

investigate-a-dataset-movie

March 25, 2019

1 Project: Investigate a Dataset The Movie

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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 popularity level?

What movie genre that associated with revenue level?

What movie genre that associated with vote average level?

What movie genre that associated with profit level?

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 '${:,.2f}'.format(amount) # return positive data in dollar version with
    else:
        return '-${:,.2f}'.format(-amount) # return negative data in dollar version with

In [16]: # get movie information
def get_movie_info(index, title):
    info = pd.DataFrame(df.loc[index]) # set some Data frame by index

    currency_col = ['budget', 'revenue', 'profit', 'budget_adj', 'revenue_adj', 'profit_adj']
    # for each currency in list above, do the following procedure
    for idx in currency_col:
        info.loc[idx] = as_currency(info.loc[idx].item()) # change value number into currency

    info.columns = [title] # change column name so it the reader will be clear what the data is
    return info

In [17]: # get highest and lowest 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 lowest 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]:
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')
```

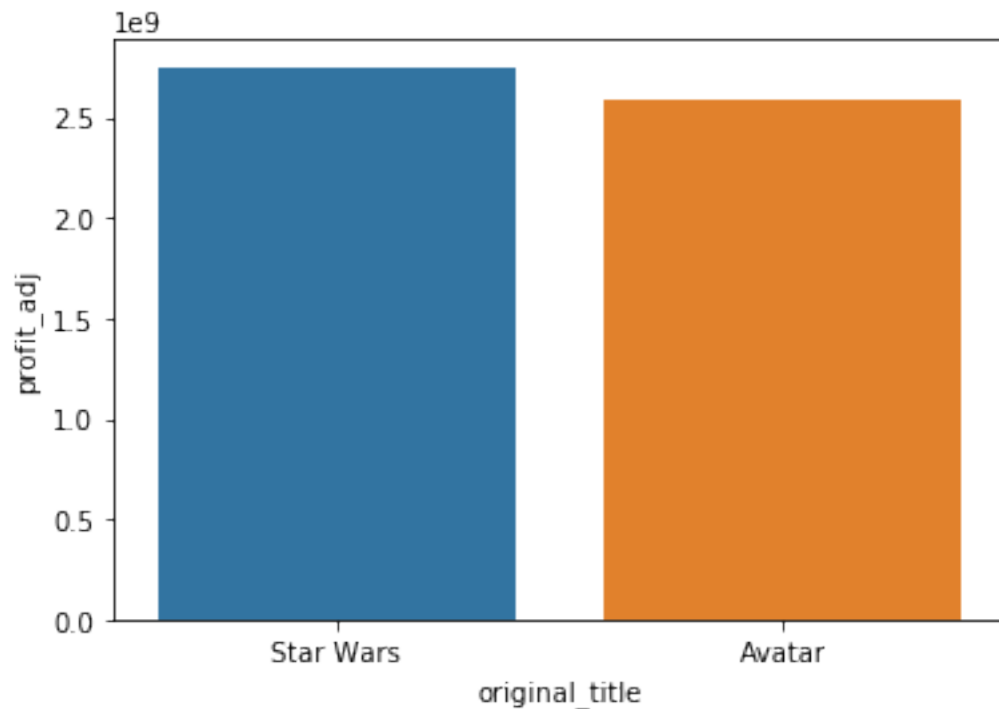
```
Out[21]:
Highest profit_adj \
id 11
popularity 12.0379
```

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', 'Avatar']")
sns.barplot(x="original_title", y="profit_adj", data=highest_profit)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fdd5cc88588>



Answer Question General 1

- The highest profit movie is Avatar(2009), but if we check the inflation over time so the highest profit move 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	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
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 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 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 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

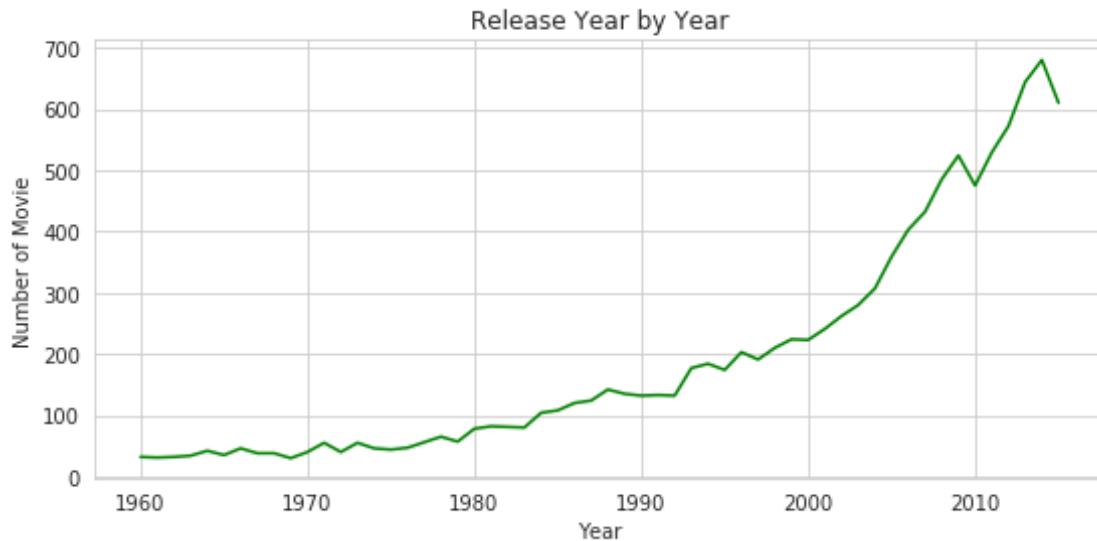
- The longest runtime movie is The Story of Film: An Odyssey(2011) that is 900 minutes
- The shortest runtime movie is Batman: Strange Days(2014) that is 3 minutes

