Tip: Welcome to the Investigate a Dataset project! You will find tips in quoted sections like this to help organize your approach to your investigation. Before submitting your project, it will be a good idea to go back through your report and remove these sections to make the presentation of your work as tidy as possible. First things first, you might want to double-click this Markdown cell and change the title so that it reflects your dataset and investigation.

Project: Investigate a Dataset (TMDb_Movies Dataset)

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- Introduction
- Data Wrangling
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Introduction

I'm going to investigate the (TMDb Movies Dataset) which I dowloaded from Kaggle web page.

The dataset has information about 10,000 movies and consist of 21 columns such as popularity, budget, revenue, original title, cast ...etc.

I'm lookingforward to figure out which genres are most popular from year to year? and what kinds of properties are associated with movies that have high revenues?

```
In [357]: # Use this cell to set up import statements for all of the packages that you
# plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
# inline with the notebook. See this page for more:
# http://ipython.readthedocs.io/en/stable/interactive/magics.html
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns
from collections import Counter
%matplotlib inline
```

Data Wrangling

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

General Properties

Out[358]:

b_	idb_id	popularity	budget	revenue	original_title	cast	
40	44056	0.006925	-	-	The Story of Film: An Odyssey	Mark Cousins Jean- Michel Frodon Cari Beauchamp	http://www.cha
983	89830	0.469332	-	-	Taken	Dakota Fanning Matt Frewer Eric Close Emily Be	
590	85906	0.537593	-	125,000,000	Band of Brothers	Damian Lewis Ron Livingston Frank John Hughes	http://wv

3 rows × 21 columns

```
In [359]: # Count number of rows and columns tmdb.shape
```

Out[359]: (10866, 21)

```
In [360]: tmdb.describe()
```

Out[360]:

	id	popularity	runtime	vote_count	vote_average	release_year	
count	10866.000000	10866.000000	10866.000000	10866.000000	10866.000000	10866.000000	1.0
mean	66064.177434	0.646441	102.070863	217.389748	5.974922	2001.322658	1.
std	92130.136561	1.000185	31.381405	575.619058	0.935142	12.812941	3.4
min	5.000000	0.000065	0.000000	10.000000	1.500000	1960.000000	0.0
25%	10596.250000	0.207583	90.000000	17.000000	5.400000	1995.000000	0.0
50%	20669.000000	0.383856	99.000000	38.000000	6.000000	2006.000000	0.0
75%	75610.000000	0.713817	111.000000	145.750000	6.600000	2011.000000	2.0
max	417859.000000	32.985763	900.000000	9767.000000	9.200000	2015.000000	4.1

In [361]: tmdb.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):

Data	columns (total 21 colu	umns):	
#	Column	Non-Null Count	Dtype
0	id	10866 non-null	int64
1	imdb_id	10856 non-null	object
2	popularity	10866 non-null	float64
3	budget	10866 non-null	object
4	revenue	10866 non-null	object
5	original_title	10866 non-null	object
6	cast	10790 non-null	object
7	homepage	2936 non-null	object
8	director	10822 non-null	object
9	tagline	8042 non-null	object
10	keywords	9373 non-null	object
11	overview	10862 non-null	object
12	runtime	10866 non-null	int64
13	genres	10843 non-null	object
14	<pre>production_companies</pre>	9836 non-null	object
15	release_date	10866 non-null	<pre>datetime64[ns]</pre>
16	vote_count	10866 non-null	int64
17	vote_average	10866 non-null	float64
18	release_year	10866 non-null	int64
19	<pre>budget_adj</pre>	10866 non-null	float64
20	revenue_adj	10866 non-null	float64
dtype	es: datetime64[ns](1),	float64(4), into	64(4), object(12)
memor	ry usage: 1.7+ MB		

```
# Check duplicate data
In [362]:
           duplicats = tmdb[tmdb.duplicated(keep='last')]
           duplicats
Out[362]:
                     id
                         imdb_id popularity
                                               budget revenue original_title
                                                                                   cast homepage
                                                                            Jon Foo|Kelly
                                                                           Overton|Cary-
            9025 42194 tt0411951
                                    0.59643 30,000,000
                                                      967,000
                                                                  TEKKEN
                                                                                             NaN
                                                                                Hiroyuki
                                                                            Tagawa|lan...
           1 rows × 21 columns
In [363]:
           # Count all zero value in each colunms
           (tmdb == 0).sum()
Out[363]:
           id
                                         0
           imdb_id
                                         0
           popularity
                                         0
            budget
                                         0
            revenue
                                         0
           original_title
                                         0
                                         0
           cast
                                         0
           homepage
           director
                                         0
                                         0
           tagline
           keywords
                                         0
           overview
                                         0
           runtime
                                        31
           genres
                                         0
                                         0
           production companies
           release_date
                                         0
           vote_count
                                         0
           vote_average
                                         0
           release year
                                         0
           budget_adj
                                      5696
           revenue_adj
                                      6016
           dtype: int64
```

```
In [364]: # Count all null value in each columns
tmdb.isnull().sum()
```

	<pre>tmdb.isnull().sum()</pre>					
Out[364]:	id	0				
	imdb_id	10				
	popularity	0				
	budget	0				
	revenue	0				
	original_title	0				
	cast	76				
	homepage	7930				
	director	44				
	tagline	2824				
	keywords	1493				
	overview	4				
	runtime	0				
	genres	23				
	<pre>production_companies</pre>	1030				
	release_date	0				
	vote_count	0				
	vote_average	0				
	release_year	0				
	budget_adj	0				
	revenue_adj	0				
	dtype: int64					

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

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

Data Cleaning (Delete unnecessary information)

From the data wrangling results I confiermed that there are a unesessary columns and duplicated data and there are some rows with null data and others with zero budget, zero revenue and zero runtime, so these data need to be cleaned by doing the following steps:

- 1. Delet unesessary columns which are (id, imdb_id, homepage, keywords, overview, production_companies, vote_count)
- 2. Delet duplicated rows.
- 3. Delet all rows which have zero value.
- 4. Replace zero with NAN value.

```
In [365]: # Delete unesessary columns

del_columns=[ 'id','imdb_id', 'homepage', 'keywords', 'overview', 'production_
    companies', 'vote_count']
    tmdb_clean_columns= tmdb.drop(del_columns,1)

tmdb_clean_columns.head()
```

Out[365]:

director	cast	original_title	revenue	budget	popularity	
Mark Cousins	Mark Cousins Jean- Michel Frodon Cari Beauchamp	The Story of Film: An Odyssey	-	-	0.006925	0
Breck Eisner∣Félix EnrÃquez AlcaláJJohn Faw	Dakota Fanning Matt Frewer Eric Close Emily Be	Taken	-	-	0.469332	1
Phil Alden Robinson Richard Loncraine Mikael S	Damian Lewis Ron Livingston Frank John Hughes	Band of Brothers	125,000,000	-	0.537593	2
Claude Lanzmann	Simon Srebnik Michael Podchlebnik Motke Zaidl	Shoah	-	-	0.147489	3
NaN	Patrick Swayze Philip Casnoff Kirstie Alley Ge	North and South, Book I	-	-	0.000065	4
	Mark Cousins Breck Eisner Félix EnrÃquez Alcalá John Faw Phil Alden Robinson Richard Loncraine Mikael S Claude Lanzmann	Mark Cousins Jean- Michel Frodon Cari Beauchamp Dakota Fanning Matt Frewer Eric Close Emily Be Damian Lewis Ron Livingston Frank John Hughes Simon Srebnik Michael Podchlebnik Motke Zaidl Patrick Swayze Philip Casnoff Kirstie	The Story of Film: An Odyssey Taken Taken Band of Brothers Shoah Shoah North and South, Book North and South, Book Tilm: An Odyssey Mark Cousins Breck Eisner Félix EnrÃquez AlcaláJohn Faw Phil Alden Robinson Richard Loncraine Mikael S Claude Lanzmann Patrick Swayze Philip Casnoff Kirstie NaN	The Story of Film: An Odyssey The Story of Film: An Odyssey Taken Taken Taken Taken Taken Taken Taken Taken Dakota Fanning Matt Frewer Eric Close Emily Be Taken Damian Lewis Ron Livingston Frank John Hughes Taken Simon Srebnik Michael Podchlebnik Motke Zaidl North and South, Book Swayze Philip Casnoff Kirstie Mark Cousins Breck Eisner Félix EnrÃquez AlcaláJohn Faw Phil Alden Robinson Richard Loncraine Mikael S Claude Lanzmann NaN	The Story of Film: An Odyssey The Story of Film: An Odyssey Taken Taken Taken Taken Taken Taken Taken Dakota Fanning Matt Frewer Eric Close Emily Be Taken Taken Damian Lewis Ron Livingston Frank John Hughes Damian Lewis Ron Livingston Frank John Hughes Phil Alden Robinson Richard Loncraine Mikael S Simon Srebnik Michael Podchlebnik Motke Zaidl North and South, Book Swayze Philip Casnoff Kirstie NaN	0.006925 - - The Story of Film: An Odyssey Cousins Jean-Michel Frodon Cari Beauchamp Mark Cousins 0.469332 - - - Taken Dakota Fanning Matt Frewer Eric Close Emily Be Eisner Félix EnrÃquez Alcalá John Faw 0.537593 - 125,000,000 Band of Brothers Damian Lewis Ron Livingston Frank John Hughes Phil Alden Robinson Richard Loncraine Mikael S 0.147489 - - Shoah Podchlebnik Michael Podchlebnik Motke Zaidl Claude Lanzmann Swayze Philip Casnoff Kirstie 0.000065 - - North and South, Book Casnoff Kirstie Swayze Philip Casnoff Kirstie

```
In [366]: tmdb.shape
```

