113.50

from information above we know that the highest revenue movie from all movie in our data is Avatar(2009) which is \ \$2,781,505,847 The lowest movie revenue is still Shattered Glass(2003) which is -\ \$2.37

Answer Question General 2

- The highest revenue movie is Avatar(2009)
- The lowest revenue movie is Shattered Glass(2003)

From answer question 1 we found that profit Avatar is lower than Star Wars so we can make conclusion that budget Star Wars is lower than Avatar because revenue Avatar is bigger than Star Wars

Go To List Question

3. Which movie have the highest and lowest budget?

list used function: Function get_hi_low

```
In [25]: # Highest and lowest budget
         get_hi_low('budget')
```



```

Out[25]:
Highest budget \
id 46528
popularity 0.25054
budget $425,000,000.00
revenue $11,087,569.00
original_title The Warrior's Way
cast Kate Bosworth|Jang Dong-gun|Geoffrey Rush|Dann...
director Sngmoo Lee
keywords assassin|small town|revenge|deception|super speed
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 $425,000,000.00
revenue_adj $11,087,569.00
profit -$413,912,431.00
profit_adj -$413,912,431.00

Lowest budget
id 287524
popularity 0.177102
budget $1.00
revenue -$nan
original_title Fear Clinic
cast Thomas Dekker|Robert Englund|Cleopatra Coleman...
director Robert Hall
keywords phobia|doctor|fear
runtime 95
genres Horror
production_companies Dry County Films|Anchor Bay Entertainment|Movi...
release_date 2014-10-31 00:00:00
vote_count 15
vote_average 4.1
release_year 2014
budget_adj $0.92
revenue_adj -$nan
profit -$nan
profit_adj -$nan

```

from information above we know that the highest budget movie is The Warrior's Way(2010) which is \\$425,000,000 The lowest movie budget is Fear Clinic(2014) which is \\$1.

list used function: Function get_hi_low

```
In [26]: # Highest and lowest budget_adj
```

```
get_hi_low('budget_adj')
```

Out[26] :

	Highest budget_adj \
id	46528
popularity	0.25054
budget	\$425,000,000.00
revenue	\$11,087,569.00
original_title	The Warrior's Way
cast	Kate Bosworth Jang Dong-gun Geoffrey Rush Dann...
director	Sngmoo Lee
keywords	assassin small town revenge deception super speed
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	\$425,000,000.00
revenue_adj	\$11,087,569.00
profit	-\$413,912,431.00
profit_adj	-\$413,912,431.00

	Lowest budget_adj
id	287524
popularity	0.177102
budget	\$1.00
revenue	-\$nan
original_title	Fear Clinic
cast	Thomas Dekker Robert Englund Cleopatra Coleman...
director	Robert Hall
keywords	phobia doctor fear
runtime	95
genres	Horror
production_companies	Dry County Films Anchor Bay Entertainment Movi...
release_date	2014-10-31 00:00:00
vote_count	15
vote_average	4.1
release_year	2014
budget_adj	\$0.92
revenue_adj	-\$nan
profit	-\$nan
profit_adj	-\$nan

from information above we know that the highest budget_adj movie is The Warrior's Way(2010) which is \ \$425,000,000 The lowest movie budget_adj is Fear Clinic(2014) which is \ \$1.

Answer Question General 3

- The highest budget movie is The Warrior's Way(2010)
- The lowest budget movie is Fear Clinic(2014) From answer question 1 we found that profit The Warrior's Way(2010) is lowest maybe because it is have a highest budget

Go To List Question

4. Which movie have the longest and shortest runtime?

list used function: Function get_hi_low

```
In [27]: # Highest and lowest runtime
         get_hi_low('runtime')
```

```
Out[27]:
```

	Highest runtime \
id	125336
popularity	0.006925
budget	-\$nan
revenue	-\$nan
original_title	The Story of Film: An Odyssey
cast	Mark Cousins Jean-Michel Frodon Cari Beauchamp...
director	Mark Cousins
keywords	cinema nouvelle vague hindi cinema cinema novo...
runtime	900
genres	Documentary
production_companies	NaN
release_date	2011-09-03 00:00:00
vote_count	14
vote_average	9.2
release_year	2011
budget_adj	-\$nan
revenue_adj	-\$nan
profit	-\$nan
profit_adj	-\$nan

	Lowest runtime
id	264170
popularity	0.202776
budget	-\$nan
revenue	-\$nan
original_title	Batman: Strange Days
cast	Kevin Conroy Brian George Tara Strong
director	Bruce Timm
keywords	dc comics superhero based on comic book noir p...
runtime	3
genres	Action Animation
production_companies	DC Comics
release_date	2014-04-09 00:00:00
vote_count	20
vote_average	7.6
release_year	2014

budget_adj	-\$nan
revenue_adj	-\$nan
profit	-\$nan
profit_adj	-\$nan

Answer Question General 4

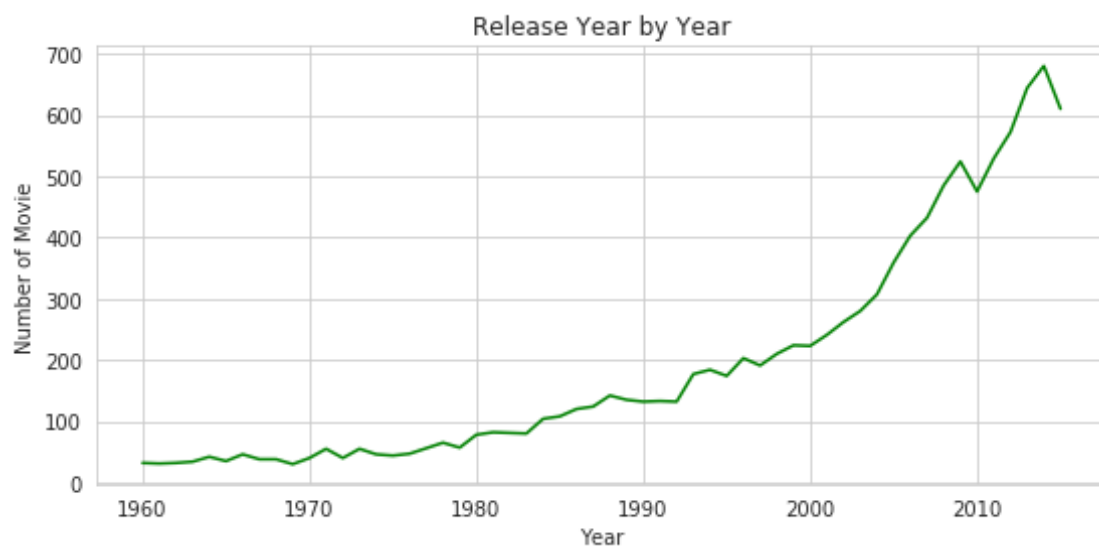
- The longest runtime movie is The Story of Film: An Odyssey(2011) that is 900 minutes
- The shortest runtime movie is Batman: Strange Days(2014) that is 3 minutes

