Project: Investigate TMDb Movies Dataset

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1. Introduction

'TMDB Movies Data' is a data set that contains information about 10,000 movies including user ratings and revenue. In this analysis, I will try to answer to the following three questions:

- 1. How does the profit of movies change from year to year?**
- 2. What are the top 10 movies with highest and least profit?**
- 3. What Are Top Genres, Cast, Directors and Production Companies in Cinema History? **
- 4. Who are Top 5 Actors who have been casted the most?**
- 5. What Are the Average Runtime of Movies and how does it change over years?**
- 6. What is the relationship between budget & popularity, director & popularity, cast & popularity?**
- 7. What is the most Popular Keyword?**

```
In [232]: # Use this cell to set up import statements for all of the packages that
    you
    # plan to use.
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from datetime import datetime
    %matplotlib inline
```

2. Data Wrangling

General Properties

In [233]: # Load your data and print out a few lines. Perform operations to inspec
 t data
 # types and look for instances of missing or possibly errant data.
 df = pd.read_csv('tmdb-movies.csv')
 df.shape

Out[233]: (10866, 21)

In [234]: df.head(5)

Out[234]:

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

5 rows × 21 columns

In [235]: df.tail(5)

Out[235]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Nat
10862	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	Nat
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Naf
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	Nat
10865	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren Tom Neyman John Reynolds Dian	Naf

5 rows × 21 columns

Observations:

- 1. There's no unit for currency; I assume it is USD (US Dollar)
- 2. There are many movies have '0' values on 'budget', 'revenue', 'budget_adj', 'revenue_adj' columns
- 3. The data format of 'release_date' column should be changed to Datetime Format

A. Data Cleaning

In this section, I will clean delete unnecessary columns, duplicated columns (if any) and change data type for release_date column.

Delete Unnecessary Columns

First, I chose following columns, ['id','imdb__id','homepage','tagline','overview','budget_adj','revenue_adj'], to be deleted since those are not needed for this analysis.

```
In [236]: delete_col = ['id', 'imdb_id', 'homepage', 'tagline', 'overview', 'budge
    t_adj', 'revenue_adj']
    df.drop(delete_col, axis=1, inplace=True)
In [237]: df.head(5)
```

Out[237]:

	director	cast	original_title	revenue	budget	popularity	
monste re	Colin Trevorrow	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Jurassic World	1513528810	150000000	32.985763	0
apocalypt	George Miller	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	Mad Max: Fury Road	378436354	150000000	28.419936	1
novel revolution dy	Robert Schwentke	Shailene Woodley Theo James Kate Winslet Ansel	Insurgent	295238201	110000000	13.112507	2
android spaceship	J.J. Abrams	Harrison Ford Mark Hamill Carrie Fisher Adam D	Star Wars: The Force Awakens	2068178225	200000000	11.173104	3
car race speed re	James Wan	Vin Diesel Paul Walker Jason Statham Michelle 	Furious 7	1506249360	190000000	9.335014	4

Remove Duplicates

```
In [238]: df.duplicated().sum()
Out[238]: 1
In [239]: df.drop_duplicates(inplace=True)
In [240]: df.shape
Out[240]: (10865, 14)
```