Out[366]: (10866, 21)

```
In [367]: tmdb_clean_columns.shape
```

Out[367]: (10866, 14)

```
In [368]: # Delete duplicate rows
    tmdb_clean_columns.drop_duplicates(keep='last', inplace=True)
    tmdb_clean_columns.shape
```

Out[368]: (10865, 14)

```
In [369]:
          tmdb_clean_columns.dtypes
Out[369]: popularity
                                     float64
            budget
                                      object
                                      object
            revenue
           original_title
                                      object
                                      object
           cast
           director
                                      object
           tagline
                                      object
           runtime
                                       int64
           genres
                                      object
           release_date
                              datetime64[ns]
                                     float64
           vote average
           release_year
                                        int64
                                     float64
           budget adj
           revenue_adj
                                     float64
           dtype: object
In [370]:
           (tmdb_clean_columns == 0).sum()
Out[370]: popularity
                                 0
            budget
                                 0
                                 0
            revenue
           original_title
                                 0
           cast
                                 0
           director
                                 0
                                 0
           tagline
           runtime
                                31
                                 0
           genres
           release_date
                                 0
           vote_average
                                 0
                                 0
           release_year
           budget adj
                              5696
           revenue_adj
                              6016
           dtype: int64
In [371]:
          tmdb_clean_columns.isnull().sum()
Out[371]: popularity
                                 0
                                 0
            budget
                                 0
            revenue
                                 0
           original_title
                                76
           cast
           director
                                44
           tagline
                              2824
           runtime
                                 0
                                23
           genres
           release_date
                                 0
                                 0
           vote average
                                 0
           release_year
           budget_adj
                                 0
                                 0
           revenue adj
           dtype: int64
```

```
In [372]: # Delete all rows with zero values.
           budget_revenue_runtime = [' budget ', ' revenue ', 'budget_adj', 'revenue_adj'
           , 'runtime'
           # This will replace all zero values from '0' to NAN.
           tmdb clean columns[budget revenue runtime] = tmdb clean columns[budget revenue
           runtime].replace(0, np.NAN)
           # Removing all row which has NaN value in budget revenue
           tmdb_clean_columns.dropna(subset = budget_revenue_runtime, inplace = True)
           tmdb clean columns.shape
Out[372]: (3854, 14)
In [373]: (tmdb clean columns == 0).sum()
Out[373]: popularity
                             0
           budget
                             0
           revenue
                             0
          original_title
                             0
          cast
                             0
          director
                             0
          tagline
                             0
          runtime
                             0
          genres
                             0
          release date
          vote average
                             0
                             0
          release_year
          budget_adj
                             0
          revenue_adj
                             0
          dtype: int64
In [374]: | tmdb_clean_columns=tmdb_clean_columns.fillna(" ")
In [375]: | tmdb_clean_columns.isnull().sum()
Out[375]: popularity
                             0
           budget
                             0
           revenue
                             0
          original_title
                             0
          cast
                             0
                             0
          director
                             0
          tagline
                             0
          runtime
          genres
                             0
                             0
          release_date
          vote_average
                             0
                             0
          release year
          budget adj
                             0
          revenue_adj
                             0
          dtype: int64
```

In [376]: tmdb_clean_columns

Out[376]:

	popularity	budget	revenue	original_title	cast	director	tag
20	9.432768	237,000,000	2,781,505,847	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameron	Enter Worl Pand
37	11.173104	200,000,000	2,068,178,225	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	E\ genera has a st
59	4.355219	200,000,000	1,845,034,188	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	Nothinç Earth co co betw th
60	7.637767	220,000,000	1,519,557,910	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedon	Sc assen requi
61	32.985763	150,000,000	1,513,528,810	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	The pai or
10506	0.578849	15,000,000	5	Bordello of Blood	Dennis Miller Erika Eleniak Angie Everhart Joh	Gilbert Adler	
10511	0.208637	10	5	Kid's Story	Clayton Watson Keanu Reeves Carrie- Anne Moss K	Shinichiro Watanabe	
10607	0.352054	200,000	3	Dr. Horrible's Sing-Along Blog	Neil Patrick Harris Nathan Fillion Felicia Day	Joss Whedon	He ha Ph.[horriblena
10642	0.462609	6,000,000	2	Shattered Glass	Hayden Christensen Peter Sarsgaard Chloë Sevi	Billy Ray	
10696	0.552091	6,000,000	2	Mallrats	Jason Lee Jeremy London Shannen Doherty Claire	Kevin Smith	They're ther sł They're there
3854 rc	ows × 14 co	lumns					
4							

Exploratory Data Analysis

Questions that can analyised from this data set:

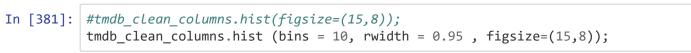
- 1. Find the top 10 Highest Runtime Movies?
- 2. Find the top 10 Highest Revenues Movies?
- 3. Find the top 10 Highest Budgets Movies?
- 4. Find the top 10 Highest Rating Movies?
- 5. Find the top 10 Highest Net Profits Movies?

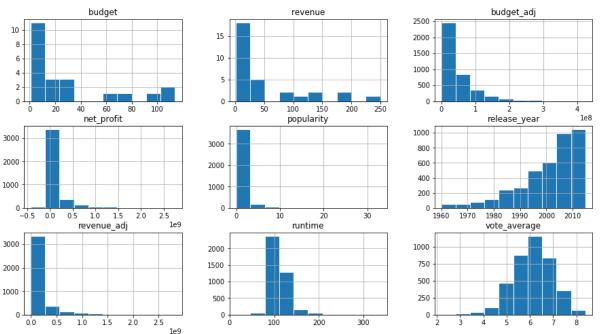
```
In [377]: # Change the dtype fo the fields budget and revenue from object to float64
          tmdb clean columns[[' budget ', ' revenue ']] = tmdb clean columns[[' budget '
           , ' revenue ']].apply(pd.to numeric, errors='coerce')
In [378]: | tmdb clean columns.dtypes
Out[378]: popularity
                                    float64
           budget
                                    float64
           revenue
                                    float64
                                     object
          original_title
                                     object
          cast
          director
                                     object
          tagline
                                     object
                                    float64
          runtime
          genres
                                     object
                             datetime64[ns]
          release date
                                    float64
          vote average
          release_year
                                      int64
          budget adj
                                    float64
                                    float64
          revenue_adj
          dtype: object
In [379]: # Add new column for the Net Profit of the each movie
          tmdb clean columns.insert(2,'net profit',tmdb clean columns['revenue adj'] - t
          mdb_clean_columns['budget_adj'])
```

In [380]: tmdb_clean_columns.head()

Out[380]:

	popularity	budget	net_profit	revenue	original_title	cast	director	tag
20	9.432768	NaN	2.586237e+09	NaN	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameron	Enter Worl Pand
37	11.173104	NaN	1.718723e+09	NaN	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	E\ genera ha st
59	4.355219	NaN	2.234714e+09	NaN	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	Noth on E cc cc betw th
60	7.637767	NaN	1.234248e+09	NaN	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedon	Sc assen requi
61	32.985763	NaN	1.254446e+09	NaN	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	The r is or
4								>



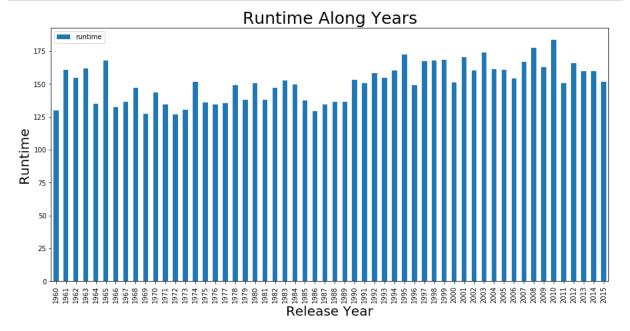


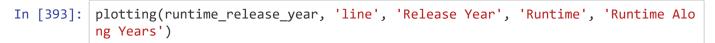
Research Question 01 - Top 10 Highest Runtime Movies

