Project: Investigate TMDb Movie Data

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Introduction

Key notes: "This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. Certain columns, like ‘cast’ and ‘genres’, contain multiple values separated by pipe (|) characters. There are some odd characters in the ‘cast’ column. The final two columns ending with “_adj” show the budget and revenue of the" "associated movie in terms of 2010 dollars, accounting for inflation over time."

Questions to explore:

- 1. What is the highest popularity score? Which movie is it corresponding to?
- 2. What is the highest vote_count? Which movie is it corresponding to?
- 3. What is the relationship between popularity and vote_count?
- 4. What are the best and worst box office records in terms of revenue_adj, and corredponding to >which leading actor, director and movies, respectively?
- 5. What are the relationship bewteen popularity and box office as well vote_counts and box office?
- 6. What are the highest and lowerest budgets? Which movies are they corrsponding to respectivly?
- 7. Selecting 1983 as watershed, what is the total gross before and after it respectively?
- 8. What is the sum of gross of all movies in 2009?
- 9. In which day, month and year of release, respectively, the movies possess the highest box /office record ?
- 10. Which actor/actress participated in most movies?
- 11. Which compamy produced the most movies?
- 12. What is the most frequent type of movie?
- 13. Which leading actor/actress possess highest box office record by average and in total, >respectively?
- 14. Does the highest ratio of revenue versus budget or budget versus revenue of movie suggest >anything?
- 15. What is the distribution of box office?
- 16. What is the distribution of vote_average?
- 17. In which day, month and year does most movies released?
- 18. What is the relationsip of budget and revenue?
- 19. Does the lenghth of movie affect its revenue? Group the movie by the lengh intervals, eg, >below 120 mins, between 120 to 180 mins, above 180min, then compare the mean revenue of each group of movies?
- 20. Which genres are most popular from year to year?
- 21. What kinds of properties are associated with movies that have high revenues?

In [1]:

```
# Set up import statements for all of the packages that are planed to use
# Include a 'magic word' so that visualizations are plotted
# call on dataframe to display the first 5 rows

import pandas as pd
import numpy as np
import datetime
from statistics import mode
% matplotlib inline
import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'retina'
import seaborn as sns
sns.set_style('darkgrid')
df = pd.read_csv('tmdb-movies.csv')
```

Data Wrangling

> **Key notes**: In this section of the report, the following work will be done: load the data; check for cleanliness; trim and clean dataset for analysis.

General Properties

In [2]:

```
# Load data and print out a few lines

df.head()
```

Out[2]:

	id	imdb_id	popularity	budget	revenue	original_title	cas
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce 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|Michelle ...

5 rows × 21 columns

In [3]:

```
# return a tuple of the dimensions of the dataframe

df.shape
```

Out[3]:

```
(10866, 21)
```

In [4]:

```
# print the column labels in the dataframe

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
```

In [5]:

```
# return the datatypes of the columns

df.dtypes
```

Out[5]:

```
id                        int64
imdb_id                  object
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
homepage                 object
director                 object
tagline                  object
keywords                 object
overview                 object
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
revenue_adj             float64
dtype: object
```

In [6]:

```
# check for duplicates in the data

sum(df.duplicated())
```

Out[6]:

```
1
```

In [7]:

```
#  check if any value is NaN in DataFrame and in how many columns

df.isnull().any().any(), sum(df.isnull().any())
```

Out[7]:

```
(True, 9)
```

In [8]:

```
# displays a concise summary of the dataframe
# including the number of non-null values in each column

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 [9]:

```
df.release_year.sort_values(ascending=True).unique()
```

Out[9]:

```
array([1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1
970,
       1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1
981,
       1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1
992,
       1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2
003,
       2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2
014,
       2015])
```

In [10]:

```
# Generates descriptive statistics, excluding NaN values

df.describe()
```

Out[10]:

	id	popularity	budget	revenue	runtime	vo
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	1086
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.3
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.6
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.0
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.0
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.0
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.7
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767

Data Cleaning

In [11]:

```
# drop duplicates
# confirm correction

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

Out[11]:

0

In [12]:

```
# As the NaN values are of string type therefore they can't be treated by fillin
g with means
# Since they don't affect the arithmetic calculation nor satistical analysis
# so it is better to replace those NaN values with a common string type value wh
ich doesn't indicate anything

df.fillna('No record', inplace = True)
df.isnull().any().any()
```

Out[12]:

```
False
```

In [13]:

```
# Generates descriptive statistics, excluding NaN values

df.describe()
```

Out[13]:

	id	popularity	budget	revenue	runtime	vo
count	10865.000000	10865.000000	1.086500e+04	1.086500e+04	10865.000000	1086
mean	66066.374413	0.646446	1.462429e+07	3.982690e+07	102.071790	217.3
std	92134.091971	1.000231	3.091428e+07	1.170083e+08	31.382701	575.6
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.00
25%	10596.000000	0.207575	0.000000e+00	0.000000e+00	90.000000	17.00
50%	20662.000000	0.383831	0.000000e+00	0.000000e+00	99.000000	38.00
75%	75612.000000	0.713857	1.500000e+07	2.400000e+07	111.000000	146.0
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767

In [14]:

```
# shouw columns

df.columns
```

Out[14]:

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original
_title',
       'cast', 'homepage', 'director', 'tagline', 'keywords', 'overv
iew',
       'runtime', 'genres', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
       'revenue_adj'],
      dtype='object')
```

In [15]:

```
# Filter the colmuns according to the exploring questions and export to a new da
taframe
# Confirm the changes

df_analysis = df.iloc[:,np.r_[2:3, 5:7, 8, 12:21]]

df_analysis.columns
```

Out[15]:

```
Index(['popularity', 'original_title', 'cast', 'director', 'runtime'
, 'genres',
       'production_companies', 'release_date', 'vote_count', 'vote_a
verage',
       'release_year', 'budget_adj', 'revenue_adj'],
      dtype='object')
```

In [16]:

```
# Set the index by 'original title'
# Confirm the changes

df_analysis.set_index('original_title', inplace =True)
df_analysis.index
```

Out[16]:

```
Index(['Jurassic World', 'Mad Max: Fury Road', 'Insurgent',
       'Star Wars: The Force Awakens', 'Furious 7', 'The Revenant',
       'Terminator Genisys', 'The Martian', 'Minions', 'Inside Out',
       ...
       'The Ugly Dachshund', 'Nevada Smith',
       'The Russians Are Coming, The Russians Are Coming', 'Seconds'
,
       'Carry On Screaming!', 'The Endless Summer', 'Grand Prix',
       'Beregis Avtomobilya', 'What's Up, Tiger Lily?',
       'Manos: The Hands of Fate'],
      dtype='object', name='original_title', length=10865)
```

In [17]:

```
# Extract the leading actor from cast, and transfer them into a new column

df_analysis['lead'] = df_analysis.cast.apply(lambda x: x.split('|')[0])
df_analysis.head()
```

```
/Users/shilinli/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing
imports until
```

Out[17]:

	popularity	cast	director	runtime	genres
original_title					
Jurassic World	32.985763	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller
Mad Max: Fury Road	28.419936	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller
Insurgent	13.112507	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller
Star Wars: The Force Awakens	11.173104	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy
Furious 7	9.335014	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller

In [18]:

```
# Convert date infomation into datetime format

df_analysis['release_date'] = pd.to_datetime(df_analysis['release_date'], errors
='coerce')
df_analysis.head()
```

```
/Users/shilinli/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing
imports until
```

Out[18]:

	popularity	cast	director	runtime	genres
original_title					
Jurassic World	32.985763	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller
Mad Max: Fury Road	28.419936	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller
Insurgent	13.112507	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller
Star Wars: The Force Awakens	11.173104	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy
Furious 7	9.335014	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller

Exploratory Data Analysis

Research Question 1: What is the highest popularity score? Which movie is it corresponding to?

In [19]:

```
# Find the index which points to the highest popuarity score

ind_pop = df_analysis.index[df['popularity'] == df_analysis['popularity'].max()]
ind_pop
```

Out[19]:

```
Index(['Jurassic World'], dtype='object', name='original_title')
```

In [20]:

```
# print out the row of indicated index to see the complete information

round(df_analysis.loc[ind_pop], 2)
```

Out[20]:

	popularity	cast	director	runtime	genres	pro
original_title						
Jurassic World	32.99	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller	Uni Ent

> The highest popularity score among all the movies of the dataset was 32.99, and the title of this movie is "Jurassic World" which was released in 2015.

Research Question 2: What is the highest vote? Which movie is it corresponding to?

In [21]:

```
# Find the index which points to the highest vote

ind_vote = df_analysis.index[df['vote_count'] == df_analysis['vote_count'].max()
]
ind_vote
```

Out[21]:

```
Index(['Inception'], dtype='object', name='original_title')
```

In [22]:

```
# print out the row of indicated index to see the complete information

df_analysis.loc[ind_vote]
```

Out[22]:

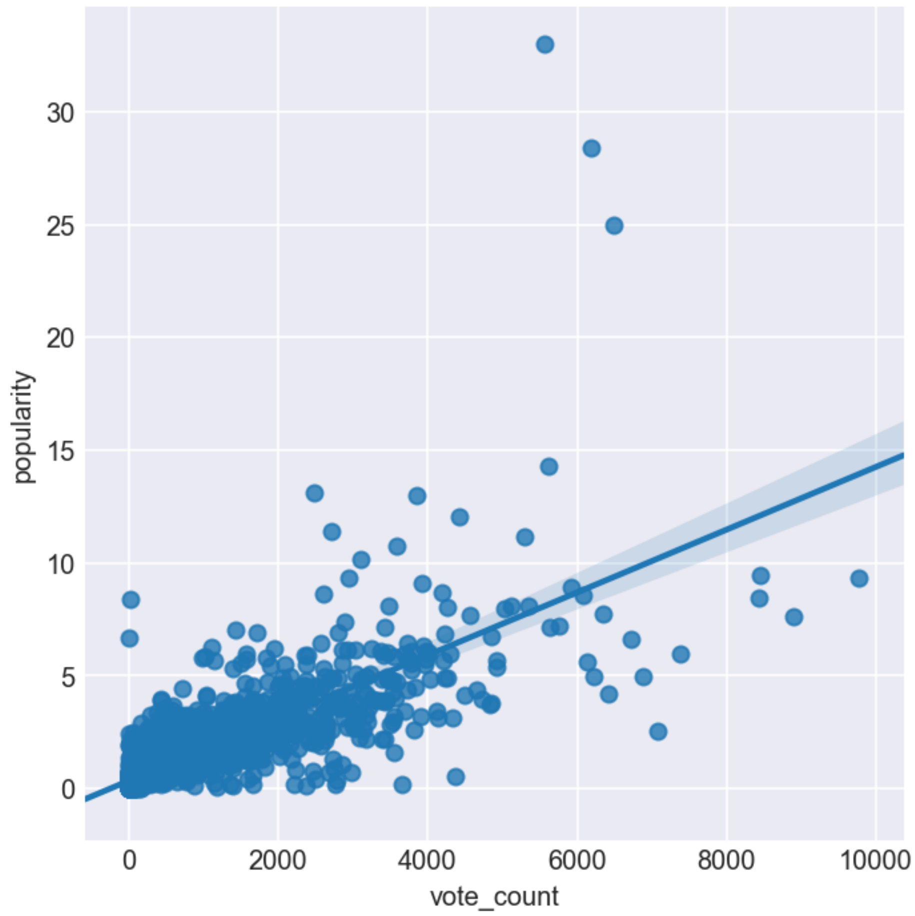
	popularity	cast	director	runtime	genres
original_title					
Inception	9.363643	Leonardo DiCaprio|Joseph Gordon-Levitt|Ellen P...	Christopher Nolan	148	Action|Thriller|Science Fiction|Mystery|Adventure

> The highest votes among all the movies of the dataset is 9767, and the title of this movie is "Inception" which was released in 2010.

Research Question 3: What is the relationship between popularity and vote_count?

In [23]:

```
sns.lmplot(x='vote_count', y='popularity', data=df_analysis);
```



There is positive correlation between populatity and vote_count. The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

Reach Question 4: What are the best and worst box office records in terms of revenue_adj, and corredponding to which leading actor, director and movies, respectively?

In [24]:

```
# Find the index which points to the highest box office

ind_box_high = df_analysis.index[df['revenue_adj'] == df_analysis['revenue_adj']
.max()]
ind_box_high
```

Out[24]:

```
Index(['Avatar'], dtype='object', name='original_title')
```

In [25]:

```
# print out the row of indicated index to see the complete information

df_analysis.loc[ind_box_high]
```

Out[25]:

	popularity	cast	director	runtime	genres
original_title					
Avatar	9.432768	Sam Worthington|Zoe Saldana|Sigourney Weaver|S...	James Cameron	162	Action|Adventure|Fantasy| Fiction

> The highest box office among all the movies of the dataset was 2.827124e+09 dollor, and the title of this movie is "Avatar" which was released in 2009, the leading actor and director are 'Sam Worthington' and 'James Cameron', respectively.

In [26]:

```
# Find the index which points to the lowest box office which is higher than 0

box_low = df_analysis[df_analysis['revenue_adj']>0]
box_worst = box_low.index[box_low['revenue_adj'] == box_low['revenue_adj'].min()
]
box_worst
```

Out[26]:

```
Index(['Shattered Glass'], dtype='object', name='original_title')
```

In [27]:

```
# print out the row of indicated index to see the complete information

round(df_analysis.loc[box_worst], 2)
```

Out[27]:

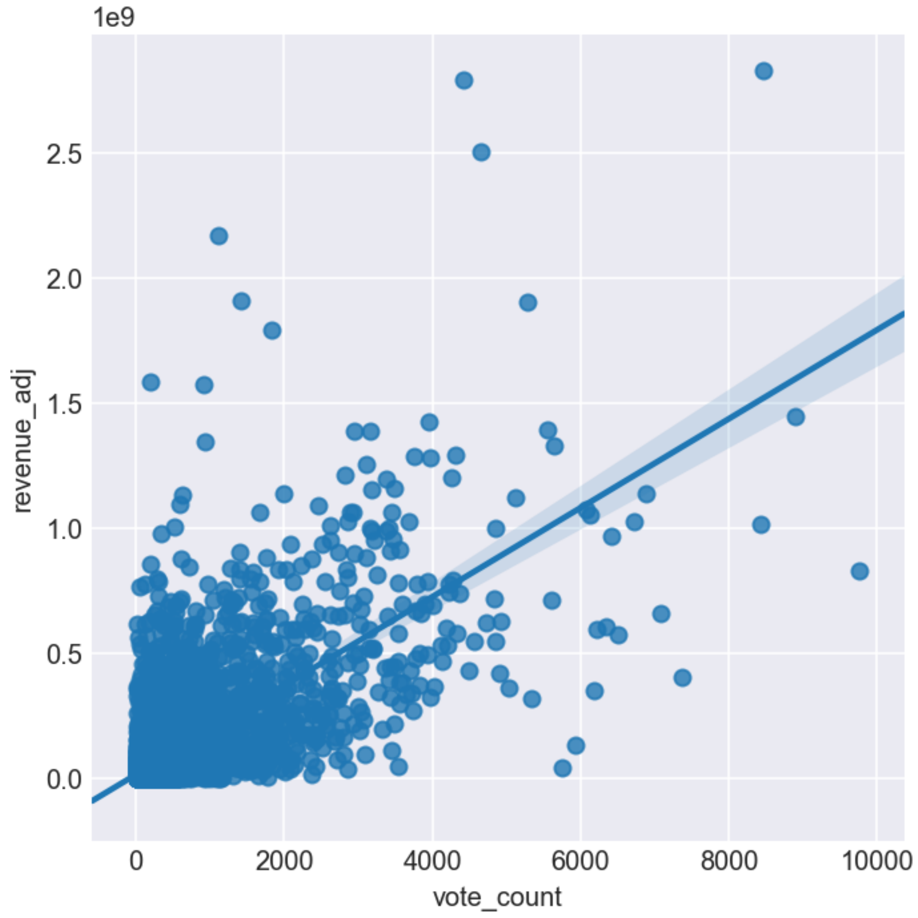
	popularity	cast	director	runtime	genres	production
original_title						
Shattered Glass	0.46	Hayden Christensen|Peter Sarsgaard|ChloÃ« Sevi...	Billy Ray	94	Drama|History	Lions Gate Films|Cruise Productions

The lowest box office among all the movies of the dataset was 2.37 dollor, and the title of this movie is 'Shattered Glass', which was released in 2003, the leading actor and director are 'Hayden Christensen' and 'Billy Ray', respectively.

Research Question 5: What are the relationship bewteen popularity and box office as well vote_counts and box office?

In [28]:

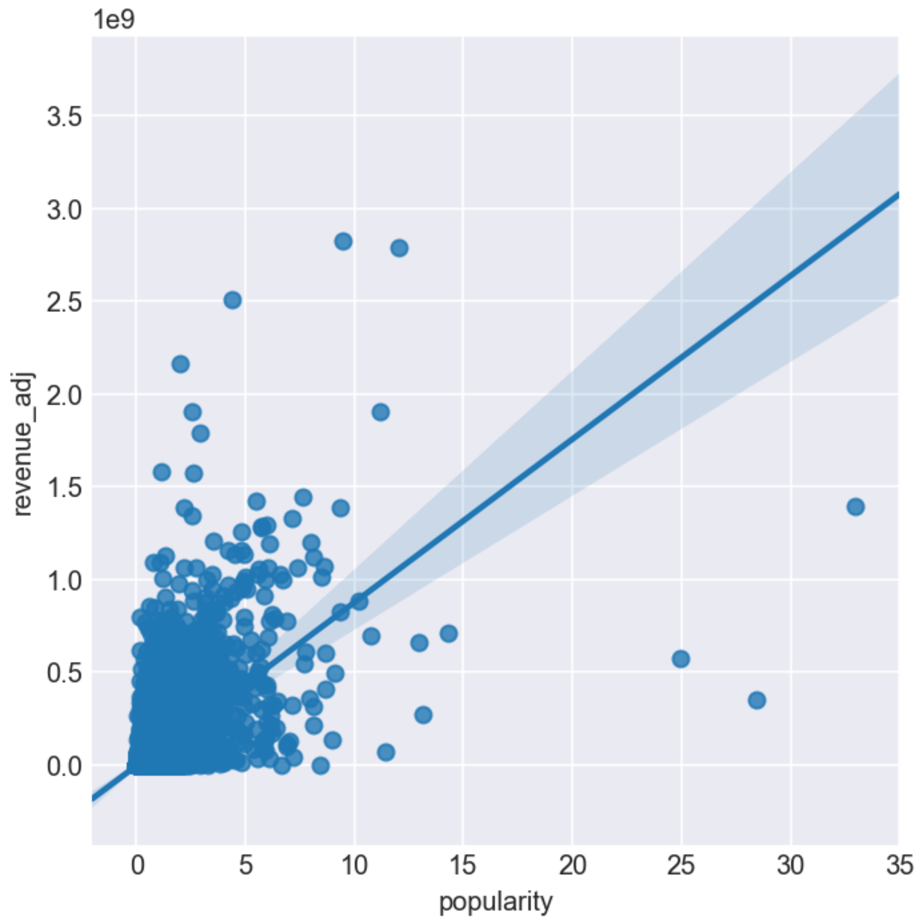
```
sns.lmplot(x='vote_count', y='revenue_adj', data=df_analysis);
```



There is positive correlation between vote_counts and box office. The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

In [29]:

```
sns.lmplot(x='popularity', y='revenue_adj', data=df_analysis);
```



There is positive correlation between populatity and box office. The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

Research Question 6: What are the highest and lowerest budgets? Which movies are they corrsponding to respectivly?

In [30]:

```
# Find the index which points to the highest budget

ind_bud_high = df_analysis.index[df['budget_adj'] == df_analysis['budget_adj'].m
ax()]
ind_bud_high
```

Out[30]:

```
Index(['The Warrior's Way'], dtype='object', name='original_title')
```

In [31]:

```
# print out the row of indicated index to see the complete information

df_analysis.loc[ind_bud_high]
```

Out[31]:

	popularity	cast	director	runtime	genres
original_title					
The Warrior's Way	0.25054	Kate Bosworth|Jang Dong-gun|Geoffrey Rush|Dann...	Sngmoo Lee	100	Adventure|Fantasy|Action|Wes

> The highest budget among all the movies of the dataset is 425000000 dollor, and the title of this movie is 'The Warrior's Way', which was released in 2010.

In [32]:

```
# Find the index which points to the lowest budget which is greater than 0

bud_low = df_analysis[df_analysis['budget_adj'] > 0]
ind_bud_worst = bud_low.index[bud_low['budget_adj'] == bud_low['budget_adj'].min
()]
ind_bud_worst
```

Out[32]:

```
Index(['Fear Clinic'], dtype='object', name='original_title')
```

In [33]:

```
round(df_analysis.loc[ind_bud_worst], 2)
```

Out[33]:

	popularity	cast	director	runtime	genres	production_comp
original_title						
Fear Clinic	0.18	Thomas Dekker|Robert Englund|Cleopatra Coleman...	Robert Hall	95	Horror	Dry County Films|Anchor Bay Entertainment|Mo

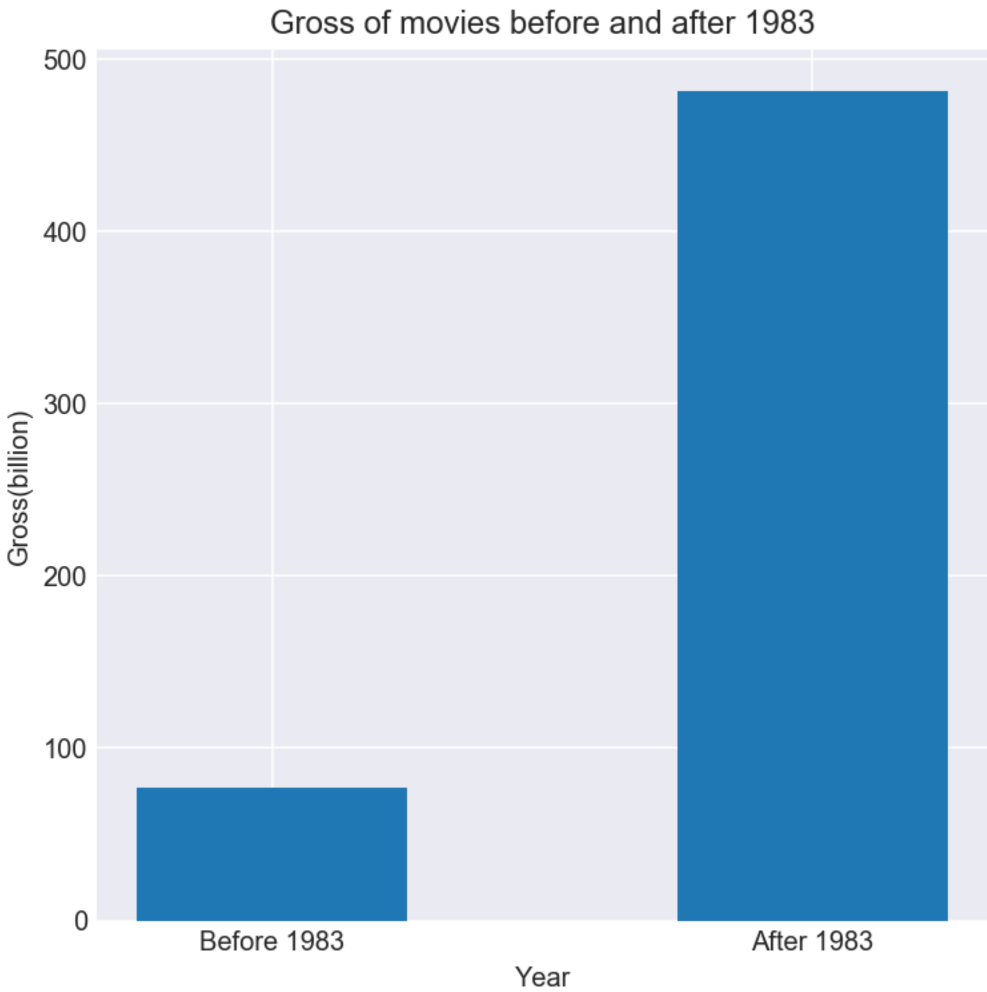
> The lowest budget among all the movies of the dataset was 0.92 dollor, and the title of this movie is 'Fear Clinic', which was released in 2014.

Research Question 7: Selecting 1983 as inflation watershed, what is the total gross before and after it respectively?

In [34]:

```
# Select rows of which the released_date is prior to 1975

pre1983 = df_analysis.query('release_year < 1983')

# Select rows of which the released_date is greater than 1975

after1983 = df_analysis.query('release_year >= 1983')

# Calculate the sum of box office in terms of revenue_adj before and after 1975,
respectively

sum_pre1983 = pre1983.revenue_adj.sum()

sum_after1983 = after1983.revenue_adj.sum()

# print out the result with the unit of billion

print('The total gross before 1983 and after were {0:.2f} billion and \
{1:.2f} billion, respectively.'.format(sum_pre1983/(1e+9), sum_after1983/(1e+9))
)

# Plot the resluts with bar chart

plt.figure(figsize=(6,6))
plt.bar([1,2], [round(sum_pre1983/(1e+9), 2), round(sum_after1983/(1e+9), 2)]\
        , tick_label=['Before 1983', 'After 1983'], width=0.5)

plt.title('Gross of movies before and after 1983')
plt.xlabel('Year')
plt.ylabel('Gross(billion)');
```

```
The total gross before 1983 and after were 76.93 billion and 481.20
billion, respectively.
```



Research Question 8: What is the sum of gross of all movies in 2009?

In [35]:

```
# Find the rows of which the released_date is equal to 2009

box_2009 = df_analysis.query('release_year == 2009')

# Calculate the sum of box office

print('The total gross in 2009 was {:.2f} billion.'.format(box_2009.revenue_adj.
sum()/(1e+9)))
```

```
The total gross in 2009 was 22.54 billion.
```

Research Question 9: In which day, month and year of release, respectively, the movies possess the highest box office record ?

In [36]:

```
# Use groupby function to obtain the sum of box office in each year

box_year = df_analysis.groupby(['release_year'])['revenue_adj'].sum()

# Find out the index which points to the highest box office record by year

box_year.idxmax()
```

Out[36]:

```
2015
```

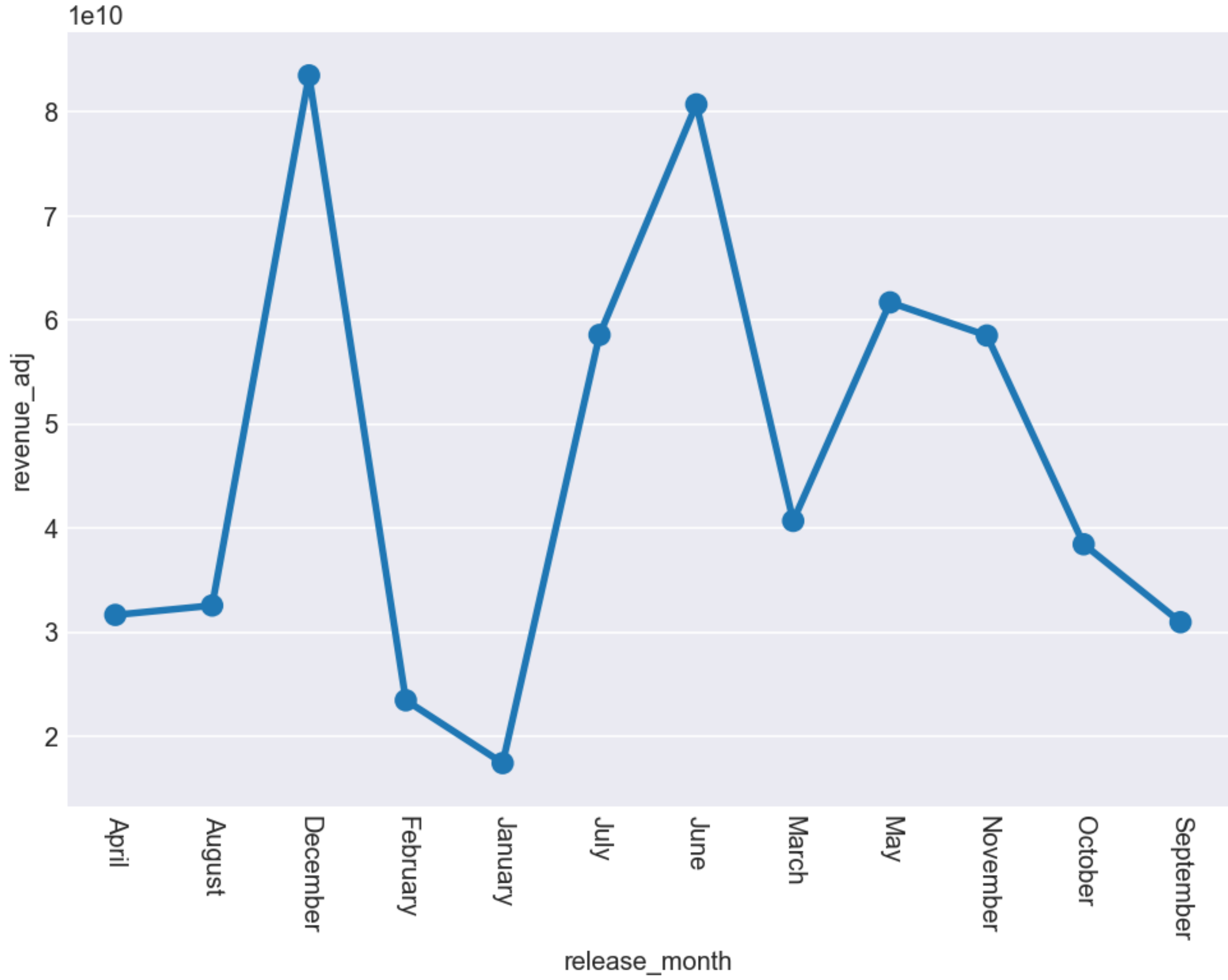
In [37]:

```
print('The highest box office record in terms of released year is in 2015, \
which is {:.2f} billion dollor.'.format(box_year.loc[2015]/(1e+8)))
```