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, dfyear):
```

```

# set the positions and width for the bars
position = list(range(len(df.query('%s == "Low"' % column))))
width = 0.2

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

# create the bar with Low data, in position
plt.bar(position,df.query('%s == "Low"' % column)[object_column], width, alpha=0.8,

# create the bar with Medium data, in position pos + some width buffer
plt.bar([p + width for p in position], df.query('%s == "Medium"' % column)[object_col
        color='#FFD700', label='Medium'])

# create the bar with High data, in position + some width buffer so they not inters
plt.bar([p + width*2 for p in position], df.query('%s == "High"' % column)[object_co
        color='#ADFF2F', label='High'])

# create the bar with Very High data,
# in position + some width buffer so they not intersect each other
plt.bar([p + width*3 for p in position], df.query('%s == "Very High"' % column)[objec
        color='#008000', label='Very High'])

# set x axis and y axis
ax.set_ylabel(object_column) # set the y-axis label
ax.set_title('%s in different %s levels in recent 10 years' % (object_column,column))
ax.set_xticks([p + 1.5 * width for p in position]) # set the position of the x-ticks
ax.set_xticklabels(dfyear) # set the labels for the x ticks
ax.set_ylim([min(df[object_column]),max(df[object_column])]) # set the y ticks

# add 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  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  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

release_year	popularity_levels	runtime	vote_count	vote_average \
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

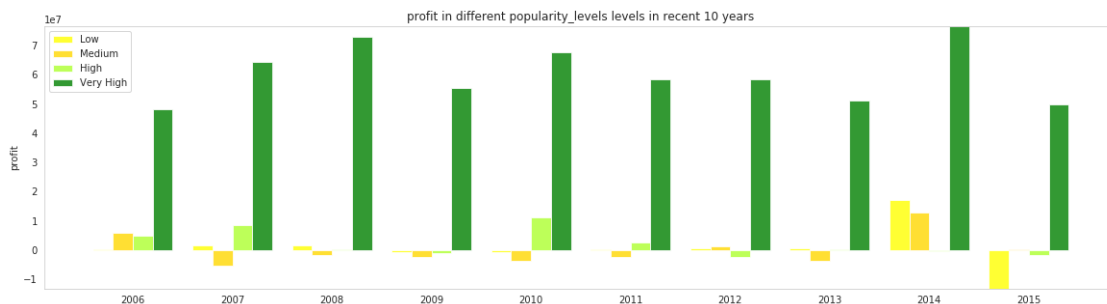
release_year	popularity_levels	budget_adj	revenue_adj	profit \
2006	Low	7.571684e+06	5.070612e+06	166000.0
	Medium	9.194188e+06	1.221233e+07	5796544.0
	High	2.163338e+07	2.555975e+07	4910153.5
	Very High	4.326677e+07	1.007697e+08	48197993.0
2007	Low	1.051669e+07	1.087160e+07	1392364.0
	Medium	1.051669e+07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

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	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  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

