Project 2: Investigate a Dataset (TMDb Movies Data)

The goal of the project is making the exploratory data analysis using numpy, pandas, seaborn and matplotlib library. The important thing is that we need to note down the questions first, that needs to be answered. The next step would be finding by the answers for the questions by analysing the dataset.

Questions:

1.Most popular movies yearwise.

2.Top 3 Director with most popular movies.

3.Top 10 movies of All Time based on popularity.

4.Most profitable movies, yearwise.

5.Top 10 most profitable movie of All Time.

Library Importing

importing library that used for analysis the data.

In [58]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing data set by using pandas library.

This data set contains informationabout 10,000 movies collected fromThe Movie Database (TMDb).

In [59]:

```
df=pd.read_csv('tmdb-movies.csv')
df.head()
```

Out[59]:

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

5 rows × 21 columns

by using head function we are not get all column name so we use info() function to investigate about the column name,missing value,duplicates etc.

In [60]:

```
df.info()
```

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

In [61]:

```
for i,v in enumerate(df.columns):
    print(i,v)
```

```
0 id
1 imdb_id
2 popularity
3 budget
4 revenue
5 original_title
6 cast
7 homepage
8 director
9 tagline
10 keywords
11 overview
12 runtime
13 genres
14 production_companies
15 release_date
16 vote_count
17 vote_average
18 release_year
19 budget_adj
20 revenue_adj
```

cleaning data

Removing unwanted column i.e not use for analysis.

In [62]:

```
df.drop(['homepage', 'tagline', 'keywords','overview','release_date','runtime','imdb_i
d','budget_adj','revenue_adj'], axis=1,inplace=True)
```

In [63]:

```
df.head()
```

Out[63]:

	id	popularity	budget	revenue	original_title	cast	direc
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrc
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller
2	262500	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwen
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan

checking the null value,duplicates and spelling mistakes etc.

In [64]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 12 columns):
id                      10866 non-null int64
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
director                10822 non-null object
genres                  10843 non-null object
production_companies    9836 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
dtypes: float64(2), int64(5), object(5)
memory usage: 1018.8+ KB
```

here we see that few colums(cast,director,genres,production_companies) has missing value.so first we have to fix these problems.

In [65]:

```
df.fillna("unknown",inplace=True) #by this code the we can fix the problem of missing v
alues.
```

2nd problem is checking duplicates.

In [66]:

```
df.duplicated().sum()
```

Out[66]:

```
1
```

number of duplicates is 1. Now we have to fix duplicate problem.

In [67]:

```
df.drop_duplicates(inplace=True)
```

Remove outlier in this case there are some movies that has 0 budget and revenue

In [68]:

```
df[['budget','revenue']] = df[['budget','revenue']].replace(0,np.NAN)
df.dropna(subset=['budget', 'revenue'], inplace=True)
```

In [69]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3854 entries, 0 to 10848
Data columns (total 12 columns):
id                      3854 non-null int64
popularity              3854 non-null float64
budget                  3854 non-null float64
revenue                 3854 non-null float64
original_title          3854 non-null object
cast                    3854 non-null object
director                3854 non-null object
genres                  3854 non-null object
production_companies    3854 non-null object
vote_count              3854 non-null int64
vote_average            3854 non-null float64
release_year            3854 non-null int64
dtypes: float64(4), int64(3), object(5)
memory usage: 391.4+ KB
```

we use statistics to know about the data behaviours.

In [70]:

```
df.describe()
```

Out[70]:

	id	popularity	budget	revenue	vote_count	vote_a
count	3854.000000	3854.000000	3.854000e+03	3.854000e+03	3854.000000	3854.0
mean	39888.185262	1.191554	3.720370e+07	1.076866e+08	527.720291	6.1681
std	67222.527399	1.475162	4.220822e+07	1.765393e+08	879.956821	0.7949
min	5.000000	0.001117	1.000000e+00	2.000000e+00	10.000000	2.2000
25%	6073.500000	0.462368	1.000000e+07	1.360003e+07	71.000000	5.7000
50%	11321.500000	0.797511	2.400000e+07	4.480000e+07	204.000000	6.2000
75%	38573.250000	1.368324	5.000000e+07	1.242125e+08	580.000000	6.7000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	9767.000000	8.4000