Change Datetime datatypes

```
In [241]:
          df.info()
          <class 'pandas.core.frame.DataFrame'>
          Int64Index: 10865 entries, 0 to 10865
          Data columns (total 14 columns):
          popularity
                                   10865 non-null float64
          budget
                                   10865 non-null int64
          revenue
                                   10865 non-null int64
                                   10865 non-null object
          original_title
                                   10789 non-null object
          cast
                                   10821 non-null object
          director
                                   9372 non-null object
          keywords
                                   10865 non-null int64
          runtime
                                   10842 non-null object
          genres
                                   9835 non-null object
          production_companies
          release_date
                                   10865 non-null object
                                   10865 non-null int64
          vote count
          vote average
                                   10865 non-null float64
          release year
                                   10865 non-null int64
          dtypes: float64(2), int64(5), object(7)
          memory usage: 1.2+ MB
In [242]: | df['release date'] = pd.to datetime(df['release date'])
In [243]: df.info()
          <class 'pandas.core.frame.DataFrame'>
          Int64Index: 10865 entries, 0 to 10865
          Data columns (total 14 columns):
          popularity
                                   10865 non-null float64
          budget
                                   10865 non-null int64
          revenue
                                   10865 non-null int64
          original title
                                   10865 non-null object
          cast
                                   10789 non-null object
          director
                                   10821 non-null object
          keywords
                                   9372 non-null object
                                   10865 non-null int64
          runtime
          genres
                                   10842 non-null object
          production companies
                                   9835 non-null object
          release date
                                   10865 non-null datetime64[ns]
          vote_count
                                   10865 non-null int64
          vote average
                                   10865 non-null float64
          release year
                                   10865 non-null int64
          dtypes: datetime64[ns](1), float64(2), int64(5), object(6)
          memory usage: 1.2+ MB
```

Handling 0 values in 'budget', 'revenue', 'runtime' columns

```
In [244]: row, col = df.query('budget == 0').shape
          print('There are {} rows and {} columns where budget is 0'.format(row, c
          ol))
```

There are 5696 rows and 14 columns where budget is 0

```
In [245]: row, col = df.query('revenue == 0').shape
          print('There are {} rows and {} columns where revenue is 0'.format(row,
          col))
```

There are 6016 rows and 14 columns where revenue is 0

```
In [246]: row, col = df.query('runtime == 0').shape
          print('There are {} rows and {} columns where runtime is 0'.format(row,
          col))
```

There are 31 rows and 14 columns where runtime is 0

Now, we will convert those columns to NaN values and delete them by using 'dropna' function

```
In [247]: # Create a list of budget, revenue, runtime columns
          tem_col = ['budget', 'revenue', 'runtime']
          # Convert all 0 values to NaN by using np.NAN
          df[tem col] = df[tem col].replace(0, np.NAN)
          # Delete/drop all NaN values
          df.dropna(inplace = True)
          row, col = df.shape
          print('After cleaning rows and columns, we have {} rows and {} columns'.
          format(row, col-1))
```

After cleaning rows and columns, we have 3677 rows and 13 columns

```
In [248]: | df.isna().sum()
Out[248]: popularity
                                     0
                                     0
           budget
                                     0
           revenue
           original title
                                     0
           cast
                                     0
           director
                                     0
           keywords
                                     0
           runtime
           genres
                                     0
           production companies
                                     0
           release date
                                     0
           vote count
                                     0
                                     0
           vote average
           release year
                                     0
           dtype: int64
```

```
In [249]: | df.info()
          <class 'pandas.core.frame.DataFrame'>
          Int64Index: 3677 entries, 0 to 10848
          Data columns (total 14 columns):
          popularity
                                   3677 non-null float64
          budget
                                   3677 non-null float64
          revenue
                                   3677 non-null float64
          original title
                                   3677 non-null object
                                   3677 non-null object
          cast
                                   3677 non-null object
          director
          keywords
                                   3677 non-null object
          runtime
                                   3677 non-null float64
          genres
                                   3677 non-null object
          production companies
                                   3677 non-null object
          release date
                                   3677 non-null datetime64[ns]
          vote_count
                                   3677 non-null int64
          vote average
                                   3677 non-null float64
          release_year
                                   3677 non-null int64
          dtypes: datetime64[ns](1), float64(5), int64(2), object(6)
          memory usage: 430.9+ KB
```

Split Columns separted by "

```
In [250]: def split_col(data):
    return data.str[0:].str.split('|',expand = True)
    genres = split_col(df['genres'])
    cast = split_col(df['cast'])
    production_companies = split_col(df['production_companies'])
    genres.head()
```

Out[250]:

	0	1	2	3	4
0	Action	Adventure	Science Fiction	Thriller	None
1	Action	Adventure	Science Fiction	Thriller	None
2	Adventure	Science Fiction	Thriller	None	None
3	Action	Adventure	Science Fiction	Fantasy	None
4	Action	Crime	Thriller	None	None

```
cast.head()
In [251]:
Out[251]:
                                  0
                                                                           2
                                                                                               3
                                                       1
                         Chris Pratt
                                     Bryce Dallas Howard
               0
                                                                  Irrfan Khan
                                                                                Vincent D'Onofrio
                                                                                                    Nick Robinson
                1
                         Tom Hardy
                                          Charlize Theron
                                                          Hugh Keays-Byrne
                                                                                  Nicholas Hoult
                                                                                                      Josh Helman
                   Shailene Woodley
                                             Theo James
                                                                 Kate Winslet
                                                                                     Ansel Elgort
                                                                                                        Miles Teller
                       Harrison Ford
                                             Mark Hamill
                                                                Carrie Fisher
                                                                                    Adam Driver
                3
                                                                                                      Daisy Ridley
                          Vin Diesel
                                              Paul Walker
                                                              Jason Statham
                                                                              Michelle Rodriguez
                                                                                                  Dwayne Johnson
               production companies.head()
In [252]:
Out[252]:
                                     0
                                                                                  2
                                                                                                     3
                                                            1
                                                                                                                   4
                                                                                         Fuji Television
                0
                      Universal Studios
                                         Amblin Entertainment
                                                                 Legendary Pictures
                                                                                                              Dentsu
                                                                                              Network
                      Village Roadshow
                                                Kennedy Miller
                                                                                                               None
                                                                              None
                                                                                                 None
                               Pictures
                                                  Productions
                                Summit
                                                                        Red Wagon
                2
                                              Mandeville Films
                                                                                              NeoReel
                                                                                                               None
                          Entertainment
                                                                      Entertainment
                              Lucasfilm
                                         Truenorth Productions
                                                                         Bad Robot
                                                                                                               None
                                                                                                 None
                3
                                                                                                           One Race
                4
                      Universal Pictures
                                                  Original Film
                                                                Media Rights Capital
                                                                                                Dentsu
                                                                                                               Films
```

3. Exploratory Data Analysis

Research Question 1: How does the profit of movies change from year to year?

```
In [253]: # Insert a new column for the net profit of each movie
    df['net_profit'] = df['revenue'] - df['budget']
```

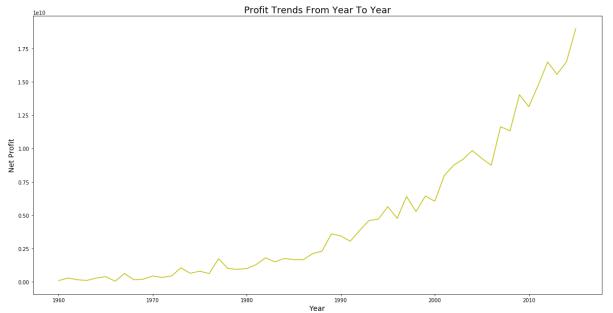
```
In [254]: df.head(3)
```

Out[254]:

Howard Irrfan Khan Vi Tom Mad Max: Hardy Charlize George		popularity	ularity budget	revenue	original_title	cast	director	
3.784364e+08 Mad Max: Hardy Charlize George Theron Hugh Miller apocaly	0	32.985763	85763 150000000.0	1.513529e+09		Pratt Bryce Dallas Howard Irrfan		mons
- '	1	28.419936	19936 150000000.0	3.784364e+08		Hardy Charlize Theron Hugh Keays-	•	apocaly
Shailene 2.952382e+08 Insurgent Woodley Theo Robert James Kate Schwentke novel revolution @ Winslet Ansel	2	13.112507	12507 110000000.0	2.952382e+08	Insurgent	Woodley Theo James Kate		novel revolution c

```
In [255]: net_profit_by_year = df.groupby('release_year').net_profit.sum()
In [256]: net_profit_by_year.plot(kind = 'line', figsize = (20,10), color = 'y')
    plt.title('Profit Trends From Year To Year', fontsize = 18)
```

net_profit_by_year.plot(kind = 'line', figsize = (20,10), color = 'y')
plt.title('Profit Trends From Year To Year', fontsize = 18)
plt.xlabel('Year', fontsize = 14)
plt.ylabel('Net Profit', fontsize = 14);



Analysis: The trend of net profit of movies has been gradually increasing from 1960 to 1990 and rapidly increasing from 1990 to 2015.