```

```

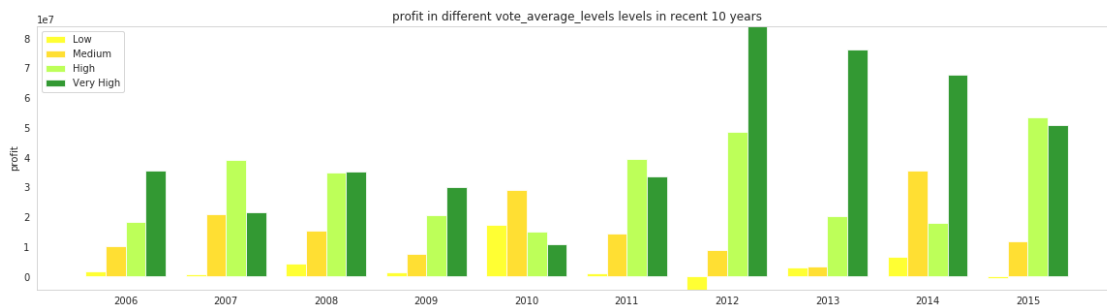
      profit  profit_adj
count  1.712000e+03  1.712000e+03
mean   8.334300e+07  8.133364e+07
std    1.793768e+08  1.743710e+08
min   -4.139124e+08 -4.139124e+08

```

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'])
# visualization
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() # make set to save what unique column we need it
    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("|") # get array
        # for each word list temp, do the following procedure
        for j in range(len(temp)):
            last_name = remove_punctuation(temp[j].lower()).split(" ")[-1] # get last word
            if last_name != '' and last_name != 'nan': # if that is not missing value, save it
                names.add(last_name) # it will save all unique word split by / in column

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

    # for each data, do the following procedure
    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)] # add metric value
        temp = str(remove_punctuation(old_df.iloc[i, old_df.columns.get_loc(column)]).lower().split("/"))
        # for each word in set names, do the following procedure
        for name in names:
            dict_column[name] += temp.count(name) # add number if the name exist in this row
        df_add = pd.DataFrame(dict_column, index=[i]) # add the dict to dataframe so it has index
        df_temp = df_temp.append(df_add, ignore_index=True, sort=False) # add to data frame

    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]:
mystery western romance action history thriller drama fantasy war fiction \
0         0         0         0         1         0         1         0         1         0         1
1         1         0         0         0         1         0         0         0         1         0

```

```

2      0      0      0      0      0      0      0      0      0      0      0

... movie horror adventure documentary music crime animation family comedy \
0 ...      0      0      0      0      0      0      0      0      0      0
1 ...      0      0      1      0      0      0      0      0      0      0
2 ...      0      0      1      0      0      0      1      1      1      1

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 mov*
df_genres.sum()

```

Out[44]: mystery                359
western                36
romance                747
action                1052
history                141
thriller              1482
drama                2291
fantasy                398
war                   106
fiction               549
foreign                91
movie                 95
horror                884
adventure             618
documentary           363
music                 195
crime                 569
animation             383
family                519
comedy                1690
popularity_levels      Very HighVery HighVery HighVery HighVery HighV...
dtype: object

```

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

```

Out[45]:      mystery  western  romance  action  history  thriller \
popularity_levels
High           76         11        192      263        39       411
Low            75          4        171      151        29       266
Medium         89          7        174      249        40       375