In [71]:

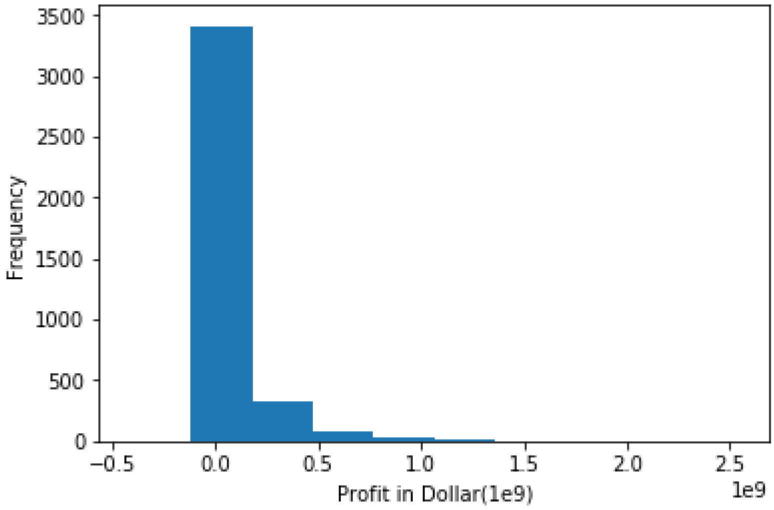
```
df['profit'] = df['revenue']-df['budget']
df['profit'] = df['profit'].apply(np.int64)
```

In [80]:

```
df['profit'].plot(kind='hist')
plt.xlabel("Profit in Dollar(1e9)")
```

Out[80]:

Text(0.5,0,'Profit in Dollar(1e9)')

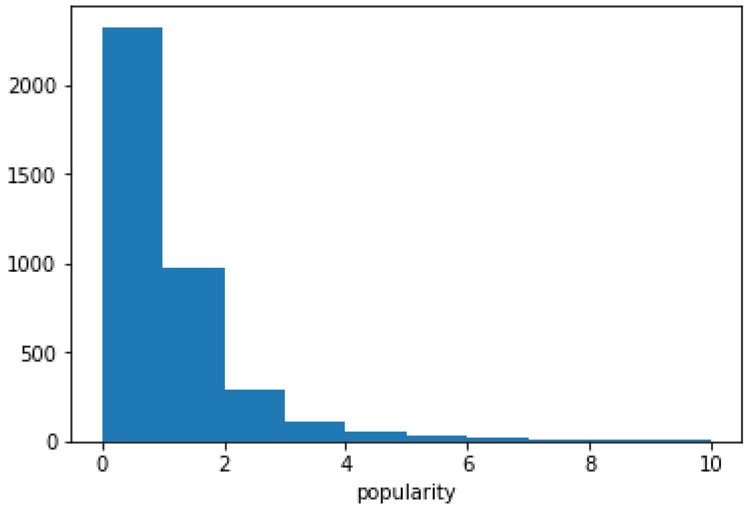


In [81]:

```
plt.hist(df.popularity,bins=[0,1,2,3,4,5,6,7,8,9,10])
plt.xlabel("popularity")
```

Out[81]:

Text(0.5,0,'popularity')



Note: The plot is right skewed. And most of the movies have popularity in range(0-2)

Most popular movie (yearwise)

In [93]:

```
li=df.groupby("release_year")["popularity"].max()
temp=pd.merge(df,li)
temp.sort_values(by=['release_year'], inplace=True)
temp[["release_year","original_title","popularity"]].reset_index(drop=True)
```