```
The highest box office record in terms of released year is in 2015,
which is 246.21 billion dollor.
```

In [38]:

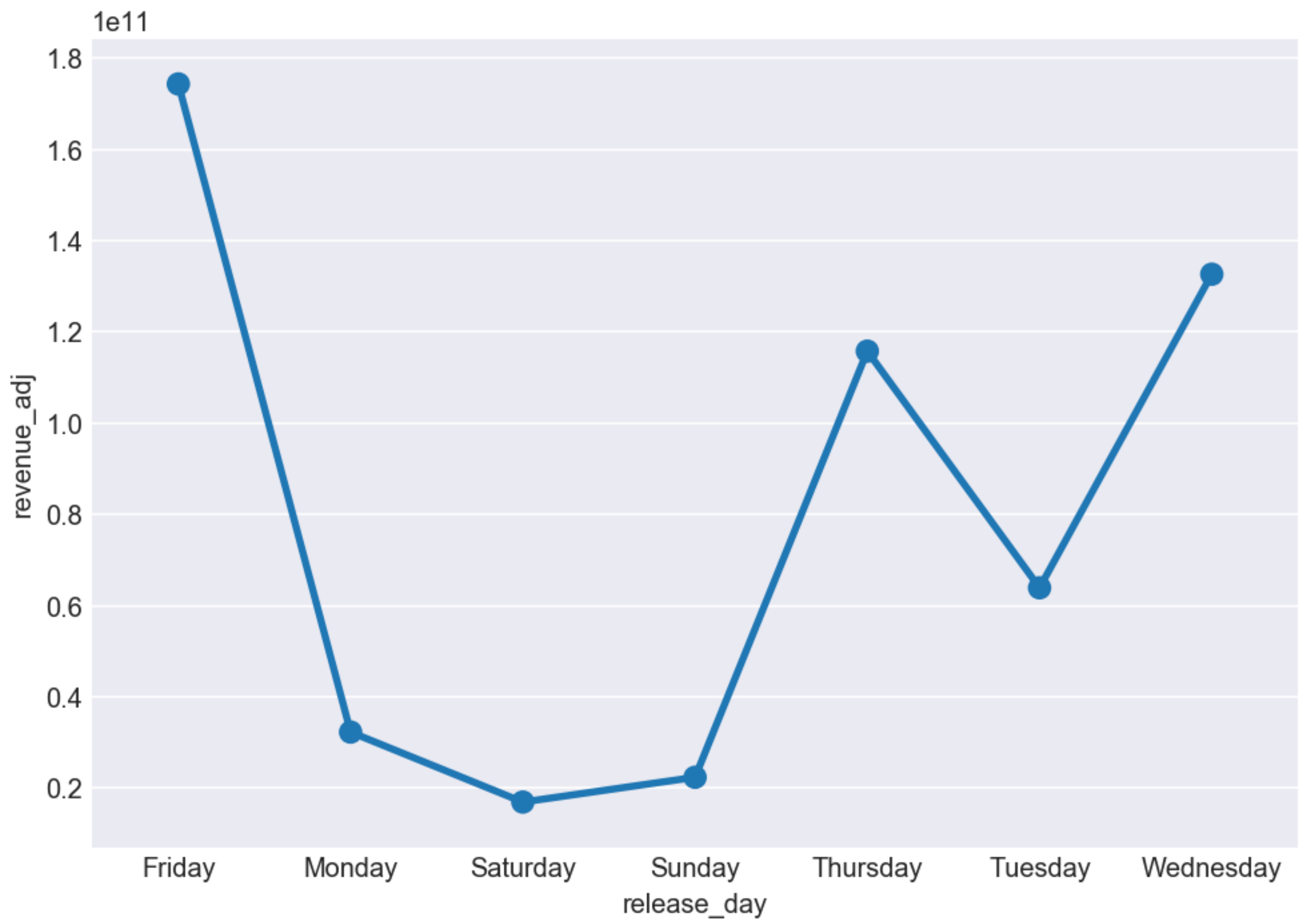
```
# Extract month from datetime column (release_date)

month_data = df_analysis.release_date.dt.strftime("%B")

# make a copy of data_analysis

df_month = df_analysis.copy()

# Add a new column of month

df_month['release_month'] = month_data

# Use groupby function to obtain the sum of box office in each month.

box_month = df_month.groupby(['release_month'], as_index = False)['revenue_adj']
.sum()

# Use factor plots which is easy to separate plots by categorical classes

sns.factorplot( x = 'release_month', y= 'revenue_adj', data = box_month, size =5
, aspect=1.4);

plt.xticks(rotation=-90);
```



Movies released in December possesses the highest box office record, which is around 90 billion dollors.

In [39]:

```
# Extract day from datetime column (release_date)

day_data = df_analysis.release_date.dt.strftime("%A")

# make a copy of data_analysis

df_day = df_analysis.copy()

# Add a new column of week day

df_day['release_day'] = day_data

# Use groupby function to obtain the sum of box office in each weekd day

box_day = df_day.groupby(['release_day'], as_index = False)['revenue_adj'].sum()

# Use factor plots which is easy to separate plots by categorical classes
sns.factorplot( x = 'release_day', y= 'revenue_adj', data = box_day, size =5, as
pect=1.4);
```



The highest box office record in terms of released day is Friday, which holds around 180 billion dollor as shown in figure.

Research Question 10: Which actor/actress participated in most movies?

In [40]:

```
# Remove the symobl '|' between actors/actress

cast_list = df_analysis.cast.apply(lambda x: x.split('|')).values

# Use function to put all the actors/actress in a list

def clean_cast(cast):
    actor_list = []
    for c in cast:
            actor_list.append(list.pop(c))

    return actor_list

actor_list_cleaned = clean_cast(cast_list)

# find the actor/actress who participated in most movies?

mode(actor_list_cleaned)
```

Out[40]:

```
'No record'
```

In [41]:

```
# remove the 'No record' which is NaN values

for element in actor_list_cleaned:
    if 'No record' in actor_list_cleaned:
        actor_list_cleaned.remove('No record')

mode(actor_list_cleaned)
```

Out[41]:

```
'Steve Buscemi'
```

> According to the analysis, actor Steve Buscemi had participated the most amount of movies.

Research Question 11: Which compamy produced the most movies?

In [42]:

```
# Remove the symobl '|' between production companies

companies_list = df_analysis.production_companies.apply(lambda x: x.split('|')).
values