Research Question 2: What are the Top Ten Movies that recorded that highest profits and the least profit

In [257]: df.sort_values('net_profit', ascending=False).head(10)

Out[257]:

	popularity	budget	revenue	original_title	cast	director	
1386	9.432768	237000000.0	2.781506e+09	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameron	С
3	11.173104	200000000.0	2.068178e+09	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	anc
5231	4.355219	200000000.0	1.845034e+09	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	1
0	32.985763	150000000.0	1.513529e+09	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	
4	9.335014	190000000.0	1.506249e+09	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle 	James Wan	CE
4361	7.637767	220000000.0	1.519558e+09	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedon	
3374	5.711315	125000000.0	1.327818e+09	Harry Potter and the Deathly Hallows: Part 2	Daniel Radcliffe Rupert Grint Emma Watson Alan	David Yates	self
14	5.944927	280000000.0	1.405036e+09	Avengers: Age of Ultron	Robert Downey Jr. Chris Hemsworth Mark Ruffalo	Joss Whedon	CI
5422	6.112766	150000000.0	1.274219e+09	Frozen	Kristen Bell Idina Menzel Jonathan Groff Josh	Chris Buck Jennifer Lee	queen ı
8094	1.136610	22000000.0	1.106280e+09	The Net	Sandra Bullock Jeremy Northam Dennis Miller We	Irwin Winkler	

- 1. 'Avartar',
- 2. 'Star Wars: The Force Awakens',
- 3. 'Titanic',
- 4. 'Jurassic World',
- 5. 'Furious 7'

are the top 5 movies with highest profit

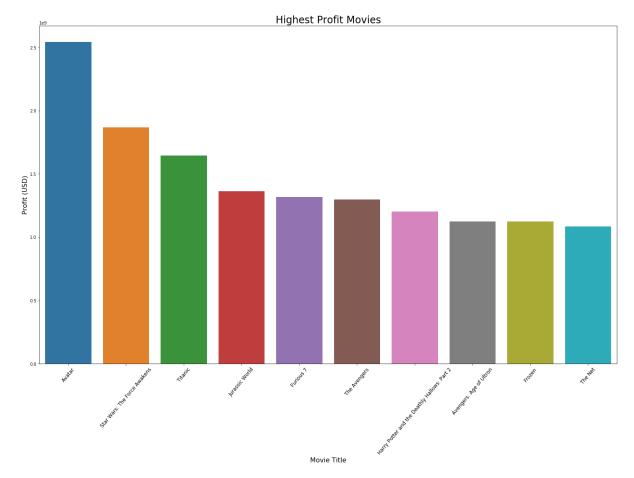
```
In [258]: movies_sorted_by_profit = df.sort_values(by = 'net_profit', ascending =
    False)[0:10]
    movies_sorted_by_profit

    plt.figure(figsize= (25,15))

    ax = sns.barplot(x = 'original_title' , y = 'net_profit', data = movies_
        sorted_by_profit)
    ax.set_xticklabels(ax.get_xticklabels(), rotation = 50, horizontalalignm
    ent = "center", fontsize = 12)

    plt.title('Highest Profit Movies',fontsize = 24)
    plt.xlabel('Movie Title' , fontsize = 16)
    plt.ylabel('Profit (USD)' , fontsize = 16)
```

Out[258]: Text(0, 0.5, 'Profit (USD)')



In [259]: df.sort_values('net_profit', ascending=False).tail(1)

Out[259]:

	popularity	budget	revenue	original_title	cast	director	
2244	0.25054	425000000.0	11087569.0	The Warrior's Way	Kate Bosworth Jang Dong- gun Geoffrey Rush Dann	Sngmoo Lee	ass town revenge decs