Out[93]:

	release_year	original_title	popularity
0	1960	Psycho	2.610362
1	1961	One Hundred and One Dalmatians	2.631987
2	1962	Dr. No	3.170651
3	1963	From Russia With Love	2.508235
4	1964	Goldfinger	3.153791
5	1965	Thunderball	1.910465
6	1966	Who's Afraid of Virginia Woolf?	0.670274
7	1967	The Jungle Book	2.550704
8	1968	2001: A Space Odyssey	3.309196
9	1969	On Her Majesty's Secret Service	1.778746
10	1970	The Aristocats	1.936962
11	1971	A Clockwork Orange	3.072555
12	1972	The Godfather	5.738034
13	1973	Robin Hood	2.272486
14	1974	The Godfather: Part II	3.264571
15	1975	One Flew Over the Cuckoo's Nest	3.258151
16	1976	Taxi Driver	2.582657
17	1977	Star Wars	12.037933
18	1978	Grease	1.697618
19	1979	Alien	4.935897
20	1980	The Empire Strikes Back	5.488441
21	1981	Raiders of the Lost Ark	4.578300
22	1982	Blade Runner	4.215642
23	1983	Return of the Jedi	4.828854
24	1984	The Terminator	4.831966
25	1985	Back to the Future	6.095293
26	1986	Aliens	2.485419
27	1987	Predator	3.474728
28	1988	Die Hard	3.777441
29	1989	The Little Mermaid	4.143585
30	1990	Total Recall	2.679627
31	1991	Beauty and the Beast	3.852269
32	1992	Reservoir Dogs	4.586426

	release_year	original_title	popularity
33	1993	Groundhog Day	2.571339
34	1994	Pulp Fiction	8.093754
35	1995	Se7en	4.765359
36	1996	Independence Day	4.480733
37	1997	Titanic	4.355219
38	1998	The Truman Show	4.180540
39	1999	Fight Club	8.947905
40	2000	Gladiator	4.271452
41	2001	The Lord of the Rings: The Fellowship of the Ring	8.575419
42	2002	The Lord of the Rings: The Two Towers	8.095275
43	2003	The Lord of the Rings: The Return of the King	7.122455
44	2004	Harry Potter and the Prisoner of Azkaban	5.827781
45	2005	Harry Potter and the Goblet of Fire	5.939927
46	2006	Underworld: Evolution	5.838503
47	2007	Pirates of the Caribbean: At World's End	4.965391
48	2008	The Dark Knight	8.466668
49	2009	Avatar	9.432768
50	2010	Inception	9.363643
51	2011	Captain America: The First Avenger	7.959228
52	2012	The Avengers	7.637767
53	2013	Frozen	6.112766
54	2014	Interstellar	24.949134
55	2015	Jurassic World	32.985763

In [94]:

```
df.popularity.describe()
```

Out[94]:

```
count    3854.000000
mean        1.191554
std         1.475162
min         0.001117
25%         0.462368
50%         0.797511
75%         1.368324
max        32.985763
Name: popularity, dtype: float64
```

Movies with popularity > 1.368324 (which is 3rd Quartile Value) is considered among most popular movies.

In [96]:

```
popular=df[df['popularity']>1.368324]
```

In [97]:

```
popular.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 964 entries, 0 to 10756
Data columns (total 13 columns):
id                      964 non-null int64
popularity              964 non-null float64
budget                  964 non-null float64
revenue                 964 non-null float64
original_title          964 non-null object
cast                    964 non-null object
director                964 non-null object
genres                  964 non-null object
production_companies    964 non-null object
vote_count              964 non-null int64
vote_average            964 non-null float64
release_year            964 non-null int64
profit                  964 non-null int64
dtypes: float64(4), int64(4), object(5)
memory usage: 105.4+ KB
```

Top 3 Director with most popular movies

In [98]:

```
popular.director.value_counts()
```

Out[98]:

```
Steven Spielberg    18
Tim Burton          13
Ridley Scott        13
David Fincher       10
Martin Scorsese      9
                    ..
Mark Rosman          1
Terrence Malick      1
James Wong           1
Robert Stevenson     1
Scott Speer          1
Name: director, Length: 524, dtype: int64
```

Top three directors are Steven Spielberg,Tim Burton and Ridley Scott

Top 10 movies of All Time based on popularity.