```

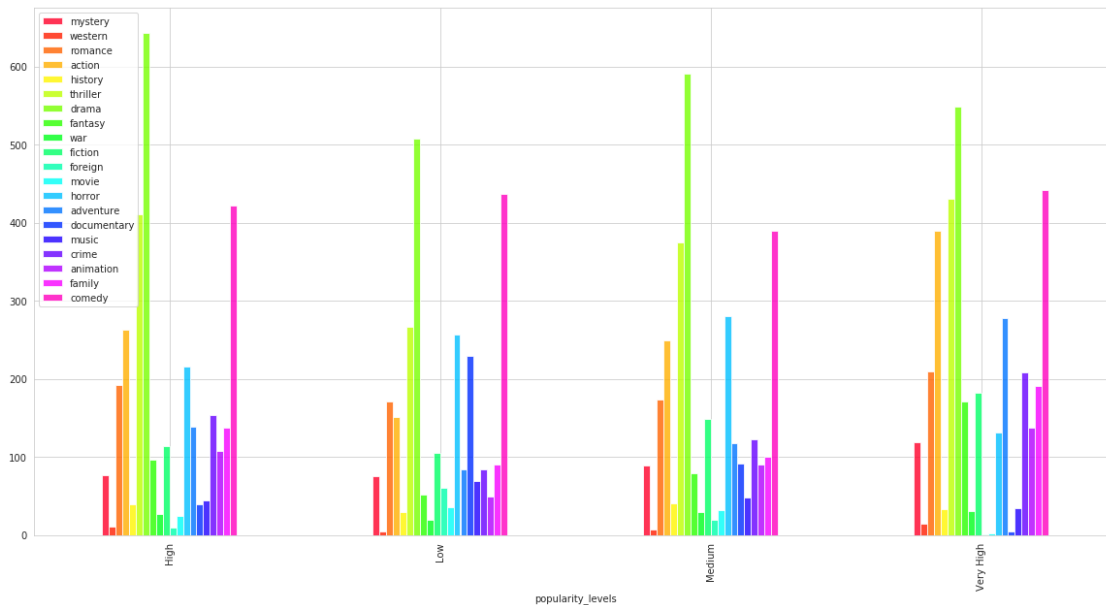
Very High	119	14	210	389	33	430
-----------	-----	----	-----	-----	----	-----

	drama	fantasy	war	fiction	foreign	movie	horror	\
popularity_levels								
High	643	96	27	114	10	25	216	
Low	508	52	19	105	60	36	257	
Medium	591	79	29	148	20	32	280	
Very High	549	171	31	182	1	2	131	

	adventure	documentary	music	crime	animation	family	\
popularity_levels							
High	139	39	44	154	107	138	
Low	84	229	69	84	49	90	
Medium	117	91	48	123	90	100	
Very High	278	4	34	208	137	191	

	comedy
popularity_levels	
High	422
Low	437
Medium	389
Very High	442

In [46]: *# plot sum of genre use in each level of popularity*
df_genre_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow',alpha=0.8).legend



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()
# make class or level from metric
df_new = get_class(df_new,metric)
metric_name = '{}_levels'.format(metric) # declare the metric name to the next process
df_genre_new = get_data_frame(df_new.copy(),column,metric_name) # get the binary data

# let's count the genre alomst use group by metric we decide before
df_genre_new_rank = df_genre_new.groupby([metric_name]).sum() # make binary data to rank

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]:
```

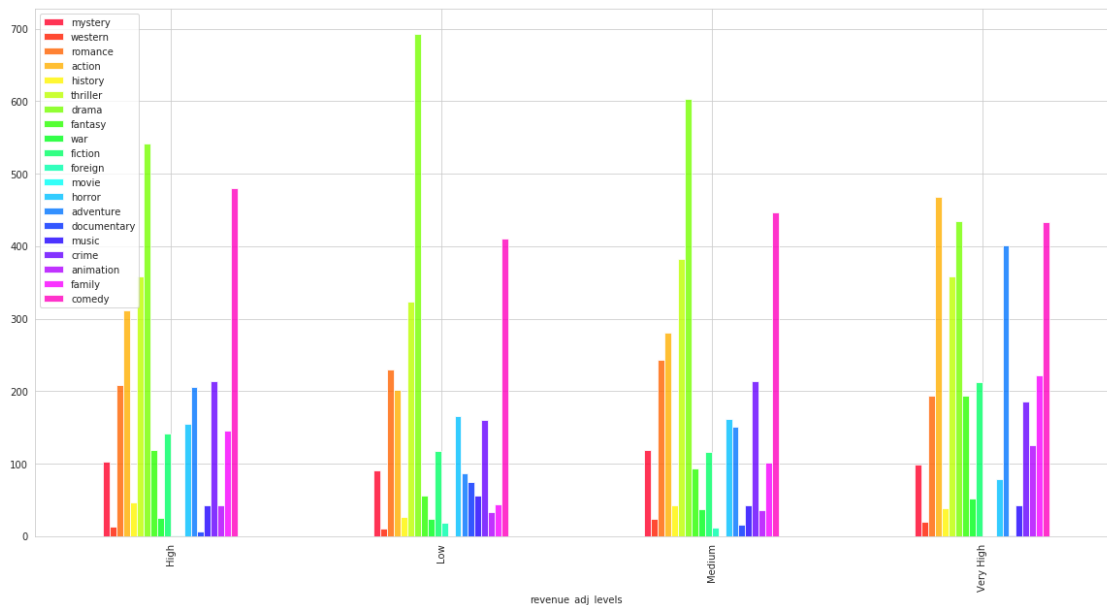
	mystery	western	romance	action	history	thriller	\
revenue_adj_levels							
High	102	13	209	311	47	358	
Low	91	10	230	201	26	324	
Medium	119	23	243	280	42	382	
Very High	98	19	194	468	38	358	

	drama	fantasy	war	fiction	foreign	movie	horror	\
revenue_adj_levels								
High	541	118	25	141	1	1	155	
Low	693	56	23	117	18	0	166	
Medium	603	93	37	116	11	0	161	
Very High	434	194	52	212	0	0	79	

	adventure	documentary	music	crime	animation	family	\
revenue_adj_levels							
High	205		6	42	214	43	146
Low	86		74	56	160	33	44
Medium	151		16	43	214	35	101

Very High	401	1	43	185	126	222
comedy						
revenue_adj_levels						
High	480					
Low	411					
Medium	446					
Very High	433					