Go To List Question

5. How much movie released year by year?

```
In [28]: # get number of movie group by release year
release = df.groupby('release_year').size()
# get index number of movie group by release year
release_idx = release.index
```

```
In [29]: # visualisation
# set style
sns.set_style('whitegrid')
# set x, y axis data
x, y = release_idx, release
# set size
plt.figure(figsize=(9, 4))
# plot line chart for number of release
plt.plot(x, y, color = 'g', label = 'mean')
# set title and labels
plt.title('Release Year by Year')
plt.xlabel('Year')
plt.ylabel('Number of Movie');
```



Answer Question General 5

from figure above we know that movie number always increasing every year, but in 2010 we have some slope.

Go To List Question

6. How distribution of profit in different popularity levels in recent ten years?

To help the next process, I will make some function

list function name: Function get_class Function plot_by_year

```
In [30]: # make level from quantile to help categories column
def get_class(df, column):
    # find quantile to decide that class
    min_value = df[column].min()
    quantile_1 = df[column].describe()[4]
    quantile_2 = df[column].describe()[5]
    quantile_3 = df[column].describe()[6]
    max_value = df[column].max()

    # Bin edges that will be used to "cut" the data into groups
    bin_level = [min_value, quantile_1, quantile_2, quantile_3, max_value]
    # Labels for the four budget level groups
    bin_name = ['Low', 'Medium', 'High', 'Very High']
    # Creates budget_levels column
    name = '{}_levels'.format(column)
    df[name] = pd.cut(df[column], bin_level, labels=bin_name, include_lowest = True)
    return df

In [31]: # plot data group by year of year
def plot_by_year(df, column, object_column, dyear):
    # Setting the positions and width for the bars
    pos = list(range(len(df.query('%s == "Low"' % column))))
    width = 0.2

    # Plotting the bars
    fig, ax = plt.subplots(figsize=(20,5))

    # Create a bar with Low data, in position pos,
    plt.bar(pos,
            #using 'Low' data,
            df.query('%s == "Low"' % column)[object_column],
            # of width
            width,
            # with alpha 0.5
            alpha=0.5,
            # with color
            color='#FFFF00',
```

```

        # with label Low
        label= 'Low')

# Create a bar with Medium data, in position pos + some width buffer
plt.bar([p + width for p in pos],
        #using Medium data,
        df.query('%s == "Medium"' % column)[object_column],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#FFD700',
        # with label Medium
        label='Medium')

# Create a bar with High data, in position pos + some width buffer,
plt.bar([p + width*2 for p in pos],
        #using Moderately High data,
        df.query('%s == "High"' % column)[object_column],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#ADFF2F',
        # with label High
        label='High')

# Create a bar with Very High data,
# in position pos + some width buffer,
plt.bar([p + width*3 for p in pos],
        #using High data,
        df.query('%s == "Very High"' % column)[object_column],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#008000',
        # with label High
        label='Very High')

# Set the y axis label
ax.set_ylabel(object_column)

# Set the chart's title
ax.set_title('%s in different %s levels in recent 10 years' % (object_column, column))

```

```

# Set the position of the x ticks
ax.set_xticks([p + 1.5 * width for p in pos])

# Set the labels for the x ticks
ax.set_xticklabels(dfyear)

# Set the y ticks
ax.set_ylim([min(df[object_column]),max(df[object_column])])

# Adding the legend and showing the plot
plt.legend( loc='upper left')
plt.grid()
plt.show()

```

Lets find distribution of profit in different popularity levels in recent ten years

list used function: Function get_class

```

In [32]: # get popularity level
# choose the recent 10 years
dfyear = np.sort(df.release_year.unique())[-10:]
# creat a empty df to assign df with popularity levels
df_popularity = pd.DataFrame()

#for each year, do the following procedure
for year in dfyear:
    df_temp = df.query('release_year == "%s"' % year).copy() # filter data with the sel
    df_temp = get_class(df_temp, 'popularity') # get popularity level
    df_popularity = df_popularity.append(df_temp) # append to df_popularity
df_popularity.head(3)

```

```

Out[32]:
      id  popularity      budget      revenue \
6554  834    5.838503  500000000.0  1.113408e+08
6555   58    4.205992  200000000.0  1.065660e+09
6556  920    3.941265  120000000.0  4.619831e+08

      original_title \
6554      Underworld: Evolution
6555  Pirates of the Caribbean: Dead Man's Chest
6556      Cars

      cast \
6554  Kate Beckinsale|Scott Speedman|Tony Curran|Sha...
6555  Johnny Depp|Orlando Bloom|Keira Knightley|Bill...
6556  Owen Wilson|Paul Newman|Bonnie Hunt|Larry the ...

      director \
6554      Len Wiseman

```

```

6555          Gore Verbinski
6556 John Lasseter|Joe Ranft

```

```

                                keywords runtime \
6554          budapest|key|light|werewolf|evolution    106.0
6555 witch|fortune teller|bondage|exotic island|mon...    151.0
6556   car race|car journey|village and town|road|auto    117.0

```

```

                                genres \
6554 Fantasy|Action|Science Fiction|Thriller
6555          Adventure|Fantasy|Action
6556          Animation|Adventure|Comedy|Family

```

```

                                production_companies release_date \
6554          Lakeshore Entertainment|Screen Gems    2006-01-12
6555 Walt Disney Pictures|Jerry Bruckheimer Films|S...    2006-06-20
6556          Walt Disney Pictures|Pixar Animation Studios    2006-06-08

```

```

vote_count vote_average release_year budget_adj revenue_adj \
6554      1015          6.3         2006 5.408346e+07 1.204339e+08
6555      3181          6.8         2006 2.163338e+08 1.152691e+09
6556      2336          6.4         2006 1.298003e+08 4.997129e+08

```

```

profit profit_adj popularity_levels
6554 61340801.0 6.635045e+07 Very High
6555 865659812.0 9.363575e+08 Very High
6556 341983149.0 3.699126e+08 Very High

```

```

In [33]: # lets find statistic summary from popularity to know how the quantile cut the levels,
df_popularity.describe()