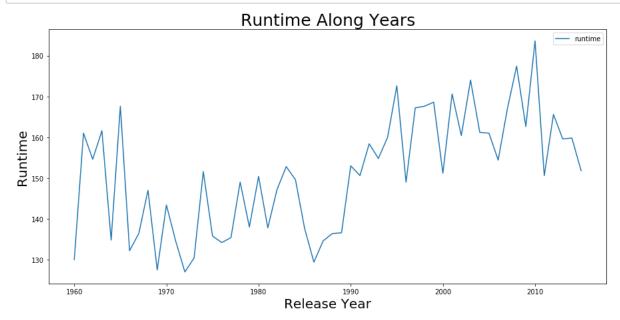
```
In [382]:
            by runtime = tmdb clean columns.sort values(['release year', 'runtime'], ascend
            ing=[True, False])
In [383]:
            by runtime.shape
Out[383]: (3854, 15)
            top by runtime = by runtime.groupby('release year').head().reset index(drop=Tr
In [384]:
            ue)
In [385]:
            top_by_runtime.shape
Out[385]:
            (279, 15)
In [386]:
            top by runtime.head()
Out[386]:
                popularity
                           budget
                                       net_profit
                                                 revenue original_title
                                                                                    cast
                                                                                           director
                                                                                                      tagline
                                                                                                        Mor€
                                                                                     Kirk
                                                                                                       titanic
                                                                         Douglas|Laurence
                                                                                            Stanley
             0
                  1.136943
                              NaN
                                   3.539024e+08
                                                     NaN
                                                              Spartacus
                                                                                                     than any
                                                                              Olivier|Jean
                                                                                            Kubrick
                                                                                                        story
                                                                          Simmons|Cha...
                                                                                                    ever told
                                                                                                        They
                                                                                                        were
                                                                           Yul Brynner|Eli
                                                                                                      seven
                                                                   The
                                                                            Wallach|Steve
                                                                                              John
                                                                                                     And they
                  1.872132
                              NaN 2.141847e+07
                                                     NaN
                                                             Magnificent
                                                                         McQueen|Charles
                                                                                            Sturges
                                                                                                       fough
                                                                 Seven
                                                                                                         lik€
                                                                                                       sever
                                                                                                         h..
                                                                                                       Movie
                                                                                                        wise
                                                                                    Jack
                                                                                                    there has
                                                                   The
                                                                          Lemmon|Shirley
                                                                                              Billy
                  0.947307
                                  1.622053e+08
                                                     NaN
                                                                                                        neve
                                                              Apartment
                                                                           MacLaine|Fred
                                                                                             Wilder
                                                                                                        beer
                                                                          MacMurray|Ra...
                                                                                                     anything
                                                                                                        like..
                                                                                                         Th€
                                                                                                    master o
                                                                                 Anthony
                                                                                                    suspense
                                                                             Perkins|Vera
                                                                                             Alfred
                  2.610362
                              NaN 2.299854e+08
                                                     NaN
                                                                Psycho
                                                                                                      moves
                                                                               Miles|John
                                                                                          Hitchcock
                                                                                                          his
                                                                         Gavin|Janet Le...
                                                                                                     cameras
                                                                                                       into ..
                                                                            Jerry Lewis|Ed
                                                                             Wynn|Judith
                                                                                             Frank
                  0.055821
                              NaN 3.022917e+07
                                                     NaN
                                                             Cinderfella
                                                                          Anderson|Henry
                                                                                            Tashlin
                                                                                   Silv...
In [387]:
            runtime_release_year = pd.pivot_table(top_by_runtime, index = 'release_year',
            values = 'runtime' )
```

```
In [388]: runtime_release_year.shape
Out[388]: (56, 1)
In [389]:
           runtime_release_year.head()
Out[389]:
                        runtime
            release_year
                  1960
                          130.0
                  1961
                          161.0
                  1962
                          154.6
                  1963
                          161.6
                  1964
                          134.8
In [390]:
           runtime_release_year.describe()
Out[390]:
                     runtime
                   56.000000
            count
            mean 151.019643
                   14.353681
              std
             min
                  127.000000
             25%
                  136.550000
             50%
                  151.400000
             75%
                  161.050000
             max 183.600000
In [391]: # Plotting Function
           def plotting(DATA, KIND , X_LABEL, Y_LABEL, TITLE):
               DATA.plot(kind = KIND, figsize =(15, 7))
               plt.xlabel(X LABEL , size =(20))
               plt.ylabel(Y_LABEL , size =(20))
               plt.title(TITLE , size =(25))
               plt.legend ()
```









NOTE: From the ghraph we can figure out that watching movies were popular between the year of 1960 to the eyear of 195, and then there was a reluctance of watching movies strating from 1967 up to 1987 and then started to populate again and kept growing positively.

```
In [394]: top_10_runtime = top_by_runtime.nlargest(10, 'runtime')
top_10_runtime
```

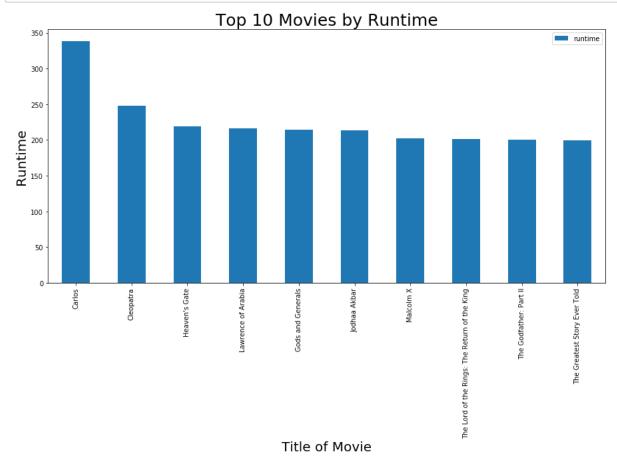
Out[394]:

	popularity	budget	net_profit	revenue	original_title	cast	
249	0.534192	NaN	-1.712872e+07	NaN	Carlos	Edgar RamÃ- rez Alexander Scheer Fadi Abi Samra	Olivier
15	0.804533	NaN	1.896460e+08	NaN	Cleopatra	Elizabeth Taylor Richard Burton Rex Harrison R	J Mankiewicz Mamouli:
99	0.418950	NaN	-1.072059e+08	NaN	Heaven's Gate	Kris Kristofferson Christopher Walken John Hur	Michae
10	1.168767	NaN	3.964647e+08	NaN	Lawrence of Arabia	Peter O'Toole Alec Guinness Anthony Quinn Jack	Da
214	0.469518	NaN	-5.106033e+07	NaN	Gods and Generals	Stephen Lang Jeff Daniels Robert Duvall Kevin	Ronald F.
239	0.389554	NaN	4.682315e+06	NaN	Jodhaa Akbar	Hrithik Roshan Aishwarya Rai Bachchan Sonu Soo	Ġ,
159	0.648937	NaN	2.202038e+07	NaN	Malcolm X	Denzel Washington Angela Bassett Albert Hall A	S
215	7.122455	NaN	1.214855e+09	NaN	The Lord of the Rings: The Return of the King	Elijah Wood lan McKellen Viggo Mortensen Liv T	Peter
69	3.264571	NaN	1.527582e+08	NaN	The Godfather: Part II	Al Pacino Robert Duvall Diane Keaton Robert De	Frai
25	0.146033	NaN	-5.536451e+07	NaN	The Greatest Story Ever Told	Max von Sydow Michael Anderson Jr. Carroll Bak	George
4							+

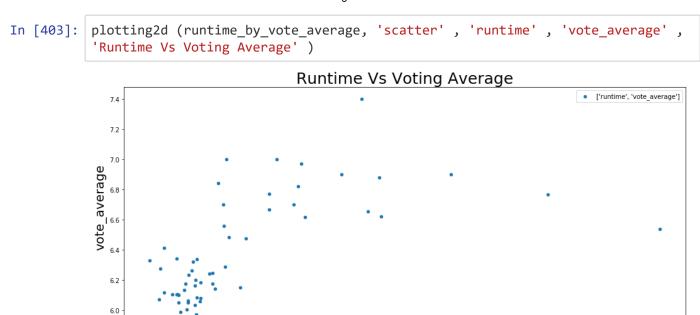
```
In [395]: # Top 10 Movies by Runtime
     top_10_runtime = pd.pivot_table(top_10_runtime, index = 'original_title', values = 'runtime')
```

```
In [396]: top_10_runtime.shape
Out[396]: (10, 1)
In [397]:
            top_10_runtime.head()
Out[397]:
                                runtime
                   original_title
                         Carlos
                                   338.0
                      Cleopatra
                                  248.0
             Gods and Generals
                                  214.0
                 Heaven's Gate
                                  219.0
                  Jodhaa Akbar
                                  213.0
In [398]:
            top_10_runtime
Out[398]:
                                                        runtime
                                          original_title
                                                Carlos
                                                          338.0
                                             Cleopatra
                                                          248.0
                                     Gods and Generals
                                                          214.0
                                         Heaven's Gate
                                                          219.0
                                         Jodhaa Akbar
                                                          213.0
                                    Lawrence of Arabia
                                                          216.0
                                                          202.0
                                            Malcolm X
                                   The Godfather: Part II
                                                          200.0
                            The Greatest Story Ever Told
                                                          199.0
             The Lord of the Rings: The Return of the King
                                                          201.0
            top_10_runtime = top_10_runtime.runtime.sort_values( ascending=False)
```

```
In [400]: plotting(top_10_runtime, 'bar', 'Title of Movie', 'Runtime', 'Top 10 Movies by Runtime')
```



Note: From the ghraph we can figur out that the highest runtime movie is Carlos.



runtime

NOTE: From the ghraph we can figure out that there is a moderate postive non-liner correlation, and there is anout lier valye.