'The Warrior's Way' had the lowest net_profit, -\$413912431.0

```
In [260]: def find_min_max(x):
    high_ind = df[x].idxmax()
    high = pd.DataFrame(df.loc[high_ind,:])
    min_ind = df[x].idxmin()
    low = pd.DataFrame(df.loc[min_ind,:])
    print("Movie with Highest profit is: ", df['original_title'][high_in d])
    print("Movie with Lowest profit is: ", df['original_title'][min_ind ])
    return pd.concat([high,low],axis = 1)

find_min_max('net_profit')
```

Movie with Highest profit is: Avatar
Movie with Lowest profit is: The Warrior's Way

Out[260]:

	1386	2244
popularity	9.43277	0.25054
budget	2.37e+08	4.25e+08
revenue	2.78151e+09	1.10876e+07
original_title	Avatar	The Warrior's Way
cast	Sam Worthington Zoe Saldana Sigourney Weaver S	Kate Bosworth Jang Dong-gun Geoffrey Rush Dann
director	James Cameron	Sngmoo Lee
keywords	culture clash future space war space colony so	assassin small town revenge deception super speed
runtime	162	100
genres	Action Adventure Fantasy Science Fiction	Adventure Fantasy Action Western Thriller
production_companies	Ingenious Film Partners Twentieth Century Fox	Boram Entertainment Inc.
release_date	2009-12-10 00:00:00	2010-12-02 00:00:00
vote_count	8458	74
vote_average	7.1	6.4
release_year	2009	2010
net_profit	2.54451e+09	-4.13912e+08

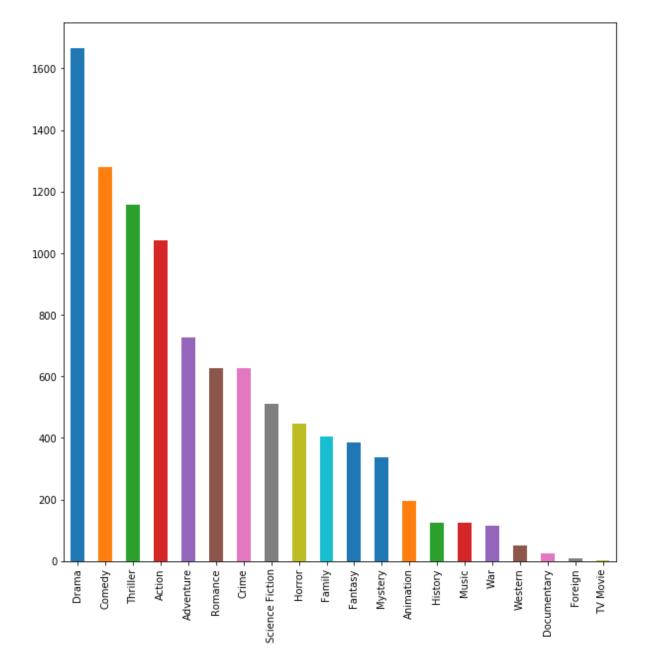
Research Question 3. What Are Top Genres, Cast, Directors, and Production Companies in Cinema History?

```
In [261]: #This function takes any column as argument and keep store values
def calculate_count(column):
    # Convert column to string and seperate it by '|'
    data = df[column].str.cat(sep = '|')

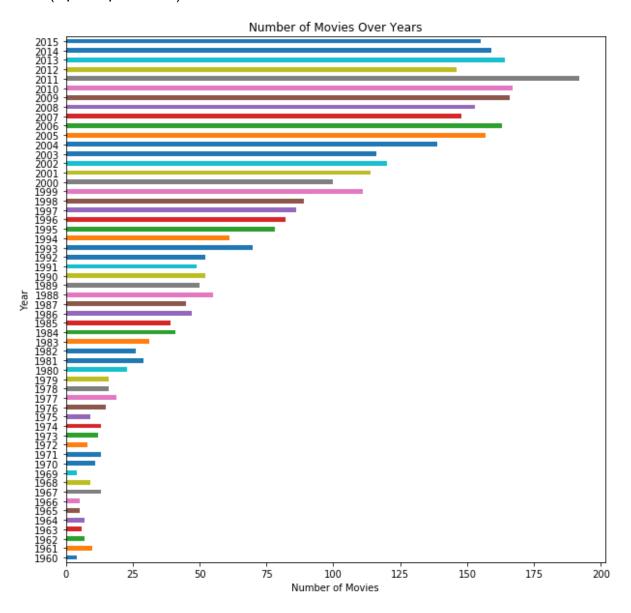
# store data
data = pd.Series(data.split('|'))
count = data.value_counts(ascending = False)
return count
```

```
In [262]: count_genres = calculate_count('genres')
count_genres.plot(kind='bar', figsize=(10,10))
```