```

```

Out[33]:
      id popularity      budget      revenue      runtime \
count  5354.000000  5354.000000  2.379000e+03  2.165000e+03  5354.000000
mean   113436.690325    0.713095  3.475924e+07  1.031749e+08   99.186029
std    107304.567574    1.219587  4.695805e+07  1.968944e+08   30.217657
min      17.000000    0.000620  1.000000e+00  3.000000e+00    3.000000
25%    19715.750000    0.206118  6.000000e+06  3.338228e+06   89.000000
50%    71861.500000    0.390016  1.700000e+07  3.155486e+07   96.000000
75%   201730.750000    0.771668  4.000000e+07  1.075972e+08  108.000000
max   417859.000000   32.985763  4.250000e+08  2.781506e+09  900.000000

```

```

      vote_count vote_average release_year budget_adj revenue_adj \
count  5354.000000  5354.000000  5354.000000  2.379000e+03  2.165000e+03
mean    268.594135    5.891688  2010.928838  3.421956e+07  1.010225e+08
std     681.641308    0.992524    2.831724  4.604534e+07  1.914991e+08
min     10.000000    1.500000   2006.000000  9.210911e-01  3.038360e+00
25%     18.000000    5.300000   2009.000000  5.816388e+06  3.171821e+06
50%     42.000000    5.900000   2011.000000  1.682670e+07  3.038360e+07

```


75%	182.000000	6.600000	2013.000000	4.065602e+07	1.055790e+08
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

	profit	profit_adj
count	1.712000e+03	1.712000e+03
mean	8.334300e+07	8.133364e+07
std	1.793768e+08	1.743710e+08
min	-4.139124e+08	-4.139124e+08
25%	-2.220506e+06	-2.191682e+06
50%	2.152898e+07	2.145700e+07
75%	9.400637e+07	9.068777e+07
max	2.544506e+09	2.586237e+09

```
In [34]: # group the dataframe we created above with each popularity_levels in each year, find t
# I choose median because it not have effect from outlier data
df_popularity_by_year = df_popularity.groupby(['release_year', 'popularity_levels']).med
df_popularity_by_year.head(8)
```

```
Out [34]:
```

		id	popularity	budget	revenue \
release_year	popularity_levels				
2006	Low	14872.0	0.113193	7000000.0	4687766.0
	Medium	12225.0	0.297434	8500000.0	11290263.5
	High	9806.5	0.546223	20000000.0	23629912.0
	Very High	7551.0	1.182280	40000000.0	93161322.5
2007	Low	15117.5	0.139703	10000000.0	10337477.0
	Medium	13517.5	0.298249	10000000.0	3478080.0
	High	10966.0	0.519439	19000000.0	22179430.0
	Very High	4748.0	1.188489	47500000.0	95652995.5

		runtime	vote_count	vote_average \
release_year	popularity_levels			
2006	Low	95.0	17.0	5.90
	Medium	95.0	27.0	5.80
	High	100.0	72.5	5.90
	Very High	106.0	306.0	6.30
2007	Low	93.5	16.0	5.85
	Medium	96.0	26.0	5.80
	High	97.5	64.0	6.00
	Very High	105.0	453.0	6.20

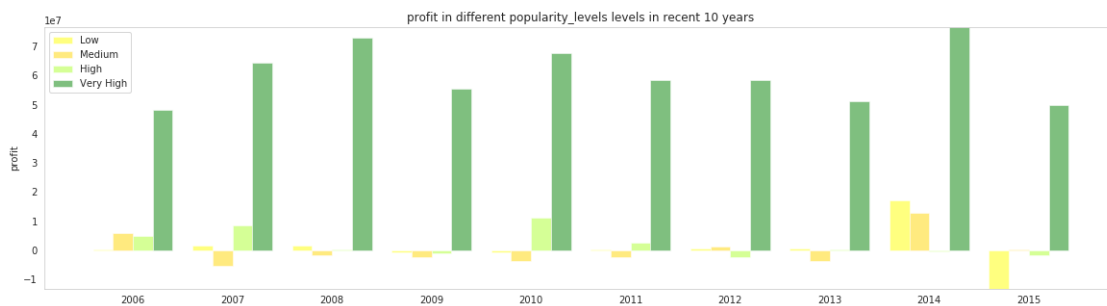
		budget_adj	revenue_adj	profit \
release_year	popularity_levels			
2006	Low	7.571684e+06	5.070612e+06	166000.0
	Medium	9.194188e+06	1.221233e+07	5796544.0
	High	2.163338e+07	2.555975e+07	4910153.5
	Very High	4.326677e+07	1.007697e+08	48197993.0
2007	Low	1.051669e+07	1.087160e+07	1392364.0
	Medium	1.051669e+07	3.657787e+06	-5349184.5

	High	1.998170e+07	2.332541e+07	8511656.5
	Very High	4.995426e+07	1.005953e+08	64373941.0

release_year	popularity_levels	profit_adj
2006	Low	1.795571e+05
	Medium	6.269943e+06
	High	5.311162e+06
	Very High	5.213428e+07
2007	Low	1.464305e+06
	Medium	-5.625569e+06
	High	8.951442e+06
	Very High	6.770005e+07

list used function: Function plot_by_year

```
In [35]: # visualitation
plot_by_year(df_popularity_by_year, 'popularity_levels', 'profit', dfyear)
```



Answer Question General 6

from figure above we found that the highest popularity didn't mean the highest profit, but for very high of popularity have highest profit. So keep the movie get very high popularity levels, with minimum popularity is 0.710151 to get high profit.

Go To List Question

7. How distribution of profit in different vote average levels in recent ten years?

list used function: Function get_class

```
In [36]: # lets make rating level just like question before
# choose the recent 10 years
dfyear = np.sort(df.release_year.unique())[-10:]
# creat a empty df to assign df with vote average levels
df_vote_average = pd.DataFrame()

#for each year, do the following procedure
for year in dfyear:
    df_temp = df.query('release_year == "%s"' % year).copy() # filter data with the sel
    df_temp = get_class(df_temp, 'vote_average') # get vote average level
```

```
df_vote_average = df_vote_average.append(df_temp) # append to df_popularity
df_vote_average.head(3)
```

Out[36]:

	id	popularity	budget	revenue	\
6554	834	5.838503	50000000.0	1.113408e+08	
6555	58	4.205992	200000000.0	1.065660e+09	
6556	920	3.941265	120000000.0	4.619831e+08	

	original_title	\
6554	Underworld: Evolution	
6555	Pirates of the Caribbean: Dead Man's Chest	
6556	Cars	

	cast	\
6554	Kate Beckinsale Scott Speedman Tony Curran Sha...	
6555	Johnny Depp Orlando Bloom Keira Knightley Bill...	
6556	Owen Wilson Paul Newman Bonnie Hunt Larry the ...	