In [102]:

```
top=df[(df.popularity >1.368324) & (df.vote_average>7)].sort_values(by=['popularity'],a
scending=False).reset_index(drop=True)
```

In [103]:

```
top10=(top[["original_title","release_year","popularity"]])[:10]
top10
```

Out[103]:

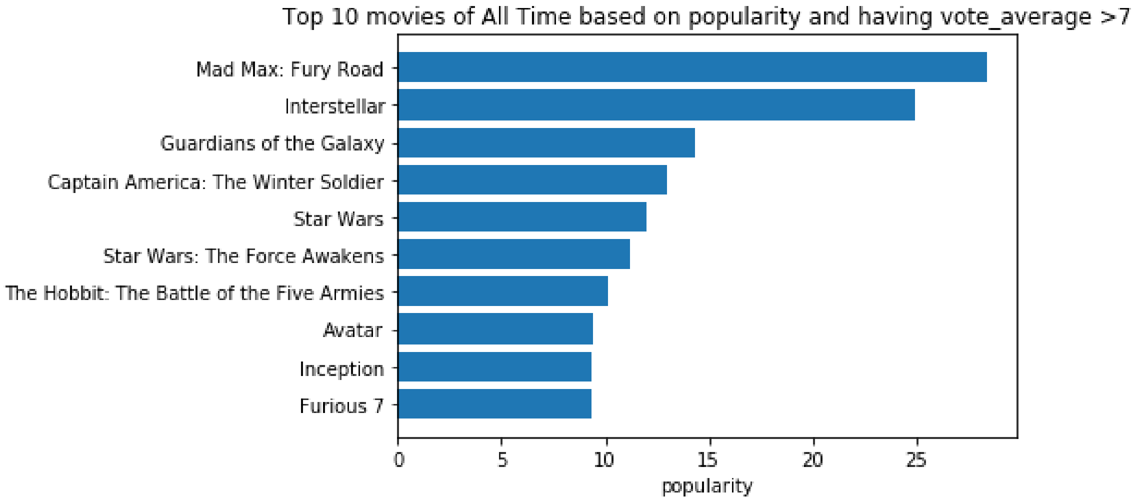
	original_title	release_year	popularity
0	Mad Max: Fury Road	2015	28.419936
1	Interstellar	2014	24.949134
2	Guardians of the Galaxy	2014	14.311205
3	Captain America: The Winter Soldier	2014	12.971027
4	Star Wars	1977	12.037933
5	Star Wars: The Force Awakens	2015	11.173104
6	The Hobbit: The Battle of the Five Armies	2014	10.174599
7	Avatar	2009	9.432768
8	Inception	2010	9.363643
9	Furious 7	2015	9.335014

In [107]:

```
temp10=top10.sort_values(by=['popularity'],ascending=True)
plt.barh(temp10.original_title,temp10.popularity)
plt.title("Top 10 movies of All Time based on popularity and having vote_average >7")
plt.xlabel("popularity")
```

Out[107]:

Text(0.5,0,'popularity')



In [111]:

```
pro=df.groupby("release_year")['profit'].max()
temp2=pd.merge(df,pro)
temp2.sort_values(by=['release_year'],inplace=True)
temp2[['release_year','original_title','profit']].reset_index(drop=True)
```

Out[111]:

	release_year	original_title	profit
0	1960	Spartacus	48000000
1	1961	One Hundred and One Dalmatians	211880014
2	1962	Dr. No	58500000
3	1963	From Russia With Love	76398765
4	1964	Goldfinger	121400000
5	1965	The Sound of Music	155014286
6	1966	Who's Afraid of Virginia Woolf?	26236689
7	1967	The Jungle Book	201843612
8	1968	2001: A Space Odyssey	44715371
9	1969	Butch Cassidy and the Sundance Kid	96308889
10	1970	Love Story	134200000
11	1971	Diamonds Are Forever	108800000
12	1972	The Godfather	239066411
13	1973	The Exorcist	433306145
14	1974	Blazing Saddles	116900000
15	1975	Jaws	463654000
16	1976	A Star Is Born	155000000
17	1977	Star Wars	764398007
18	1978	Superman	245218018
19	1979	Rocky II	193182160
20	1980	The Empire Strikes Back	520400000
21	1981	Raiders of the Lost Ark	371925971
22	1982	E.T. the Extra-Terrestrial	782410554
23	1983	Return of the Jedi	540350000
24	1984	Indiana Jones and the Temple of Doom	305000000
25	1985	Back to the Future	362109762
26	1986	Top Gun	341830601
27	1987	Fatal Attraction	306145693
28	1988	Rain Man	329825435
29	1989	Indiana Jones and the Last Crusade	426171806
30	1990	Ghost	483000000
31	1991	Terminator 2: Judgment Day	420000000
32	1992	Aladdin	476050219