```
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',alpha=0.8)
```



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]:
          mystery  western  romance  action  history  thriller \
vote_average_levels
High          233       45       534       595       104       719
Low           199       35       354       765        28       980
Medium        223       38       463       622        71       787
Very High     151       46       352       392       127       414

          drama  fantasy  war  fiction  foreign  movie  horror \
vote_average_levels
High       1381       220   75       276        47       31       257
Low         833       275   37       471        54       54       849
Medium      1170       239   65       277        37       47       401
Very High   1354       173   91       196        45       27       121

          adventure  documentary  music  crime  animation  family \
vote_average_levels
High              384           86   115   398           204       332
Low               393           18    48   249           67       311
Medium            373           47    68   364          149       308
Very High         314          316   163   341          244       261

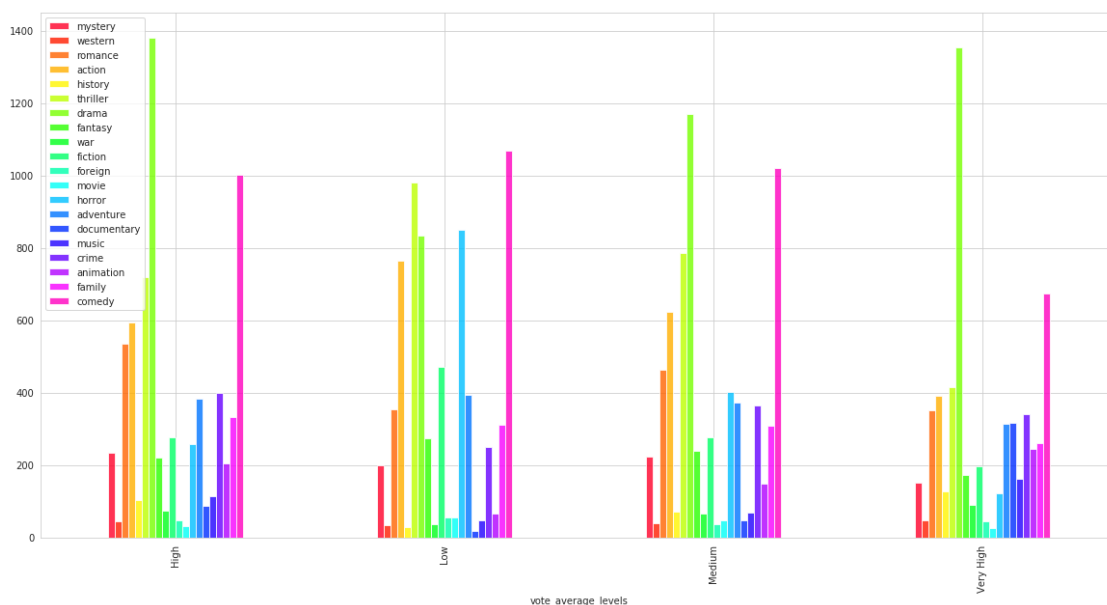
          comedy
vote_average_levels
High          1001
Low           1070
Medium        1020
Very High      674