	director	\
6554	Len Wiseman	
6555	Gore Verbinski	
6556	John Lasseter Joe Ranft	

	keywords	runtime	\
6554	budapest key light werewolf evolution	106.0	
6555	witch fortune teller bondage exotic island mon...	151.0	
6556	car race car journey village and town road auto	117.0	

	genres	\
6554	Fantasy Action Science Fiction Thriller	
6555	Adventure Fantasy Action	
6556	Animation Adventure Comedy Family	

	production_companies	release_date	\
6554	Lakeshore Entertainment Screen Gems	2006-01-12	
6555	Walt Disney Pictures Jerry Bruckheimer Films S...	2006-06-20	
6556	Walt Disney Pictures Pixar Animation Studios	2006-06-08	

	vote_count	vote_average	release_year	budget_adj	revenue_adj	\
6554	1015	6.3	2006	5.408346e+07	1.204339e+08	
6555	3181	6.8	2006	2.163338e+08	1.152691e+09	
6556	2336	6.4	2006	1.298003e+08	4.997129e+08	

	profit	profit_adj	vote_average_levels
6554	61340801.0	6.635045e+07	High
6555	865659812.0	9.363575e+08	Very High
6556	341983149.0	3.699126e+08	High

In [37]: # lets find statistic summary from vote avg to know how the quantile cut the levels, and

```
df_vote_average.describe()
```

```
Out [37]:
```

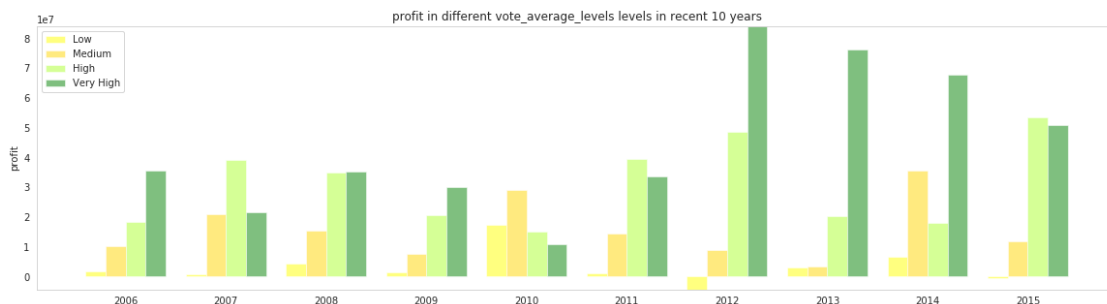
	id	popularity	budget	revenue	runtime \
count	5354.000000	5354.000000	2.379000e+03	2.165000e+03	5354.000000
mean	113436.690325	0.713095	3.475924e+07	1.031749e+08	99.186029
std	107304.567574	1.219587	4.695805e+07	1.968944e+08	30.217657
min	17.000000	0.000620	1.000000e+00	3.000000e+00	3.000000
25%	19715.750000	0.206118	6.000000e+06	3.338228e+06	89.000000
50%	71861.500000	0.390016	1.700000e+07	3.155486e+07	96.000000
75%	201730.750000	0.771668	4.000000e+07	1.075972e+08	108.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year	budget_adj	revenue_adj \
count	5354.000000	5354.000000	5354.000000	2.379000e+03	2.165000e+03
mean	268.594135	5.891688	2010.928838	3.421956e+07	1.010225e+08
std	681.641308	0.992524	2.831724	4.604534e+07	1.914991e+08
min	10.000000	1.500000	2006.000000	9.210911e-01	3.038360e+00
25%	18.000000	5.300000	2009.000000	5.816388e+06	3.171821e+06
50%	42.000000	5.900000	2011.000000	1.682670e+07	3.038360e+07
75%	182.000000	6.600000	2013.000000	4.065602e+07	1.055790e+08
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

	profit	profit_adj
count	1.712000e+03	1.712000e+03
mean	8.334300e+07	8.133364e+07
std	1.793768e+08	1.743710e+08
min	-4.139124e+08	-4.139124e+08
25%	-2.220506e+06	-2.191682e+06
50%	2.152898e+07	2.145700e+07
75%	9.400637e+07	9.068777e+07
max	2.544506e+09	2.586237e+09

list used function: Function plot_by_year

```
In [38]: # group the dataframe we created above with each popularity_levels in each year, find t
# I choose median because it not have effect from outlier data
df_vote_average_by_year = df_vote_average.groupby(['release_year', 'vote_average_levels'
# visualitation
plot_by_year(df_vote_average_by_year, 'vote_average_levels', 'profit', dfyear)
```



Answer Question General 7

from figure above we found that the highest level of vote average not always mean the movie get the highest profit, especially to 2010 which medium vote have higher profit than high and very high vote average.

Go To List Question

Associated Question

1. What genre that associated with high popularity?

Because I want to check the associate of genre and genre are multiple value with delimiter | , so I decide to devide the column into single value in each row so it will be a binner data with their popularity level to make the process easy, I make some function

list function name: Function remove_punctuation Function define_dict Function
get_data_frame

In [39]: *# remove punctuation, decimal, and space unneeded, so the string just containt character*

```
def remove_punctuation(sentence, chars: list = ['^~\w\s', '_', '\d', '\n', '\r']):
    sentence = sentence.strip()
    sentence = re.sub("|".join(chars), " ", sentence)
    sentence = sentence.replace(' +', ' ')

    return sentence
```

In [40]: *# define dictionary to help make dataframe with binner value,*
the key of dictionary will save the column name, and the value will be number

```
def define_dict(columns):
    d = {}
    for c in columns:
        d[c] = 0
    return d
```

In [41]: *# make binner dataframe with column we needed*
metric are column level name

```
def get_data_frame(old_df, column, metric):
    names = set()
    r = old_df.shape[0] # nrow of data
    c = old_df.shape[1] # nrow of columns

    # get set of data to generate column
    for i in range(0, r):
        temp = str(old_df.iloc[i, old_df.columns.get_loc(column)]).split("|")
        for j in range(len(temp)):
            last_name = remove_punctuation(temp[j].lower()).split(" ")[-1]
            if last_name != '' and last_name != 'nan':
                names.add(last_name)

    df_temp = pd.DataFrame(columns = names) # empty data frame to save the final data
```

```

for i in range(r):
    dict_column = define_dict(names) # dictionary with name as key and zero as value
    dict_column[metric] = old_df.iloc[i,old_df.columns.get_loc(metric)]
    temp = str(remove_punctuation(old_df.iloc[i,old_df.columns.get_loc(column)]).lower())
    for name in names:
        dict_column[name] += temp.count(name)
    df_add = pd.DataFrame(dict_column, index=[0])
    df_temp = df_temp.append(df_add,ignore_index=True,sort=False)

return df_temp