	release_year	original_title	profit
33	1993	Jurassic Park	857100000
34	1994	The Lion King	743241776
35	1995	The Net	1084279658
36	1996	Independence Day	741969268
37	1997	Titanic	1645034188
38	1998	Armageddon	413799566
39	1998	Star Trek: Insurrection	48000000
40	1999	Star Wars: Episode I - The Phantom Menace	809317558
41	2000	Mission: Impossible II	421388105
42	2001	Harry Potter and the Philosopher's Stone	851475550
43	2002	The Lord of the Rings: The Two Towers	847287400
44	2003	The Lord of the Rings: The Return of the King	1024888979
45	2004	Shrek 2	769838758
46	2005	Harry Potter and the Goblet of Fire	745921036
47	2006	Pirates of the Caribbean: Dead Man's Chest	865659812
48	2007	Harry Potter and the Order of the Phoenix	788212738
49	2008	The Dark Knight	816921825
50	2009	Avatar	2544505847
51	2010	Toy Story 3	863171911
52	2011	Harry Potter and the Deathly Hallows: Part 2	1202817822
53	2012	The Avengers	1299557910
54	2013	Frozen	1124219009
55	2014	The Hobbit: The Battle of the Five Armies	705119788
56	2015	Star Wars: The Force Awakens	1868178225

In [116]:

```
prof=df.sort_values(by=['profit'],ascending = False).reset_index(drop= True)[:10]
prof[['release_year','original_title','profit']]
```

Out[116]:

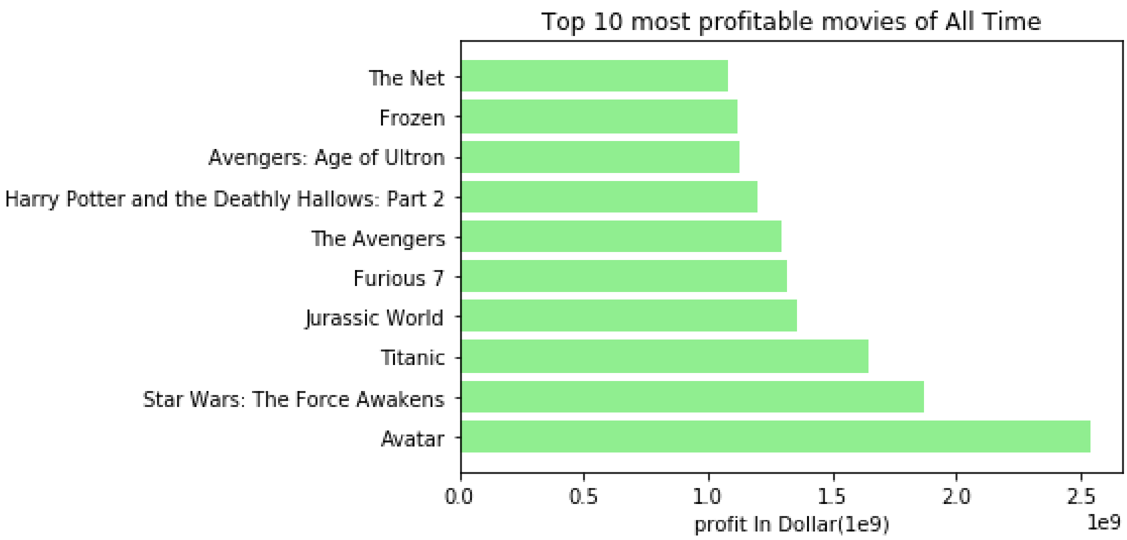
	release_year	original_title	profit
0	2009	Avatar	2544505847
1	2015	Star Wars: The Force Awakens	1868178225
2	1997	Titanic	1645034188
3	2015	Jurassic World	1363528810
4	2015	Furious 7	1316249360
5	2012	The Avengers	1299557910
6	2011	Harry Potter and the Deathly Hallows: Part 2	1202817822
7	2015	Avengers: Age of Ultron	1125035767
8	2013	Frozen	1124219009
9	1995	The Net	1084279658