Research Question 02 - Top 10 Highest Revenue Movies

	popularity	budget	net_profit	revenue	runtime	vote_average	release_y
count	3854.000000	22.000000	3.854000e+03	31.000000	3854.000000	3854.000000	3854.000
mean	1.191554	30.090909	9.282470e+07	51.516129	109.220291	6.168163	2001.261
std	1.475162	36.818615	1.940715e+08	67.591356	19.922820	0.794920	11.282
min	0.001117	1.000000	-4.139124e+08	2.000000	15.000000	2.200000	1960.000
25%	0.462368	6.500000	-1.504995e+06	11.000000	95.000000	5.700000	1995.000
50%	0.797511	13.000000	2.737064e+07	16.000000	106.000000	6.200000	2004.000
75%	1.368324	28.750000	1.074548e+08	62.000000	119.000000	6.700000	2010.000
max	32.985763	114.000000	2.750137e+09	250.000000	338.000000	8.400000	2015.000
4							>

```
In [407]:
            top by revenue = by revenue.groupby('release year').head().reset index(drop=Tr
             ue)
In [408]:
             top_by_revenue.shape
Out[408]:
            (279, 15)
In [409]:
             top_by_revenue.head()
Out[409]:
                            budget
                                        net_profit revenue original_title
                                                                                            director
                 popularity
                                                                                     cast
                                                                                                        tagline
                                                                                                         Mor€
                                                                                      Kirk
                                                                                                         titanic
                                                                          Douglas|Laurence
                                                                                             Stanley
                  1.136943
                              NaN
                                   3.539024e+08
                                                      NaN
                                                               Spartacus
                                                                                                      than any
                                                                               Olivier|Jean
                                                                                             Kubrick
                                                                                                          story
                                                                            Simmons|Cha...
                                                                                                      ever told
                                                                                                          Th€
                                                                                                      master o
                                                                                  Anthony
                                                                                                      suspense
                                                                              Perkins|Vera
                                                                                               Alfred
                  2.610362
                              NaN 2.299854e+08
                                                      NaN
                                                                 Psycho
                                                                                                        moves
                                                                                Miles|John
                                                                                           Hitchcock
                                                                                                           his
                                                                           Gavin|Janet Le...
                                                                                                      cameras
                                                                                                        into ..
                                                                                                        Movie
                                                                                                         wise
                                                                                     Jack
                                                                                                      there has
                                                                           Lemmon|Shirley
                                                                    The
                                                                                                Billy
             2
                  0.947307
                              NaN 1.622053e+08
                                                      NaN
                                                                                                         neve
                                                                            MacLainelFred
                                                                                              Wilder
                                                               Apartment
                                                                                                         beer
                                                                           MacMurray|Ra...
                                                                                                      anything
                                                                                                         like..
                                                                             Jerry Lewis|Ed
                                                                               Wynn|Judith
                                                                                               Frank
                  0.055821
                              NaN 3.022917e+07
                                                      NaN
                                                              Cinderfella
              3
                                                                            Anderson|Henry
                                                                                              Tashlin
                                                                                     Silv...
                                                                                                         The
                                                                                                          were
                                                                             Yul Brynner|Eli
                                                                                                        seven
                                                                    The
                                                                             Wallach|Steve
                                                                                                John
                                                                                                      And they
                  1.872132
                              NaN 2.141847e+07
                                                      NaN
                                                              Magnificent
                                                                          McQueen|Charles
                                                                                             Sturges
                                                                                                        fough
                                                                  Seven
                                                                                                           likε
                                                                                                         sever
                                                                                                           h..
In [410]:
             revenue release year = pd.pivot table(top by revenue, index = 'release year',
             values = 'revenue adj')
In [411]:
            runtime release year.shape
Out[411]: (56, 1)
```

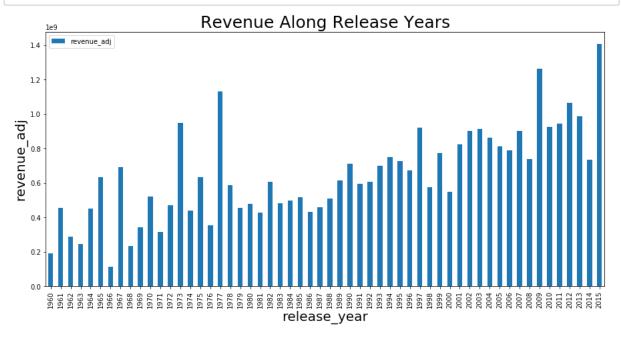
In [412]: revenue_release_year.head()

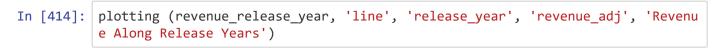
Out[412]:

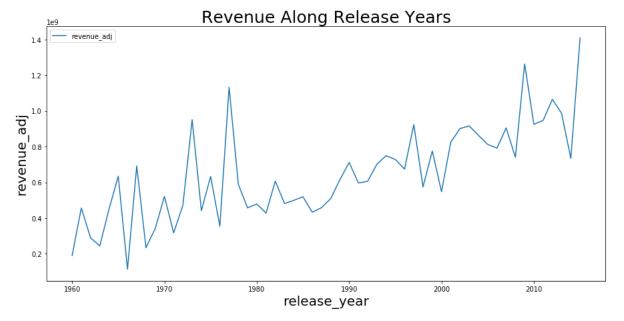
revenue_adj

release_year						
1960	1.902299e+08					
1961	4.565419e+08					
1962	2.893902e+08					
1963	2.442604e+08					
1964	4.507990e+08					

In [413]: plotting (revenue_release_year, 'bar', 'release_year', 'revenue_adj', 'Revenue
Along Release Years')







NOTE: From the graph we can figure out that there is a moderate linear positive association between revenue and release years as the revenue kept growth.

```
In [415]: # Top 10 Movies by Revenue

top_10_revenue = top_by_revenue.nlargest(10, 'revenue_adj')
top_10_revenue
```

Out[415]:

In [416]:

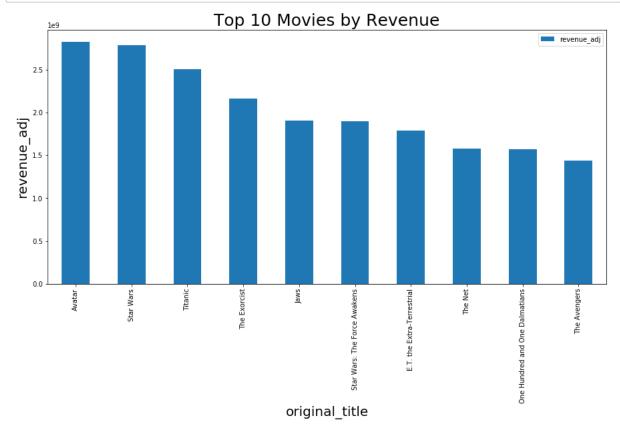
In [417]:

Out[417]: (10, 1)

	popularity	budget	net_profit	revenue	original_title	cast	directo
244	9.432768	NaN	2.586237e+09	NaN	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameroi
84	12.037933	NaN	2.750137e+09	NaN	Star Wars	Mark Hamill Harrison Ford Carrie Fisher Peter	George Lucas
184	4.355219	NaN	2.234714e+09	NaN	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameror
64	2.010733	NaN	2.128036e+09	NaN	The Exorcist	Linda Blair Max von Sydow Ellen Burstyn Jason	William Friedkiı
74	2.563191	NaN	1.878643e+09	NaN	Jaws	Roy Scheider Robert Shaw Richard Dreyfuss Lorr	Steven Spielberç
274	11.173104	NaN	1.718723e+09	NaN	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abram
109	2.900556	NaN	1.767968e+09	NaN	E.T. the Extra- Terrestrial	Henry Thomas Drew Barrymore Robert MacNaughton	Steven Spielberç
174	1.136610	NaN	1.551568e+09	NaN	The Net	Sandra Bullock Jeremy Northam Dennis Miller We	Irwin Winkle
5	2.631987	NaN	1.545635e+09	NaN	One Hundred and One Dalmatians	Rod Taylor J. Pat O'Malley Betty Lou Gerson Ma	Clyd∉ Geronimi Hamiltor Luske Wolfgan∉ Reithermar
259	7.637767	NaN	1.234248e+09	NaN	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedor
4							>
<pre>top_10_revenue = pd.pivot_table(top_10_revenue, index = 'original_title', valu es = 'revenue_adj')</pre>							
top_	10_revenue	e.shape					

```
file:///D:/Data Analytics/2nd Project/2nd Project/investigate-a-dataset-template_02.html
```

```
In [418]: top_10_revenue.head()
Out[418]:
                                          revenue_adj
                             original_title
                                  Avatar
                                         2.827124e+09
                    E.T. the Extra-Terrestrial 1.791694e+09
                                   Jaws
                                         1.907006e+09
            One Hundred and One Dalmatians
                                         1.574815e+09
                               Star Wars 2.789712e+09
           top_10_revenue = top_10_revenue.revenue_adj.sort_values(ascending = False)
In [419]:
In [420]:
           top_10_revenue
Out[420]: original_title
           Avatar
                                                2.827124e+09
           Star Wars
                                                2.789712e+09
           Titanic
                                                2.506406e+09
           The Exorcist
                                                2.167325e+09
           Jaws
                                                1.907006e+09
           Star Wars: The Force Awakens
                                                1.902723e+09
           E.T. the Extra-Terrestrial
                                                1.791694e+09
           The Net
                                                1.583050e+09
           One Hundred and One Dalmatians
                                               1.574815e+09
           The Avengers
                                                1.443191e+09
           Name: revenue adj, dtype: float64
```



NOTE: From the grapgh we can figure out that the top revenue movie ws Avatar.