Out[262]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21834908>



Out[263]: Text(0, 0.5, 'Year')



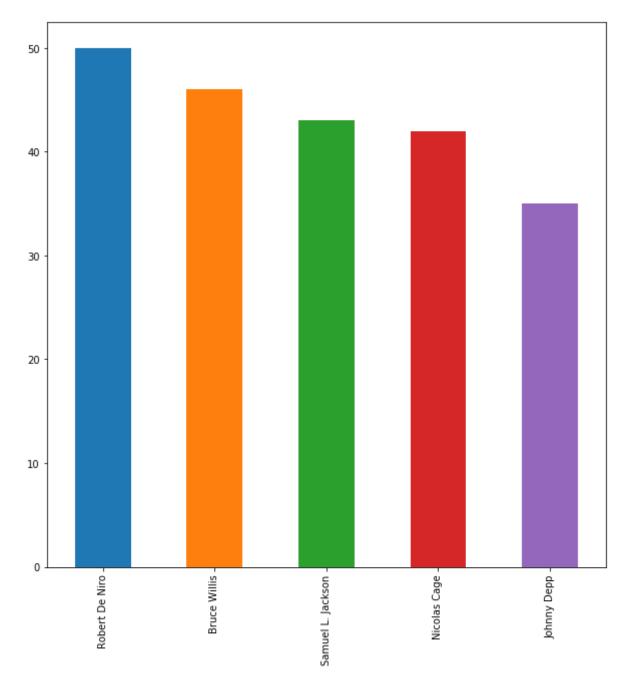
```
In [264]: count_director = calculate_count('director')
    count_director.head()
```

```
Out[264]: Steven Spielberg 28
Clint Eastwood 23
Ridley Scott 21
Tim Burton 17
Steven Soderbergh 17
dtype: int64
```

Research Question 4: Who are Top 5 Actors who have been casted the most?

```
In [267]: count_cast = calculate_count('cast')
    count_cast.head(5).plot(kind='bar', figsize=(10,10))
```

Out[267]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2b41c6a0>

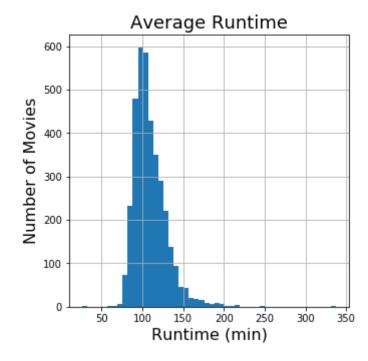


Top 5 Actors are Robert De Niro, Bruce Willis, Samuel L. Jackson, Nicolas Cage and Johnny Depp.

Research Question 5: What Are the Average Runtime of Movies and How Does it Change Over Years?

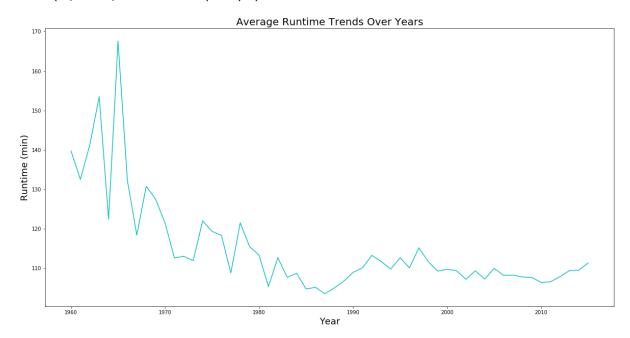
```
In [268]: df['runtime'].describe()
Out[268]: count
                    3677.000000
                     109.561327
          mean
          std
                      19.855075
                      26.000000
          min
          25%
                      96.000000
          50%
                     106.000000
          75%
                     120.000000
                     338.000000
          max
          Name: runtime, dtype: float64
In [269]:
          df['runtime'].hist(figsize=(5,5), bins=50)
          plt.title('Average Runtime', fontsize=18)
          plt.xlabel('Runtime (min)', fontsize=16)
          plt.ylabel('Number of Movies', fontsize=16)
```