In [118]:

```
plt.barh(prof.original_title,prof.profit,color="lightgreen")
plt.title("Top 10 most profitable movies of All Time")
plt.xlabel("profit In Dollar(1e9)")
```

Out[118]:

```
Text(0.5,0,'profit In Dollar(1e9)')
```



Note: Avatar made highest exceptional profit.

In [119]:

```
df[["popularity","profit","vote_average","budget","revenue"]].corr()
```

Out[119]:

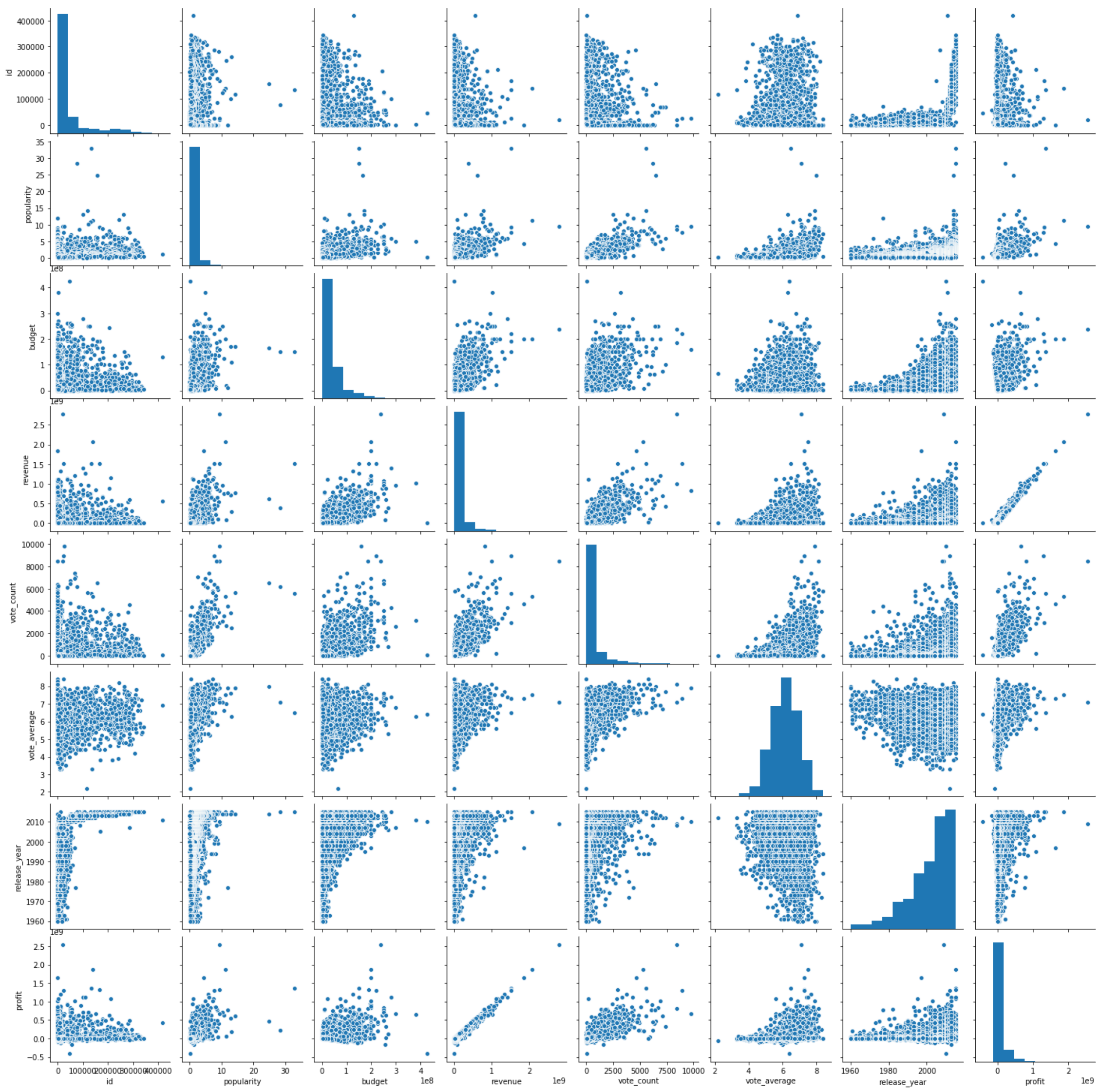
	popularity	profit	vote_average	budget	revenue
popularity	1.000000	0.596201	0.317866	0.446987	0.615535
profit	0.596201	1.000000	0.259435	0.526818	0.979133
vote_average	0.317866	0.259435	1.000000	0.024169	0.227123
budget	0.446987	0.526818	0.024169	1.000000	0.688556
revenue	0.615535	0.979133	0.227123	0.688556	1.000000