Research Question 03 - Top 10 Highest Budget Movies

```
In [422]: by_budget = tmdb_clean_columns.sort_values(['release_year','budget_adj'], asce
    nding=[True, False])
In [423]: by_budget.shape
Out[423]: (3854, 15)
```

In [424]: by_budget.describe()

Out[424]:

	popularity	budget	net_profit	revenue	runtime	vote_average	release_y
count	3854.000000	22.000000	3.854000e+03	31.000000	3854.000000	3854.000000	3854.000
mean	1.191554	30.090909	9.282470e+07	51.516129	109.220291	6.168163	2001.261
std	1.475162	36.818615	1.940715e+08	67.591356	19.922820	0.794920	11.282
min	0.001117	1.000000	-4.139124e+08	2.000000	15.000000	2.200000	1960.000
25%	0.462368	6.500000	-1.504995e+06	11.000000	95.000000	5.700000	1995.000
50%	0.797511	13.000000	2.737064e+07	16.000000	106.000000	6.200000	2004.000
75%	1.368324	28.750000	1.074548e+08	62.000000	119.000000	6.700000	2010.000
max	32.985763	114.000000	2.750137e+09	250.000000	338.000000	8.400000	2015.000

In [425]: top_by_budget = by_budget.groupby('release_year').head().reset_index(drop=Tru
e)

In [426]: top_by_budget.shape

Out[426]: (279, 15)

In [427]: top_by_budget.head()

Out[427]:

	popularity	budget	net_profit	revenue	original_title	cast	director	tagline
0	1.136943	NaN	3.539024e+08	NaN	Spartacus	Kirk Douglas Laurence Olivier Jean Simmons Cha	Stanley Kubrick	More titanic than any story ever told
1	0.947307	NaN	1.622053e+08	NaN	The Apartment	Jack Lemmon Shirley MacLaine Fred MacMurray Ra	Billy Wilder	Movie wise there has neve beer anything like
2	0.055821	NaN	3.022917e+07	NaN	Cinderfella	Jerry Lewis Ed Wynn Judith Anderson Henry Silv	Frank Tashlin	
3	1.872132	NaN	2.141847e+07	NaN	The Magnificent Seven	Yul Brynner Eli Wallach Steve McQueen Charles 	John Sturges	They were seven And they fough like sever h
4	2.610362	NaN	2.299854e+08	NaN	Psycho	Anthony Perkins Vera Miles John Gavin Janet Le	Alfred Hitchcock	The master o suspense moves his cameras into
4								•
<pre>budget_release_year = pd.pivot_table(top_by_budget, index = 'release_year', va lues = 'budget_adj')</pre>								
budget_release_year.shape								

```
In [428]
```

```
In [429]
```

Out[429]: (56, 1)

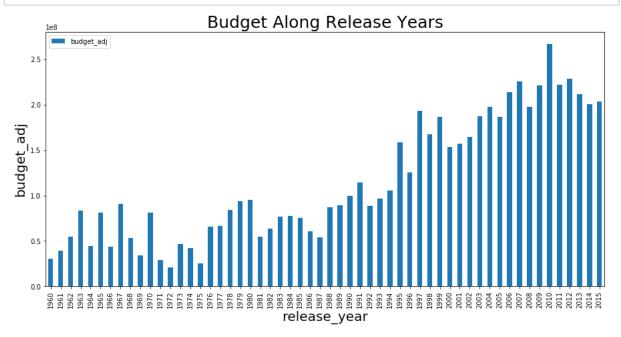
```
In [430]: budget_release_year.head()
```

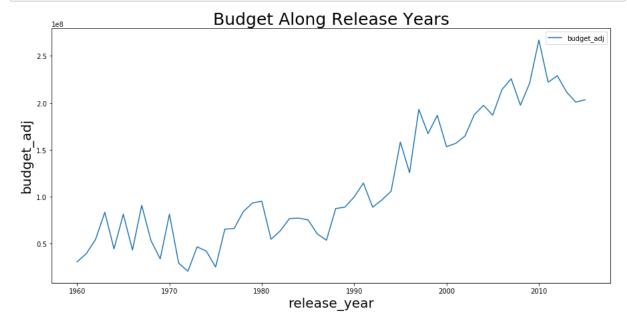
Out[430]:

budget_adj

release_year				
1960	3.068179e+07			
1961	3.944623e+07			
1962	5.456796e+07			
1963	8.346986e+07			
1964	4 448073e+07			

In [431]: plotting (budget_release_year, 'bar', 'release_year', 'budget_adj', 'Budget Al
 ong Release Years')





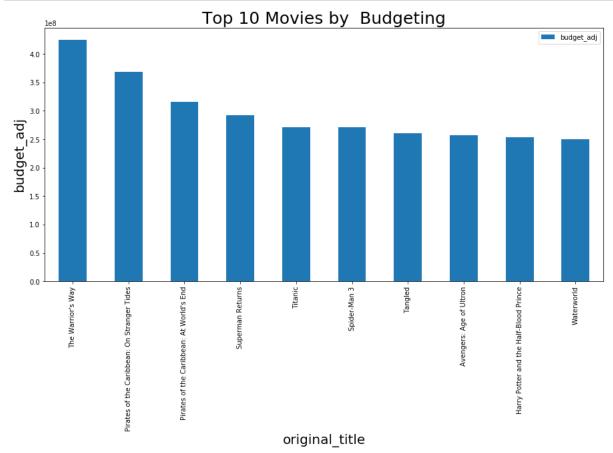
NOTE: From the graph we can figure out that budgeting of movies were increasing by the years and the highest budgeting were in the recent years after the year 2000.

Out[433]:

	popularity	budget	net_profit	revenue	original_title	cast	director	
249	0.250540	NaN	-4.139124e+08	NaN	The Warrior's Way	Kate Bosworth Jang Dong- gun Geoffrey Rush Dann	Sngmoo Lee	As L
254	4.955130	NaN	6.220462e+08	NaN	Pirates of the Caribbean: On Stranger Tides	Johnny Depp Penélope Cruz Geoffrey Rush Ian M	Rob Marshall	I
234	4.965391	NaN	6.951529e+08	NaN	Pirates of the Caribbean: At World's End	Johnny Depp Orlando Bloom Keira Knightley Geof	Gore Verbinski	en wc ad
229	1.957331	NaN	1.309698e+08	NaN	Superman Returns	Brandon Routh Kevin Spacey Kate Bosworth James	Bryan Singer	
184	4.355219	NaN	2.234714e+09	NaN	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	l o b
235	2.520912	NaN	6.655712e+08	NaN	Spider-Man 3	Tobey Maguire Kirsten Dunst James Franco Thoma	Sam Raimi	Th
250	2.865684	NaN	3.317949e+08	NaN	Tangled	Zachary Levi Mandy Moore Donna Murphy Ron Perl	Nathan Greno Byron Howard	ad [,]
274	5.944927	NaN	1.035032e+09	NaN	Avengers: Age of Ultron	Robert Downey Jr. Chris Hemsworth Mark Ruffalo	Joss Whedon	Α
244	5.076472	NaN	6.951764e+08	NaN	Harry Potter and the Half- Blood Prince	Daniel Radcliffe Rupert Grint Emma Watson Tom	David Yates	; Re
174	1.232098	NaN	1.276683e+08	NaN	Waterworld	Kevin Costner Chaim Girafi Rick Aviles R. D. C	Kevin Reynolds	s
4								•

```
In [434]:
           top 10 budget = pd.pivot table(top 10 budget, index = 'original title', values
           = 'budget adj')
In [435]: | top_10_budget.shape
Out[435]: (10, 1)
In [436]:
           top 10 budget.head()
Out[436]:
                                                  budget_adj
                                     original_title
                            Avengers: Age of Ultron
                                                 257599886.7
                Harry Potter and the Half-Blood Prince
                                                 254100108.5
              Pirates of the Caribbean: At World's End
                                                 315500574.8
            Pirates of the Caribbean: On Stranger Tides
                                                 368371256.2
                                    Spider-Man 3
                                                 271330494.3
In [437]:
           top_10_budget = top_10_budget.budget_adj.sort_values(ascending = False)
In [438]: top_10_budget
Out[438]: original title
           The Warrior's Way
                                                              425000000.0
           Pirates of the Caribbean: On Stranger Tides
                                                              368371256.2
           Pirates of the Caribbean: At World's End
                                                              315500574.8
           Superman Returns
                                                              292050672.7
           Titanic
                                                              271692064.2
           Spider-Man 3
                                                              271330494.3
           Tangled
                                                              260000000.0
           Avengers: Age of Ultron
                                                              257599886.7
           Harry Potter and the Half-Blood Prince
                                                              254100108.5
           Waterworld
                                                              250419201.7
           Name: budget adj, dtype: float64
```





NOTE: From the graph we can figur out that the highest budget of movie was The Warrior's Way.