```

```

In [42]: # make dataframe
df_genres = get_data_frame(df_popularity,'genres','popularity_levels')

```

```

In [43]: # lets see the sample value of dataframe we make
df_genres.head(3)

```

```

Out[43]:  animation war horror foreign crime drama fantasy adventure action history \
0          0  0      0          0      0      0      1          0      1      0
1          0  0      0          0      0      0      1          1      1      0
2          1  0      0          0      0      0      0          1      0      0

    ... western family mystery documentary thriller movie fiction comedy music \
0  ...          0      0      0          0      1      0      1      0      0
1  ...          0      0      0          0      0      0      0      0      0
2  ...          0      1      0          0      0      0      0      1      0

    popularity_levels
0          Very High
1          Very High
2          Very High

[3 rows x 21 columns]

```

```

In [44]: # lets find the sum in each column so we know what the genre most often used in all movies
df_genres.sum()

```

```

Out[44]: animation      383
war                    106
horror                 884
foreign                  91
crime                   569
drama                  2291
fantasy                 398
adventure               618
action                 1052
history                 141
romance                 747

```

```

western      36
family      519
mystery     359
documentary  363
thriller    1482
movie       95
fiction     549
comedy     1690
music      195
popularity_levels    Very HighVery HighVery HighVery HighVery HighV...
dtype: object

```

```

In [45]: # let's count the genre almost use group by metric we decide before
df_genre_rank = df_genres.groupby(['popularity_levels']).sum()
df_genre_rank.head(8)

```

```

Out[45]:
           animation  war  horror  foreign  crime  drama  fantasy \
popularity_levels
High              107   27   216        10   154   643      96
Low               49   19   257        60    84   508      52
Medium           90   29   280        20   123   591      79
Very High       137   31   131         1   208   549     171

           adventure  action  history  romance  western  family \
popularity_levels
High              139   263        39   192        11   138
Low               84   151        29   171         4    90
Medium           117   249        40   174         7   100
Very High       278   389        33   210        14   191

           mystery  documentary  thriller  movie  fiction  comedy \
popularity_levels
High              76          39   411    25    114   422
Low               75         229   266    36    105   437
Medium            89          91   375    32    148   389
Very High        119          4   430     2    182   442

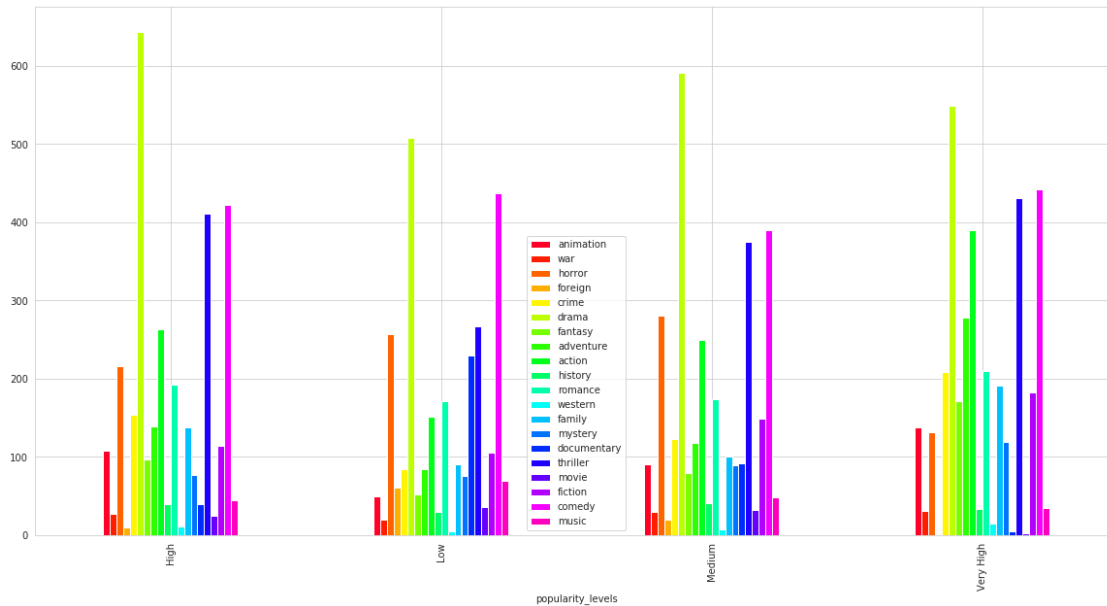
           music
popularity_levels
High          44
Low           69
Medium        48
Very High     34

```

```

In [46]: # plot sum of genre use in each level of popularity
df_genre_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow');

```



Answer Question Associate 1

from figure above we found that genre drama are high distributed in all popularity level movie which level "very high" popularity in genre movie, documentary, and foreign has the smallest amount. This means that not many movies have high popularity in that genres Go To List Question

2. What movie genre that associated with high revenue?

This calculation just like the answer before, so lets make function to make it simple and reusable

list used function: Function get_class Function get_data_frame list function name: Function get_df_rank

```
In [47]: def get_df_rank(df,column,metric):
    # make dataframe
    df_new = df.copy()
    df_new = get_class(df_new,metric)
    metric_name = '{}_levels'.format(metric)
    df_genre_new = get_data_frame(df_new.copy(),column,metric_name)

    # let's count the genre alomst use group by metric we decide before
    df_genre_new_rank = df_genre_new.groupby([metric_name]).sum()
    df_genre_new_rank.head(8)

    return df_genre_new_rank
```



```
In [48]: # lets call the function to get the df we want
```

```
df_genre_revenue_rank = get_df_rank(df, 'genres', 'revenue_adj')
df_genre_revenue_rank.head(8)
```

```
Out[48]:
```

	animation	war	horror	foreign	crime	drama	fantasy	\
revenue_adj_levels								
High	43	25	155	1	214	541	118	
Low	33	23	166	18	160	693	56	
Medium	35	37	161	11	214	603	93	
Very High	126	52	79	0	185	434	194	