Out[269]: Text(0, 0.5, 'Number of Movies')



Almost all movies have runtime between 80-120 min

```
Out[270]: Text(0, 0.5, 'Runtime (min)')
```



It's interesting to see that the average movie runtime was longer(130-170 min) during 1960-1970 and reduced to 90-110 these days

Research Question 6. What is the Relationship Between Budget, Revenue and Popularity?

```
In [271]: # compute correlation of columns
    df.corr()
```

Out[271]:

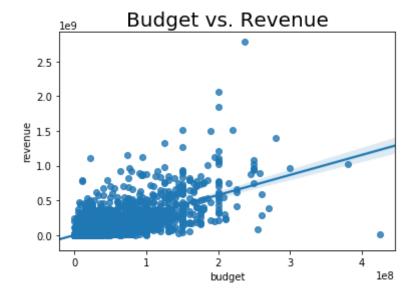
_	popularity	budget	revenue	runtime	vote_count	vote_average	release_year
popularity	1.000000	0.441203	0.611755	0.212153	0.777546	0.320195	0.181827
budget	0.441203	1.000000	0.685946	0.259281	0.554653	0.021488	0.280073
revenue	0.611755	0.685946	1.000000	0.248271	0.753014	0.228692	0.147652
runtime	0.212153	0.259281	0.248271	1.000000	0.273912	0.357544	-0.114465
vote_count	0.777546	0.554653	0.753014	0.273912	1.000000	0.391735	0.216831
vote_average	0.320195	0.021488	0.228692	0.357544	0.391735	1.000000	-0.134278
release_year	0.181827	0.280073	0.147652	-0.114465	0.216831	-0.134278	1.000000
net_profit	0.593061	0.524292	0.979260	0.218346	0.726780	0.261645	0.094807

Popularity has stronger correlation with revenue, vote_count and net_profit

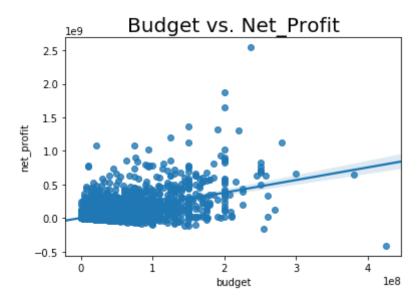
Budget has strong correlation with revenue, vote_count, net_profit

```
In [272]: # create scatter plot for budget and popularity columns
    sns.regplot(x=df['budget'], y=df['revenue']).set_title('Budget vs. Revenue', size=20)
```

Out[272]: Text(0.5, 1.0, 'Budget vs. Revenue')





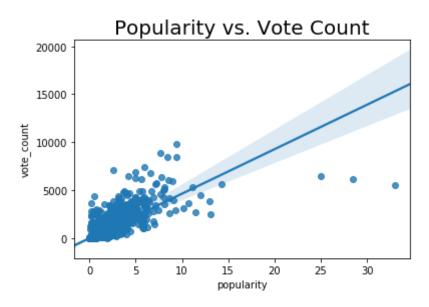


Budget vs. Revenue and Budget vs. Net Profit display strong correlation. Which means:

- 1. More budget will highly likely lead higher revenue
- 2. More budget will result in more profit