Research Question 04 - Top 10 Highest Rating Movies

```
In [440]: by_vote = tmdb_clean_columns.sort_values(['release_year','vote_average'], asce
    nding=[True, False])

In [441]: by_vote.shape

Out[441]: (3854, 15)

In [442]: top_by_vote = by_vote.groupby('release_year').head().reset_index(drop=True)

In [443]: top_by_vote.shape

Out[443]: (279, 15)
```

In [444]: top_by_vote.head()

Out[444]:

:	popularity	budget	net_profit	revenue	original_title	cast	director	tagline
o	2.610362	NaN	2.299854e+08	NaN	Psycho	Anthony Perkins Vera Miles John Gavin Janet Le	Alfred Hitchcock	The master o suspense moves his cameras into
1	0.947307	NaN	1.622053e+08	NaN	The Apartment	Jack Lemmon Shirley MacLaine Fred MacMurray Ra	Billy Wilder	Movie wise there has neve beer anything like
2	0.055821	NaN	3.022917e+07	NaN	Cinderfella	Jerry Lewis Ed Wynn Judith Anderson Henry Silv	Frank Tashlin	
3	1.872132	NaN	2.141847e+07	NaN	The Magnificent Seven	Yul Brynner Eli Wallach Steve McQueen Charles 	John Sturges	They were seven And they fough like sever h
4	1.136943	NaN	3.539024e+08	NaN	Spartacus	Kirk Douglas Laurence Olivier Jean Simmons Cha	Stanley Kubrick	More titanic than any story ever told
4								•
	<pre>vote_release_year = pd.pivot_table(top_by_vote, index = 'release_year', values = 'vote_average')</pre>							
: v	vote_release_year.shape							

```
In [445]:
```

```
In [446]:
```

Out[446]: (56, 1)

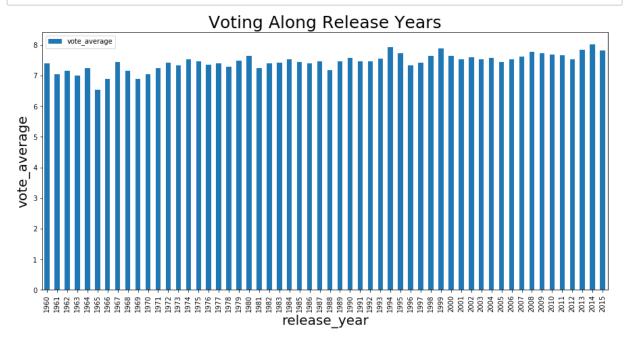
In [447]: vote_release_year.head()

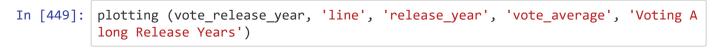
Out[447]:

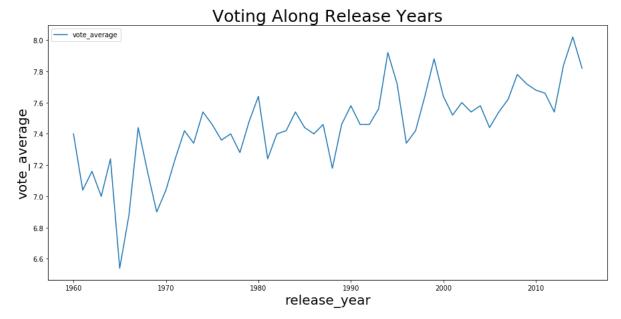
vote_average

release_year	
1960	7.40
1961	7.04
1962	7.16
1963	7.00
1964	7.24

In [448]: plotting (vote_release_year, 'bar', 'release_year', 'vote_average', 'Voting Al
 ong Release Years')







NOTES: From the graph we can figure out that voting was moderat increasing along release years except the sharp decrease between the year 1964 and the year 1967.

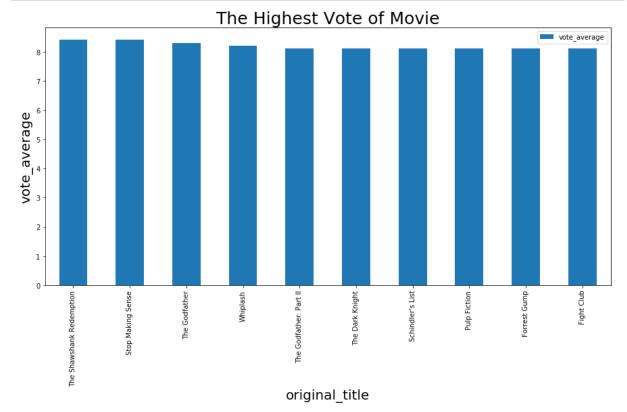
```
In [450]: # Top Movies by Rating
top_10_vote = top_by_vote.nlargest(10, 'vote_average')
top_10_vote
```

Out[450]:

	popularity	budget	net_profit	revenue	original_title	cast	director	ta
119	0.283191	NaN	7.932116e+06	NaN	Stop Making Sense	David Byrne Tina Weymouth Chris Frantz Jerry H	Jonathan Demme	Why ma se V ma Why
169	7.192039	NaN	4.915674e+06	NaN	The Shawshank Redemption	Tim Robbins Morgan Freeman Bob Gunton William 	Frank Darabont	Fea hold pris Hope set yo
59	5.738034	NaN	1.246626e+09	NaN	The Godfather	Marlon Brando Al Pacino James Caan Richard S. 	Francis Ford Coppola	An you re
269	4.780419	NaN	9.849312e+06	NaN	Whiplash	Miles Teller J.K. Simmons Melissa Benoist Aust	Damien Chazelle	The great can you t
69	3.264571	NaN	1.527582e+08	NaN	The Godfather: Part II	Al Pacino Robert Duvall Diane Keaton Robert De	Francis Ford Coppola	I don I ha every
164	2.377288	NaN	4.517327e+08	NaN	Schindler's List	Liam Neeson Ben Kingsley Ralph Fiennes Carolin	Steven Spielberg	Who saves life, s the r
170	6.715966	NaN	9.164222e+08	NaN	Forrest Gump	Tom Hanks Robin Wright Gary Sinise Mykelti Wil	Robert Zemeckis	The will r b s
171	8.093754	NaN	3.029442e+08	NaN	Pulp Fiction	John Travolta Samuel L. Jackson Uma Thurman Br	Quentin Tarantino	bec you char dc me
194	8.947905	NaN	4.955256e+07	NaN	Fight Club	Edward Norton Brad Pitt Meat Loaf Jared Leto H	David Fincher	mucl you { your you
239	8.466668	NaN	8.273675e+08	NaN	The Dark Knight	Christian Bale Michael Caine Heath Ledger Aaro	Christopher Nolan	Wł Seri
								•

```
In [451]: | top_10_vote = pd.pivot_table(top_10_vote, index = 'original_title', values =
           'vote average')
In [452]: top_10_vote.shape
Out[452]: (10, 1)
In [453]:
          top_10_vote.head()
Out[453]:
                             vote_average
                 original_title
                   Fight Club
                                     8.1
                Forrest Gump
                                     8.1
                 Pulp Fiction
                                     8.1
               Schindler's List
                                     8.1
            Stop Making Sense
                                     8.4
In [454]:
           top_10_vote = top_10_vote.vote_average.sort_values(ascending = False)
In [455]: top_10_vote
Out[455]: original title
           The Shawshank Redemption
                                         8.4
           Stop Making Sense
                                         8.4
           The Godfather
                                         8.3
           Whiplash
                                         8.2
           The Godfather: Part II
                                         8.1
           The Dark Knight
                                         8.1
           Schindler's List
                                         8.1
           Pulp Fiction
                                         8.1
           Forrest Gump
                                         8.1
           Fight Club
                                         8.1
           Name: vote_average, dtype: float64
```





NOTE: from the graph we can figur out that highest vote of movie was The Shawshank Redemption.