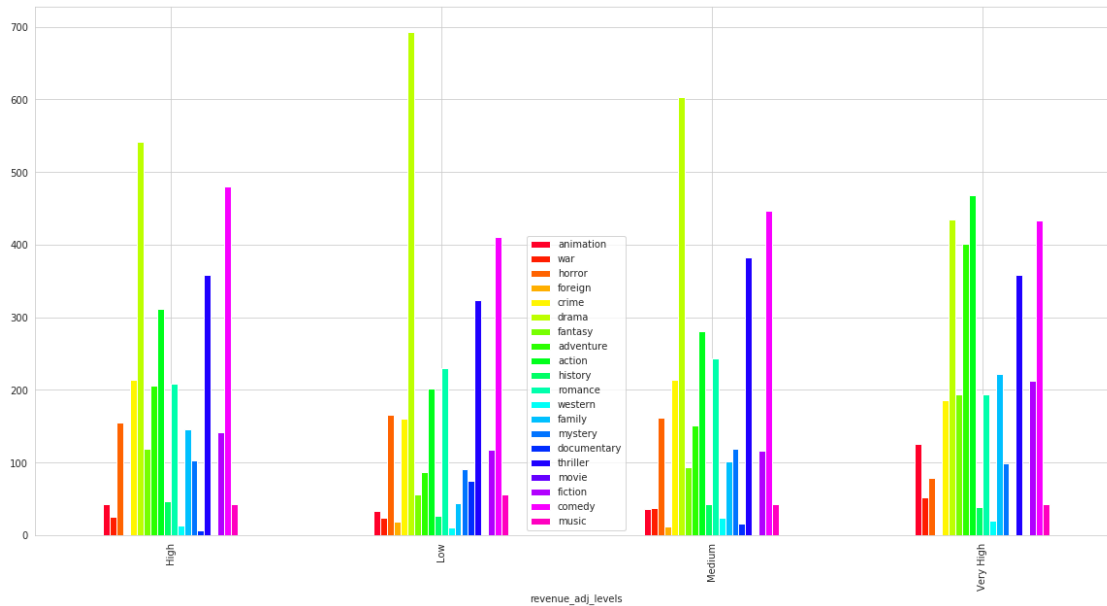
	adventure	action	history	romance	western	family	\
revenue_adj_levels							
High	205	311	47	209	13	146	
Low	86	201	26	230	10	44	
Medium	151	280	42	243	23	101	
Very High	401	468	38	194	19	222	

	mystery	documentary	thriller	movie	fiction	comedy	\
revenue_adj_levels							
High	102	6	358	1	141	480	
Low	91	74	324	0	117	411	
Medium	119	16	382	0	116	446	
Very High	98	1	358	0	212	433	

	music
revenue_adj_levels	
High	42
Low	56
Medium	43
Very High	43

```
In [49]: # plot sum of genre use in each level of revenue
```

```
df_genre_revenue_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow');
```



Answer Question Associate 2

from figure above we found that even always in all level o fpopularity (answer ques-
tion associate 1) but in revenue genre that always appear in high distribution is horror.
In very high revenue, genre documentary and foreign is not appear (or maybe too
small) so its mean they dont have a big revenue. also in high level revenue, genre for-
eign is not appear but genre documentary is appear with small distribution. Go To List
Question

3. What movie genre that associated with high vote average?

list used function: Function get_df_rank

```
In [50]: # lets call the function to get the df we want
df_genre_vote_rank = get_df_rank(df, 'genres', 'vote_average')
df_genre_vote_rank.head(8)
```

```
Out [50]:
```

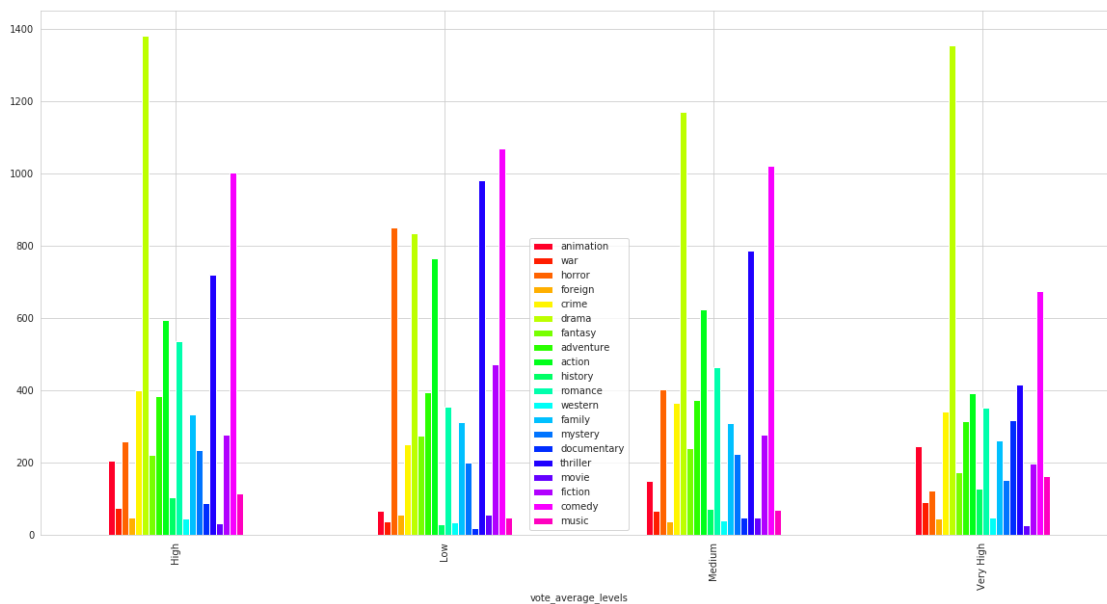
	animation	war	horror	foreign	crime	drama	fantasy	\
vote_average_levels								
High	204	75	257	47	398	1381	220	
Low	67	37	849	54	249	833	275	
Medium	149	65	401	37	364	1170	239	
Very High	244	91	121	45	341	1354	173	

	adventure	action	history	romance	western	family	\
vote_average_levels							
High	384	595	104	534	45	332	
Low	393	765	28	354	35	311	
Medium	373	622	71	463	38	308	
Very High	314	392	127	352	46	261	

	mystery	documentary	thriller	movie	fiction	comedy	\
vote_average_levels							
High	233	86	719	31	276	1001	
Low	199	18	980	54	471	1070	
Medium	223	47	787	47	277	1020	
Very High	151	316	414	27	196	674	

	music
vote_average_levels	
High	115
Low	48
Medium	68
Very High	163

```
In [51]: # plot sum of genre use in each level of vote
df_genre_vote_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow');
```



Answer Question Associate 3

from figure above we found that just like popularity level, in vote level drama still appear in all distribution. All genre drama have higher distribution except in low level. So its mean more drama movie have high vote. Just like popularity and revenue, comedy is in second place distribution in each vote level. Go To List Question