In [120]:

```
sns.pairplot(df)
```

Out[120]:

<seaborn.axisgrid.PairGrid at 0x20773bdada0>

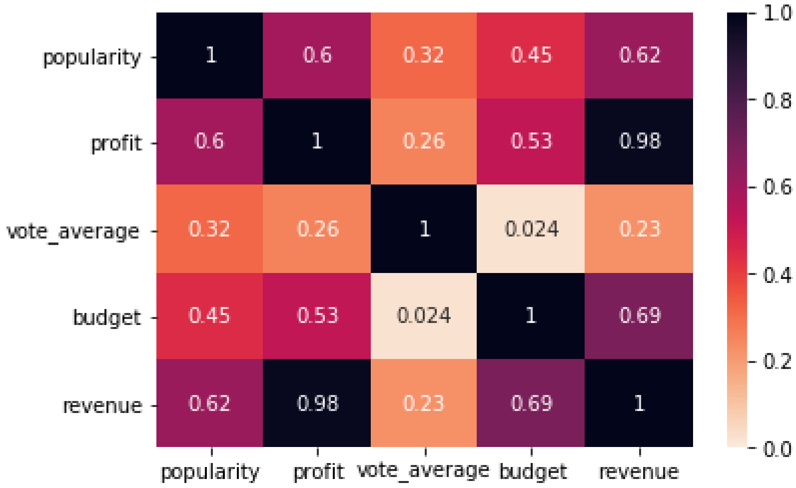


In [122]:

```
sns.heatmap(df[["popularity","profit","vote_average","budget","revenue"]].corr(),cmap=
'rocket_r',annot=True,vmin=0)
```

Out[122]:

<matplotlib.axes._subplots.AxesSubplot at 0x20778c72b00>



Moderate correlation between popularity and revenue & profit

Strong correlation betwwen revenue and profit

Moderate correlation between budget and profit

Conclusions

1. Based on correlation Moderate correlation between popularity and revenue & profit: Generally movies with high popularity generate more revenue and profit. 2.Strong correlation betwwen revenue and profit: Movies that generate more revenue, makes more profit 3.Moderate correlation between budget and profit: Movies which high budget are more likely to make more profit
2. Based on observation
3. Steven Spielberg , Ridley Scott , Ridley Scott are top 3 Director with most popular movies of all time.
4. Mad Max: Fury Road is the most popular movie of all time based on popularity and average vote.
5. Avatar is the most profitable movie of all time

Limitation

1. The movies data is from year 1960 to 2015, and all the conclusion is based according to it, thus missing recent movies.
2. There were movies with 0 revenue and budget, those movie names are removed. Therefore there popularity is not considered.