Research Question 05 - Top 10 Highest Net Profit Movies

In [461]: top_by_net_profit.head()

Out[461]:

	popularity	budget	net_profit	revenue	original_title	cast	director	tagline
0	1.136943	NaN	3.539024e+08	NaN	Spartacus	Kirk Douglas Laurence Olivier Jean Simmons Cha	Stanley Kubrick	More titanic than any story ever told
1	2.610362	NaN	2.299854e+08	NaN	Psycho	Anthony Perkins Vera Miles John Gavin Janet Le	Alfred Hitchcock	The master o suspense moves his cameras into
2	0.947307	NaN	1.622053e+08	NaN	The Apartment	Jack Lemmon Shirley MacLaine Fred MacMurray Ra	Billy Wilder	Movie wise there has neve beer anything like
3	0.055821	NaN	3.022917e+07	NaN	Cinderfella	Jerry Lewis Ed Wynn Judith Anderson Henry Silv	Frank Tashlin	
4	1.872132	NaN	2.141847e+07	NaN	The Magnificent Seven	Yul Brynner Eli Wallach Steve McQueen Charles 	John Sturges	They were seven And they fough like sever h
4								

```
In [462]:
          ear', values = 'net_profit')
```

```
In [463]: net_profit_release_year.shape
```

Out[463]: (56, 1)

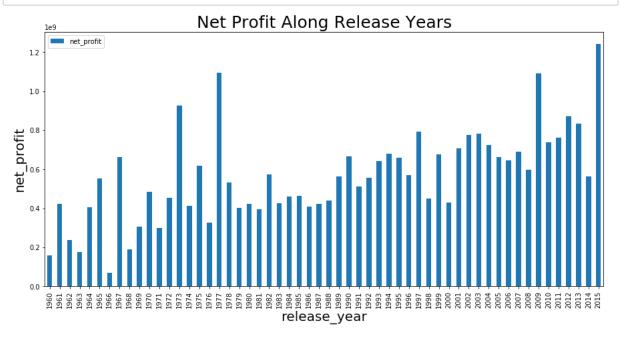
In [464]: net_profit_release_year.head()

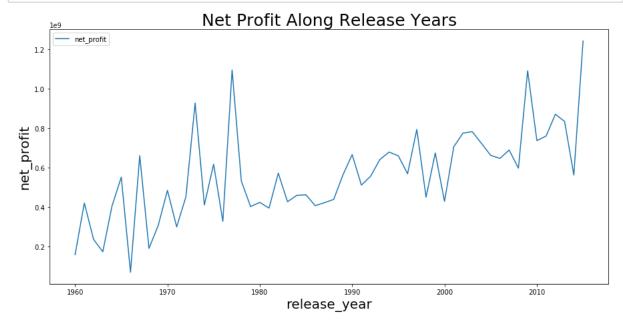
Out[464]:

net_profit

release_year 1960 1.595481e+08 1961 4.214726e+08 1962 2.370568e+08 1963 1.743189e+08 1964 4.067895e+08

In [465]: plotting (net_profit_release_year, 'bar', 'release_year', 'net_profit', 'Net P
 rofit Along Release Years')





NOTE: From the graph we can figure out that the net profit was increasing along release years and we can notice also there was a sharp increase in some years such as 1973, 1978, 2010 and also the movies after the year 2014.

Out[467]:

In [468]:

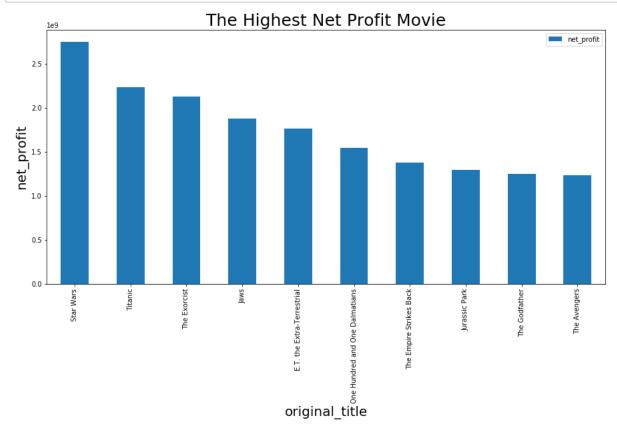
In [469]:

Out[469]: (10, 1)

	popularity	budget	net_profit	revenue	original_title	cast	director		
84	12.037933	NaN	2.750137e+09	NaN	Star Wars	Mark Hamill Harrison Ford Carrie Fisher Peter	George Lucas		
186	4.355219	NaN	2.234714e+09	NaN	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron		
67	2.010733	NaN	2.128036e+09	NaN	The Exorcist	Linda Blair Max von Sydow Ellen Burstyn Jason	William Friedkin		
76	2.563191	NaN	1.878643e+09	NaN	Jaws	Roy Scheider Robert Shaw Richard Dreyfuss Lorr	Steven Spielberg		
113	2.900556	NaN	1.767968e+09	NaN	E.T. the Extra- Terrestrial	Henry Thomas Drew Barrymore Robert MacNaughton	Steven Spielberg		
9	2.631987	NaN	1.545635e+09	NaN	One Hundred and One Dalmatians	Rod Taylor J. Pat O'Malley Betty Lou Gerson Ma	Clyde Geronimi Hamilton Luske Wolfgang Reitherman		
99	5.488441	NaN	1.376998e+09	NaN	The Empire Strikes Back	Mark Hamill Harrison Ford Carrie Fisher Billy	Irvin Kershner		
166	2.204926	NaN	1.293767e+09	NaN	Jurassic Park	Sam Neill Laura Dern Jeff Goldblum Richard Att	Steven Spielberg		
59	5.738034	NaN	1.246626e+09	NaN	The Godfather	Marlon Brando Al Pacino James Caan Richard S. 	Francis Ford Coppola		
263	7.637767	NaN	1.234248e+09	NaN	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedon		
4							>		
	<pre>top_10_net_profit = pd.pivot_table(top_10_net_profit, index = 'original_titl e', values = 'net_profit')</pre>								
top_1	10_net_pro	ofit.sh	аре						

```
In [470]: top 10 net profit.head()
Out[470]:
                                            net_profit
                             original_title
                    E.T. the Extra-Terrestrial
                                         1.767968e+09
                                   Jaws
                                         1.878643e+09
                            Jurassic Park 1.293767e+09
            One Hundred and One Dalmatians
                                         1.545635e+09
                               Star Wars 2.750137e+09
In [471]:
           top_10_net_profit = top_10_net_profit.net_profit.sort_values(ascending = False
In [472]:
           top_10_net_profit
Out[472]: original_title
           Star Wars
                                                2.750137e+09
           Titanic
                                                2.234714e+09
           The Exorcist
                                                2.128036e+09
           Jaws
                                                1.878643e+09
           E.T. the Extra-Terrestrial
                                                1.767968e+09
           One Hundred and One Dalmatians
                                                1.545635e+09
           The Empire Strikes Back
                                                1.376998e+09
           Jurassic Park
                                                1.293767e+09
           The Godfather
                                                1.246626e+09
           The Avengers
                                                1.234248e+09
           Name: net_profit, dtype: float64
```

In [473]: plotting (top_10_net_profit, 'bar', 'original_title', 'net_profit', 'The Highe
 st Net Profit Movie')



NOTE: From the graph we can figure out that the highest net profit movie was Star Wars.

In [474]: by_net_profit.head()

Out[474]:

	popularity	budget	net_profit	revenue	original_title	cast	director	taç
3190	1.136943	NaN	3.539024e+08	NaN	Spartacus	Kirk Douglas Laurence Olivier Jean Simmons Cha	Stanley Kubrick	tit than ever
4520	2.610362	NaN	2.299854e+08	NaN	Psycho	Anthony Perkins Vera Miles John Gavin Janet Le	Alfred Hitchcock	mast suspe mo cam in
5029	0.947307	NaN	1.622053e+08	NaN	The Apartment	Jack Lemmon Shirley MacLaine Fred MacMurray Ra	Billy Wilder	Mc v there n t anyt li
7363	0.055821	NaN	3.022917e+07	NaN	Cinderfella	Jerry Lewis Ed Wynn Judith Anderson Henry Silv	Frank Tashlin	
7679	1.872132	NaN	2.141847e+07	NaN	The Magnificent Seven	Yul Brynner Eli Wallach Steve McQueen Charles 	John Sturges	sev And fo
4								

In [475]: by_net_profit.shape

Out[475]: (3854, 15)

In [476]: by_net_profit.describe()

Out[476]:

	popularity	budget	net_profit	revenue	runtime	vote_average	release_y
count	3854.000000	22.000000	3.854000e+03	31.000000	3854.000000	3854.000000	3854.000
mean	1.191554	30.090909	9.282470e+07	51.516129	109.220291	6.168163	2001.261
std	1.475162	36.818615	1.940715e+08	67.591356	19.922820	0.794920	11.282
min	0.001117	1.000000	-4.139124e+08	2.000000	15.000000	2.200000	1960.000
25%	0.462368	6.500000	-1.504995e+06	11.000000	95.000000	5.700000	1995.000
50%	0.797511	13.000000	2.737064e+07	16.000000	106.000000	6.200000	2004.000
75%	1.368324	28.750000	1.074548e+08	62.000000	119.000000	6.700000	2010.000
max	32.985763	114.000000	2.750137e+09	250.000000	338.000000	8.400000	2015.000

In [477]: top_10_genres = by_net_profit.nlargest(10, 'net_profit')

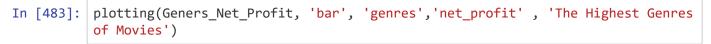
In [478]: top_10_genres.head()