4. What movie genre that associated with high profit?
list used function: Function get_df_rank

```
In [52]: # lets call the function to get the df we want
```

```
df_genre_profit_rank = get_df_rank(df, 'genres', 'profit_adj')
df_genre_profit_rank.head(8)
```

```
Out[52]:
```

	animation	war	horror	foreign	crime	drama	fantasy	\
profit_adj_levels								
High	33	30	152	1	170	414	83	
Low	36	30	94	8	175	523	96	
Medium	26	23	148	3	166	485	64	
Very High	106	36	69	0	140	331	153	

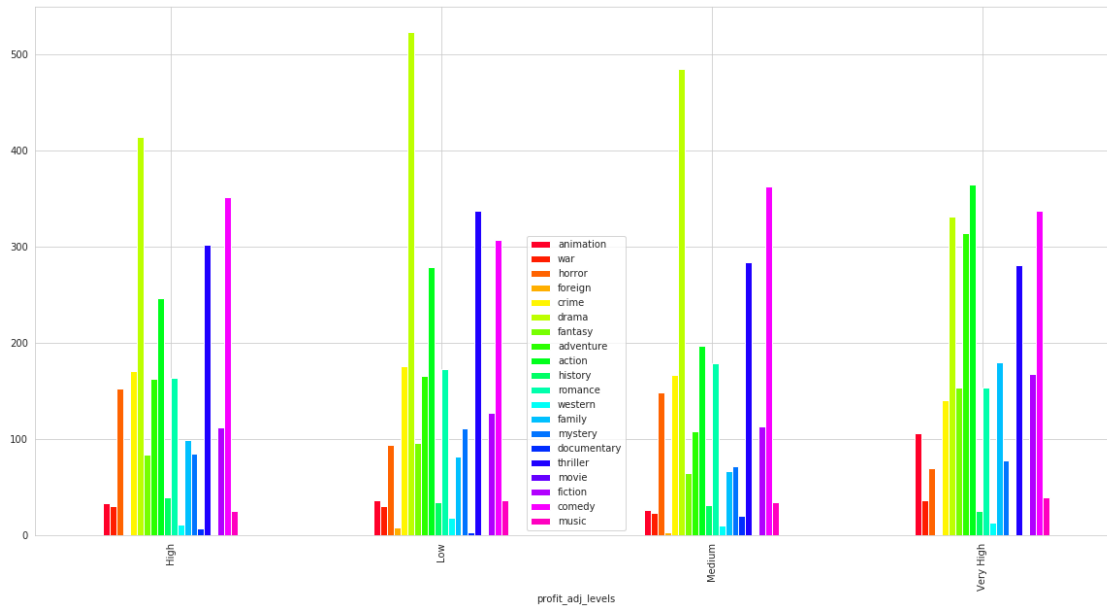
	adventure	action	history	romance	western	family	\
profit_adj_levels							
High	162	246	39	163	11	99	
Low	165	278	34	172	18	81	
Medium	108	197	31	178	10	66	
Very High	314	364	25	153	13	179	

	mystery	documentary	thriller	movie	fiction	comedy	\
profit_adj_levels							
High	85		7	302	1	112	351
Low	111		3	337	0	127	307
Medium	71		20	284	0	113	362
Very High	77		1	280	0	167	337

	music
profit_adj_levels	
High	25
Low	36
Medium	34
Very High	39

```
In [53]: # plot sum of genre use in each level of vote
```

```
df_genre_profit_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow');
```



Answer Question Associate 4

from figure above we found that just like the answer before, in profit level drama still appear in all distribution. All genre drama have higher distribution except in very high level. So its mean drama movie have good distribution in all profit level. Genre action have highest distribution in very high profit level, in another level that genre just in 4 position from higher distribution. Go To List Question

Trend Question

1. What is the trend of the genre every 10 years

```
In [54]: # sort the movie release year list.
df_sub_year= df.release_year.unique()
df_sub_year= np.sort(df_sub_year)
df_sub_year
```

```
Out[54]: array([1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970,
1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981,
1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992,
1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003,
2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014,
2015])
```

```
In [55]: # year list of 1960s
y1960s =df_sub_year[:10]
# year list of 1970s
y1970s =df_sub_year[10:20]
# year list of 1980s
y1980s =df_sub_year[20:30]
```

```

# year list of 1990s
y1990s = df_sub_year[30:40]
# year list of afer 2000
y2000s = df_sub_year[40:50]
# year list of afer 2000
y2010 = df_sub_year[50:]

```

```

In [56]: # year list devide by 10 years
times = [y1960s, y1970s, y1980s, y1990s, y2000s, y2010]
# timesline name
names = ['1960s', '1970s', '1980s', '1990s', '2000s', 'after2010']
df['decade'] = np.nan
for i in range(len(names)):
    index = df[df.release_year.isin(times[i])].index.values.tolist()
    for j in index:
        df.loc[j, 'decade'] = names[i]
df.head()

```

```

Out [56]:
      id  popularity      budget      revenue \
0  135397    32.985763  150000000.0  1.513529e+09
1   76341    28.419936  150000000.0  3.784364e+08
2  262500    13.112507  110000000.0  2.952382e+08
3  140607    11.173104  200000000.0  2.068178e+09
4  168259     9.335014  190000000.0  1.506249e+09

      original_title \
0      Jurassic World
1      Mad Max: Fury Road
2      Insurgent
3  Star Wars: The Force Awakens
4      Furious 7

      cast      director \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...  George Miller
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...  J.J. Abrams
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...  James Wan

      keywords  runtime \
0  monster|dna|tyrannosaurus rex|velociraptor|island  124.0
1  future|chase|post-apocalyptic|dystopia|australia  120.0
2  based on novel|revolution|dystopia|sequel|dyst...  119.0
3      android|spaceship|jedi|space opera|3d  136.0
4      car race|speed|revenge|suspense|car  137.0

      genres \
0  Action|Adventure|Science Fiction|Thriller

```

```

1 Action|Adventure|Science Fiction|Thriller
2      Adventure|Science Fiction|Thriller
3 Action|Adventure|Science Fiction|Fantasy
4      Action|Crime|Thriller

```

```

                                production_companies release_date  vote_count \
0 Universal Studios|Amblin Entertainment|Legenda... 2015-06-09      5562
1 Village Roadshow Pictures|Kennedy Miller Produ... 2015-05-13      6185
2 Summit Entertainment|Mandeville Films|Red Wago... 2015-03-18      2480
3      Lucasfilm|Truenorth Productions|Bad Robot 2015-12-15      5292
4 Universal Pictures|Original Film|Media Rights ... 2015-04-01      2947