```

```

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',alpha=0.8).1

```



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]:
```

	mystery	western	romance	action	history	thriller	\
profit_adj_levels							
High	85	11	163	246	39	302	
Low	111	18	172	278	34	337	
Medium	71	10	178	197	31	284	
Very High	77	13	153	364	25	280	

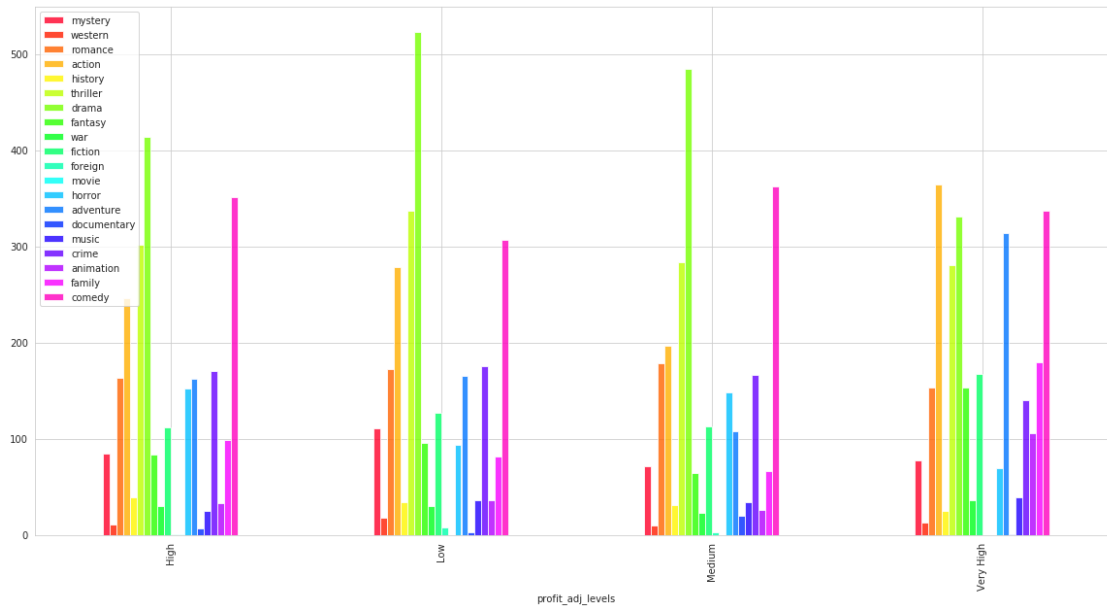
	drama	fantasy	war	fiction	foreign	movie	horror	\
profit_adj_levels								
High	414	83	30	112	1	1	152	
Low	523	96	30	127	8	0	94	
Medium	485	64	23	113	3	0	148	
Very High	331	153	36	167	0	0	69	

	adventure	documentary	music	crime	animation	family	\
profit_adj_levels							
High	162		7	25	170	33	99
Low	165		3	36	175	36	81
Medium	108		20	34	166	26	66
Very High	314		1	39	140	106	179

	comedy
profit_adj_levels	
High	351
Low	307
Medium	362
Very High	337

```
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',alpha=0.8)
```



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]: # make year list to make easy the next process
y1960s =df_sub_year[:10] # year list of 1960s
y1970s =df_sub_year[10:20] # year list of 1970s
y1980s =df_sub_year[20:30] # year list of 1980s
y1990s = df_sub_year[30:40] # year list of 1990s
y2000s = df_sub_year[40:50] # year list of after 2000
y2010s = df_sub_year[50:] # year list of after 2010
```

```
In [56]: # year list divide by 10 years
times = [y1960s, y1970s, y1980s, y1990s, y2000s, y2010s]
# timeline name
names = ['1960s', '1970s', '1980s', '1990s', '2000s', '2010s']
df['decade'] = np.nan # I make another metric to save the categorical data divide by de
for i in range(len(names)): # to fill the new metric "decade", do the following procedu
    index = df[df.release_year.isin(times[i])].index.values.tolist() # find list of idx
    for j in index: # for idx in list above, do the following procedure
        df.loc[j, 'decade'] = names[i] # insert decade name to new metric we declare bef
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	2010s
1	2.101614e+08	2010s
2	1.704191e+08	2010s
3	1.718723e+09	2010s
4	1.210949e+09	2010s

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]:
```

	mystery	western	romance	action	history	thriller	drama	fantasy	\
decade									
1960s	32	36	67	78	31	64	167	23	
1970s	56	36	51	121	23	148	238	30	
1980s	72	13	175	271	32	260	421	122	
1990s	148	25	341	455	53	495	862	188	
2000s	281	26	632	776	113	972	1605	318	
2010s	217	28	437	673	78	961	1445	226	