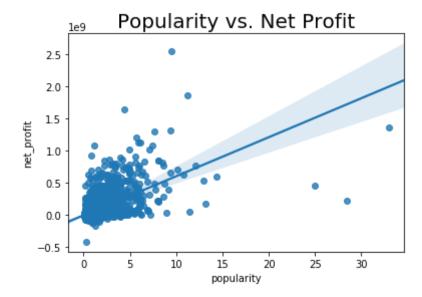
```
In [274]: # create scatter plot for popularity and vote_count columns
    sns.regplot(x=df['popularity'],y=df['vote_count']).set_title("Popularity
    vs. Vote Count",size=20)
```

Out[274]: Text(0.5, 1.0, 'Popularity vs. Vote Count')



```
In [275]: # create scatter plot for popularity and net_profit columns
    sns.regplot(x=df['popularity'],y=df['net_profit']).set_title("Popularity
    vs. Net Profit",size=20)
```

```
Out[275]: Text(0.5, 1.0, 'Popularity vs. Net Profit')
```



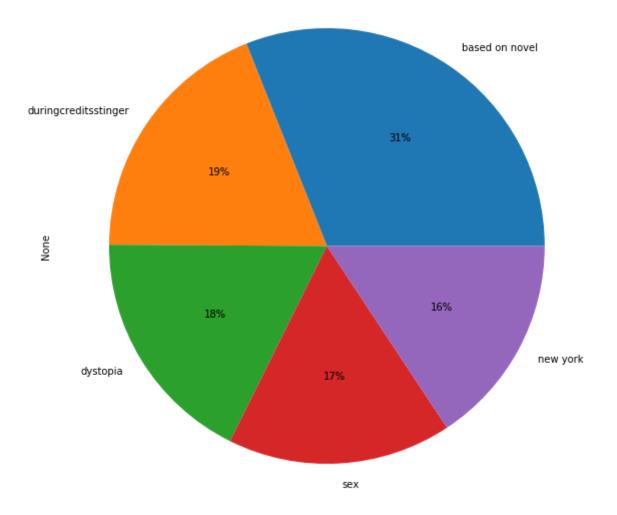
Popularity vs. Vote Count and **Popularity vs. Net Profit** clearly display strong correlation. Which means:

- 1. high popularity <-> high vote count
- 2. high popularity <-> high net profit

Research Question 7: What Are the Five Most Popular Keyword?

```
In [276]: count_keywords = calculate_count('keywords')
    count_keywords.head(5).plot(kind='pie', figsize=(10,10), autopct="%1.0f%
    %")
```

Out[276]: <matplotlib.axes._subplots.AxesSubplot at 0x1a243eb7b8>



People love to watch movies **based on novel** with **credit stinger** (a.k.a end-credit or post credit scenes)

4. Conclusions

- 1. According to the profit trends from 1960 to 2015, the movie industry has been gradually increasing from 1960 to 1990 and rapidly increasing from 1990 to 2015. Therefore, we can make a prediction about future that the profit will keep increasing.
- 2. Except Titanic (1997), the top 10 movies with highest profit is released during after 2009. This can be the fact that people are watching more movies nowadays compared to before.
- 3. Five most popular genres are: drama, comedy, thriller, action, adventure. These genres could be considered as guaranteed box office sellers!
- 4. The average runtime is about 110 min. One of the interesting findings is the average movie runtime was actually longer(130-170 min range) during 1960-1970 and reduced to 90-110 these days. In my opinion, it's becasue movie writers improved their skills on writing tight, but well-summarized stories and the developent in film technology.
- 5. The Top 5 Actors/Actress are Robert De Niro, Bruce Willis, Samuel L. Jackson, Nicolas Cage and Johnny Depp. They are all famous movie stars so no doubt!
- 6. There is also interesting findings of correlation between popularity and revenue; high popularity <-> high revenue. Apprently, there is a stronger correlation between popularity and vote count. Moreover, I found that more budget highly likely brings more net profit and revenue.
- 7. Lastly, keyword is one of the important factor of box office hit! Over 50% audiences are interested in watching movies based on novel and ending-credit-scenes, such as MARVEL movies,

Limitation

- 1. There are too much columns with 0 values. After cleaning those columns, rows reduced from 10865 to 3677. So I analyzed only 33% of the dataset.
- 2. No currency unit given. So I just assumed that it's US Dollar amount.