```

```

    vote_average  release_year  budget_adj  revenue_adj  profit \
0           6.5         2015  1.379999e+08  1.392446e+09  1.363529e+09
1           7.1         2015  1.379999e+08  3.481613e+08  2.284364e+08
2           6.3         2015  1.012000e+08  2.716190e+08  1.852382e+08
3           7.5         2015  1.839999e+08  1.902723e+09  1.868178e+09
4           7.3         2015  1.747999e+08  1.385749e+09  1.316249e+09

```

```

    profit_adj  decade
0  1.254446e+09  after2010
1  2.101614e+08  after2010
2  1.704191e+08  after2010
3  1.718723e+09  after2010
4  1.210949e+09  after2010

```

list used function: Function get_data_frame

```

In [57]: df_genre_decade = get_data_frame(df.copy(), 'genres', 'decade')
          # let's count the genre alomst use group by metric we decide before
          df_genre_decade_rank = df_genre_decade.groupby(['decade']).sum()
          df_genre_decade_rank.head(8)

```

```

Out[57]:
          animation  war  horror  foreign  crime  drama  fantasy  adventure \
decade
1960s             14   31     47         9    43    167        23         64
1970s             17   25    104         3    83    238        30         77
1980s             32   32    221         8   153    421       122        174
1990s             78   29    189        32   270    862       188        275
2000s            285   87    483        99   466   1605       318        505
after2010         238   64    584        32   337   1445       226        369

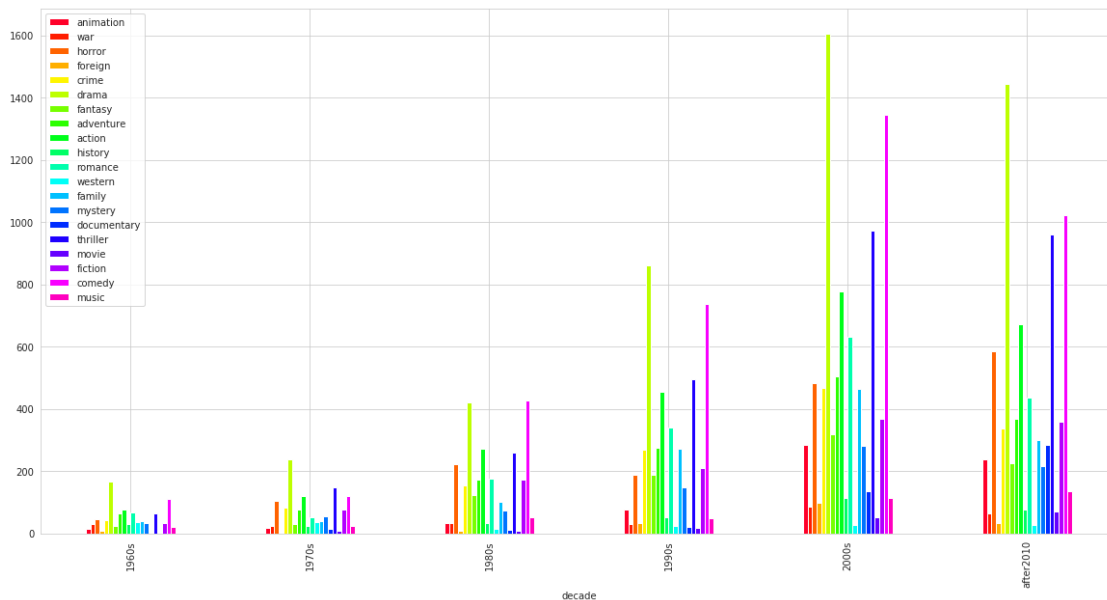
          action  history  romance  western  family  mystery  documentary \
decade
1960s          78       31       67       36       39       32           2
1970s         121       23       51       36       38       56          13
1980s         271       32      175       13      101       72          12
1990s         455       53      341       25      272      148          21

```

2000s	776	113	632	26	463	281	135
after2010	673	78	437	28	299	217	284

	thriller	movie	fiction	comedy	music
decade					
1960s	64	2	34	112	20
1970s	148	8	77	121	25
1980s	260	9	172	428	51
1990s	495	19	211	736	49
2000s	972	52	367	1346	114
after2010	961	69	359	1022	135

```
In [58]: # plot sum of genre use in each decade
df_genre_decade_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow');
```



Answer Question Trend

from figure above we found that drama genre always have high distribution in every decade, genre western getting smaller in every decade. Genre foreign always have low distribution in every decade. Go To List Question

Conclusions

The purpose of this research is to answer 3 parts of the question:

Part 1: General From this part we found that number of movie increasing every year. Movie with the highest profit is Avatar(2009), but if we check the inflation over time so the highest profit movie is Star Wars(1977) and the lowest profit movie is The Warrior's Way(2010). The Warrior's Way maybe get the lowest profit because it is movie with the highest budget. The lowest budget movie so far is Fear Clinic(2014). In this data we found the highest revenue movie is Avatar(2009),

maybe it is reason that movie become the highest profit, but because the highest profit by inflation is Star Wars so we can conclude that budget Star Wars is bigger than Avatar (of course we assumed with inflation). The lowest revenue movie is Shattered Glass(2003). The longest runtime movie is The Story of Film: An Odyssey(2011) that is 900 minutes, its is make sense because it is documantary movie. The shortest runtime movie is Batman: Strange Days(2014) that is just run in 3 minutes. The highest popularity didn't mean the highest profit, but for level "very high" in popularity have highest profit. So if we want to make a highest profit movie we must make the movie get very high popularity levels, with minimum popularity is 0.710151. We also found that the highest level of vote average not always mean the movie get the highest profit, especially to 2010 which medium vote have higher profit than high and very high vote average.

Part 2: Find Associate Variable Movie Genre with Movie Metric From this part we found that genre drama are high distributed in all popularity level. Movies with genre "documentary", "movie", or "foreign" only few get "very high" popularity level. In revenue level, genre that always appear in high distribution is horror. In level very high revenue, genre documentary and foreign is not appear (or maybe too small) so its mean they don't have a big revenue. Also in high level revenue, genre foreign is not appear but genre documentary is appear with small distribution. In vote level, drama still appear in all distribution and have higher distribution except in low level vote. So its mean many drama movie have high vote. Just like popularity and revenue, comedy is in second place distribution in each vote level. In profit level, genre drama still appear in all distribution and also have higher distribution except in very high profit level. So its mean drama movie have good distribution in all profit level. Genre action have highest distribution in very high profit level, in another level that genre just in 4th position from higher distribution.

Part 3: Find Some Trend From this part we found that drama genre always have high distribution in every decade, genre western getting smaller in every decade. Genre foreign always have low distribution in every decade.