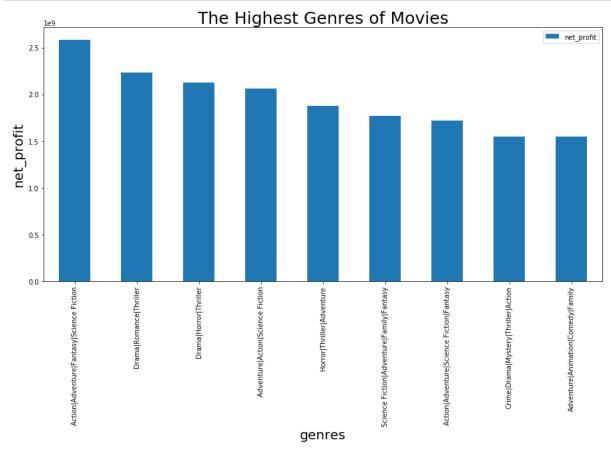
Out[478]:

	popularity	budget	net_profit	revenue	original_title	cast	director	
201	12.037933	NaN	2.750137e+09	NaN	Star Wars	Mark Hamill Harrison Ford Carrie Fisher Peter	George Lucas	A ago ir far, f
20	9.432768	NaN	2.586237e+09	NaN	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameron	
59	4.355219	NaN	2.234714e+09	NaN	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	N Ea come
410	2.010733	NaN	2.128036e+09	NaN	The Exorcist	Linda Blair Max von Sydow Ellen Burstyn Jason	William Friedkin	S almos compr is
385	2.563191	NaN	1.878643e+09	NaN	Jaws	Roy Scheider Robert Shaw Richard Dreyfuss Lorr	Steven Spielberg	Don't
4								•

In [479]: Geners_Net_Profit = pd.pivot_table(top_10_genres, index = 'genres', values =
 'net_profit')

```
In [480]:
            Geners_Net_Profit
Out[480]:
                                                      net_profit
                                           genres
             Action|Adventure|Fantasy|Science Fiction
                                                  2.586237e+09
             Action|Adventure|Science Fiction|Fantasy
                                                  1.718723e+09
                    Adventure|Action|Science Fiction
                                                  2.063567e+09
                 Adventure|Animation|Comedy|Family
                                                  1.545635e+09
                 Crime|Drama|Mystery|Thriller|Action
                                                  1.551568e+09
                              Drama|Horror|Thriller 2.128036e+09
                            Drama|Romance|Thriller 2.234714e+09
                           Horror|Thriller|Adventure
                                                  1.878643e+09
             Science Fiction|Adventure|Family|Fantasy
                                                  1.767968e+09
            Geners Net Profit = Geners Net Profit.net profit.sort values(ascending = False
In [481]:
            Geners Net Profit
In [482]:
Out[482]:
           genres
           Action | Adventure | Fantasy | Science Fiction
                                                              2.586237e+09
           Drama | Romance | Thriller
                                                              2.234714e+09
           Drama | Horror | Thriller
                                                              2.128036e+09
            Adventure | Action | Science Fiction
                                                              2.063567e+09
           Horror|Thriller|Adventure
                                                              1.878643e+09
           Science Fiction | Adventure | Family | Fantasy
                                                              1.767968e+09
           Action | Adventure | Science Fiction | Fantasy
                                                              1.718723e+09
           Crime|Drama|Mystery|Thriller|Action
                                                              1.551568e+09
           Adventure | Animation | Comedy | Family
                                                              1.545635e+09
           Name: net profit, dtype: float64
```





NOTE: From the graph we can figure out the highest genres of movies were Action, Adventure, Fantasy and Science Fiction.

```
In [484]: explorations = pd.pivot_table(by_net_profit, index = 'release_year', values =
    ['net_profit', 'runtime', 'budget_adj', 'revenue_adj', 'vote_average', 'popula
    rity', 'genres', 'cast'])
```

In [485]: explorations.describe()

Out[485]:

	budget_adj	net_profit	popularity	revenue_adj	runtime	vote_average
count	5.600000e+01	5.600000e+01	56.000000	5.600000e+01	56.000000	56.000000
mean	3.991923e+07	1.456689e+08	1.059704	1.855881e+08	114.847356	6.391060
std	1.312820e+07	1.032232e+08	0.377869	1.026257e+08	12.203451	0.339090
min	1.542484e+07	5.585189e+07	0.395168	9.509591e+07	103.304348	5.971698
25%	3.048337e+07	8.051874e+07	0.889946	1.265249e+08	107.932782	6.104961
50%	4.117684e+07	1.026524e+08	0.999123	1.453704e+08	109.718896	6.271167
75%	4.698083e+07	1.635509e+08	1.159475	2.102314e+08	118.346154	6.658974
max	8.138583e+07	5.526511e+08	2.856943	6.340369e+08	167.600000	7.400000

```
In [486]:
           explorations.shape
Out[486]: (56, 6)
In [487]:
            # Explorations array was created to explore some associations
            explorations.head()
Out[487]:
                            budget_adj
                                           net_profit popularity
                                                                 revenue_adj
                                                                                runtime vote_average
             release_year
                    1960
                         3.068179e+07
                                       1.595481e+08
                                                      1.324513
                                                               1.902299e+08
                                                                             130.000000
                                                                                             7.400000
                         2.818516e+07
                                       2.181770e+08
                                                      0.787718
                                                               2.463622e+08
                                                                             132.500000
                                                                                             6.620000
                    1962
                         4.062476e+07
                                       1.718493e+08
                                                      0.983485
                                                               2.124740e+08
                                                                             141.285714
                                                                                             6.900000
                    1963
                         7.252496e+07
                                       1.369589e+08
                                                      1.040612
                                                               2.094838e+08
                                                                             153.500000
                                                                                             6.766667
                         3.408189e+07
                                       2.959526e+08
                                                      1.377790
                                                               3.300344e+08
                                                                             122.428571
                                                                                             6.971429
            # Top explore the corelation between the Runtime and the Net Profit
            plotting2d (explorations, 'scatter', 'runtime', 'net_profit', 'Runtime Vs Net
             Profit')
                                              Runtime Vs Net Profit
                   ['runtime', 'net_profit']
             net_profit
```

NOTE: From graph we can figure out that there is a moderate positive changing correlation between runtime and net profit, and there are some outlier values.

130

140

runtime

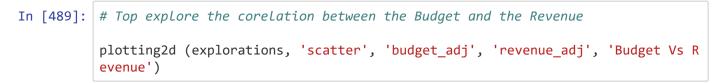
150

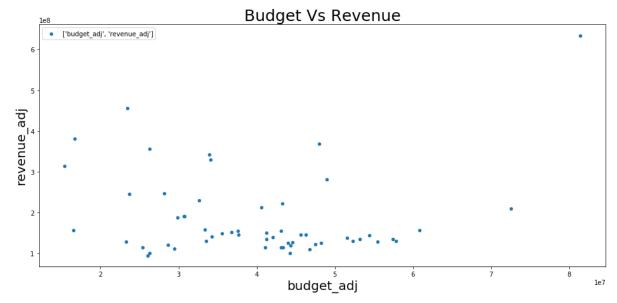
160

120

110

170





NOTE: From the graph we can figure out that there is a week negative changing correlation between budget and revenue and there are some outlier values.

Conclusions

From this investigation we can summarize the findings as follow:

- There is a moderate postive non-liner correlation, and there is anout lier valye.
- there is a moderate positive changing correlation between runtime and net profit, and there
 are some outlier values.
- there is a week negative changing correlation between budget and revenue and there are some outlier values.

The creteria of the successful movies and could genrate average revenue about 137 million dollar as follow:

- 1. The average runtime is 151 minutes
- 2. The average budget is 44 million dollar.
- 3. The genrs should be adventure, action and science fiction.

Limitations

This report was done depending on the provided dataset which which has a missing information, also we don't know the information acuracy included in this dataset or if it is up to date or no. So, droping the rows with missing information may have affetted the analysis results in this report. On the other hand the remaining complete information if we asum they are acurate we can consider the analysis result positively whic can we depend on.

Answer_Q1:

The highest runtimes movies were from the year 2008 to 2010.

The top 10 highest runtimes movies starting from the minimum runtimes are: [The Greatest Story Ever Told, The Godfather: Part II, The Lord of the Rings: The Return of the King, Malcolm X, Jodhaa Akbar, Gods and Generals, Lawrence of Arabia, Heaven's Gate, Cleopatra and Carlos.]

Answer_Q2:

The highest revenues movies were from the year 2009 to 2015.

The top 10 highest revenue movies starting from the minimum revenues are: [The Avengers , One Hundred and One Dalmatians, The Net, E.T. the Extra-Terrestrial, Star Wars: The Force Awakens, Jaws, The Exorcist, Titanic, Star Wars, Avatar.]

Answer Q3:

The highest budgets movies were from the year 2006 to 2013.

The top 10 highest budget movies starting from the minimum budgets are: [Waterworld, Harry Potter and the Half-Blood Prince, Avengers: Age of Ultron, Tangled, Spider-Man 3, Titanic, Superman, Returns, Pirates of the Caribbean: At World's End, Pirates of the Caribbean: On Stranger Tides, The Warrior's Way.]

Answer_Q4:

The highest rating movies were from the year 2013 to 2015.

The top 10 highest rating movies starting from the minimum rating are: [original_title, Fight Club, Forrest Gump, Pulp Fiction, Schindler's List, The Dark Knight, Godfather: Part II, Whiplash, The Godfather, Stop Making Sense and the The Shawshank Redemption.]

Answer Q5:

The highest net profit movies were at the year 1973, 1977 and from the year 2009 to 2015 except the year 2014.

The top 10 highest net profit movies starting from the minimum net profit are: [The Avengers, The Godfather, Jurassic Park, The Empire Strikes Back, One Hundred and One Dalmatians, E.T. the Extra-Terrestrial, Jaws, The Exorcist, Titanic and the Star Wars.]

End of the investigation.