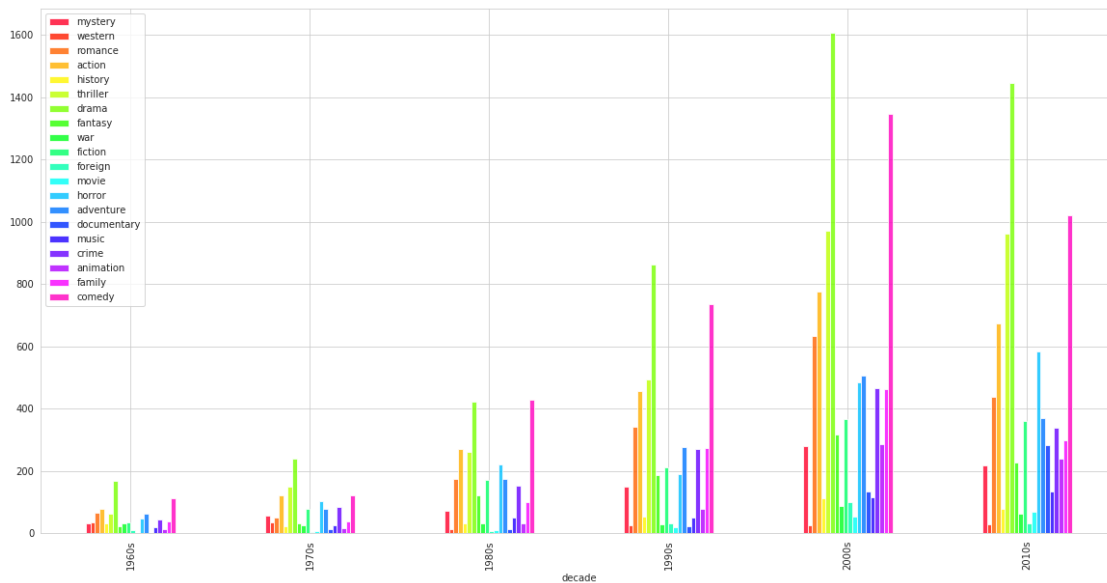
	war	fiction	foreign	movie	horror	adventure	documentary	music	\
decade									
1960s	31	34	9	2	47	64	2	20	
1970s	25	77	3	8	104	77	13	25	
1980s	32	172	8	9	221	174	12	51	
1990s	29	211	32	19	189	275	21	49	
2000s	87	367	99	52	483	505	135	114	
2010s	64	359	32	69	584	369	284	135	

	crime	animation	family	comedy
decade				
1960s	43	14	39	112
1970s	83	17	38	121

1980s	153	32	101	428
1990s	270	78	272	736
2000s	466	285	463	1346
2010s	337	238	299	1022

In [58]: *# plot sum of genre use in each decade*

`df_genre_decade_rank.plot(kind='bar',figsize=(20,10),colormap='gist_rainbow',alpha=0.8)`



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

Limitation The limitation of this project are: 1. I assumed that Null and Zero value means missing value and other else is the right value From my mini research on Mr.Holmes movie, I found that zero value is not the real number. So I assumed that zero value in 'budget', 'revenue', 'runtime','budget_adj', and 'revenue_adj' means missing value and other else is the right value. Besides that, it still consists of a small and big value that maybe in there because of human error or other. Because of that maybe exist some bias in my research. 2. I choose to delete data with the count of row is not missing value is more than 95% from the real dataset I choose 95% as threshold because I didn't want to delete too much data. I don't want it because the closer number to the actual data is, the more analytical results must be closer also. 3. I bin the data level by quantile I choose quantile because I think it fairer, so movie is only compared to the fellow movie, not in the real range. Especially in popularity and vote average, I think that metric must have constant range but I don't know what the real range on that. 4. I'm not research about impact of the combined genre on metrics In my research, there is some bias because I do not calculate the effect of combined genre. So in some conclusion maybe the large profit come from genre drama, but maybe it have large profit because that genre combines with fiction, or action, etc. 5. I'm not

counting people who vote that movie In my research, I just use vote average because I don't know the reason people want to vote or not. How if the people didn't vote because he/she agrees with another voter. Also, the vote count can not describe how much people see the movie.

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.