# Use function to put all the production companies in a list

def clean_companies(companies):
    companies_list = []
    for c in companies:
            companies_list.append(list.pop(c))

    return companies_list

companies_list_cleaned = clean_cast(companies_list)

# find the actor/actress who participated in most movies

mode(companies_list_cleaned)
```

Out[42]:

```
'No record'
```

In [43]:

```
# remove the 'No record' which is NaN values

for element in companies_list_cleaned:
    if 'No record' in companies_list_cleaned:
        companies_list_cleaned.remove('No record')

mode(companies_list_cleaned)
```

Out[43]:

```
'Warner Bros.'
```

> According to the analysis, 'Warner Bros.' company had produced the most amount movies.

Research Question 12: What is the most frequent type of movie?

In [44]:

```
# Remove the symobl '|' between genres

genres_list = df_analysis.genres.apply(lambda x: x.split('|')).values

# Use function to put all the production companies in a list

def clean_genres(genres):
    genres_list = []
    for g in genres:
            genres_list.append(list.pop(g))

    return genres_list

genres_list_cleaned = clean_cast(genres_list)

# find the actor/actress who participated in most movies

mode(genres_list_cleaned)
```

Out[44]:

```
'Thriller'
```

> According to the analysis, the most frequent type of movie is 'Thriller'.

Research Question 13: Which leading actor/actress possess highest box office record by average and in total, respectively?

In [45]:

```
# Use groupby to find the mean box office in terms of 'revenue_adj' for each act
or/actress

cast_total = df_analysis.groupby(['lead'])['revenue_adj'].mean()

# Print out the actor/actress who possess highest box office record by average

cast_total.idxmax()
```

Out[45]:

```
'Mark Hamill'
```

'Mark Hamill' possessed highest box office record by average.

In [46]:

```
# Use groupby to find the total box office in terms of 'revenue_adj' for each ac
tor/actress

cast_total = df_analysis.groupby(['lead'])['revenue_adj'].sum()

# Print out the actor/actress who possess highest box office record in total

cast_total.idxmax()
```

Out[46]:

```
'Tom Cruise'
```

'Tom Cruise' possessed highest box office record in total.

Research Question 14: Does the highest ratio of revenue versus budget or budget versus revenue of movie suggest anything?

In [47]:

```
# Calculate the ratio of revenue versus budget

rev_bud = df_analysis.revenue_adj/df_analysis.budget_adj

# replace inf value with NaN value
rev_bud = rev_bud.replace([np.inf, -np.inf], np.nan)

# Drop NaN value

rev_bud.dropna()

# Print out the max value

round(rev_bud.max(),2)
```

Out[47]:

```
1018619.28
```

In [48]:

```
# Copy df_analsis to analyze data

rev_bud_analysis = df_analysis

# Add another conlumn of ratio of revenue versus budget

rev_bud_analysis['revenue_budget_ratio'] = round(df_analysis.revenue_adj/df_anal
ysis.budget_adj, 2)

# Print out first few lines to ckeck
rev_bud_analysis.head()
```

```
/Users/shilinli/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  import sys
```

Out[48]:

	popularity	cast	director	runtime	genres
original_title					
Jurassic World	32.985763	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller
Mad Max: Fury Road	28.419936	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller
Insurgent	13.112507	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller
Star Wars: The Force Awakens	11.173104	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy
Furious 7	9.335014	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller

In [49]:

```
# Print the entire row to examine the complete info

round(rev_bud_analysis.query('revenue_budget_ratio == 1018619.28'), 2)
```

Out[49]:

	popularity	cast	director	runtime	genres
original_title					
The Karate Kid, Part II	0.77	Ralph Macchio|Pat Morita|Martin Kove|Charlie T...	John G. Avildsen	113	Adventure|Drama|Action|Roman

> The max ratio of revenue versus budget is from movie 'The Karate Kid, Part II'. Its budget was only 224.8 dollor, whereas reveuen was around 0.23 billion dollor.

In [50]:

```
# Calculate the ratio of budget versus revenue

bud_rev = df_analysis.budget_adj/df_analysis.revenue_adj

# replace inf value with NaN value
bud_rev = bud_rev.replace([np.inf, -np.inf], np.nan)

# Drop NaN value

bud_rev.dropna()

# Print out the max value

round(bud_rev.max(),2)
```

Out[50]:

```
4166666.6699999999
```

In [51]:

```
# Copy df_analsis to analyze data

bud_rev_analysis = df_analysis

# Add another conlumn of ratio of budget versus revenue

bud_rev_analysis['budget_revenue_ratio'] = round(df_analysis.budget_adj/df_analy
sis.revenue_adj, 2)

# Print out first few lines to ckeck
bud_rev_analysis.head()
```

```
/Users/shilinli/anaconda3/lib/python3.6/site-packages/ipykernel_laun
cher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  import sys
```

Out[51]:

	popularity	cast	director	runtime	genres
original_title					
Jurassic World	32.985763	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller
Mad Max: Fury Road	28.419936	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	120	Action|Adventure|Science Fiction|Thriller
Insurgent	13.112507	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	119	Adventure|Science Fiction|Thriller
Star Wars: The Force Awakens	11.173104	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy
Furious 7	9.335014	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	137	Action|Crime|Thriller

In [52]:

```
# Print the entire row to examine the complete info

round(bud_rev_analysis.query('budget_revenue_ratio == 4166666.67'), 2)
```

Out[52]:

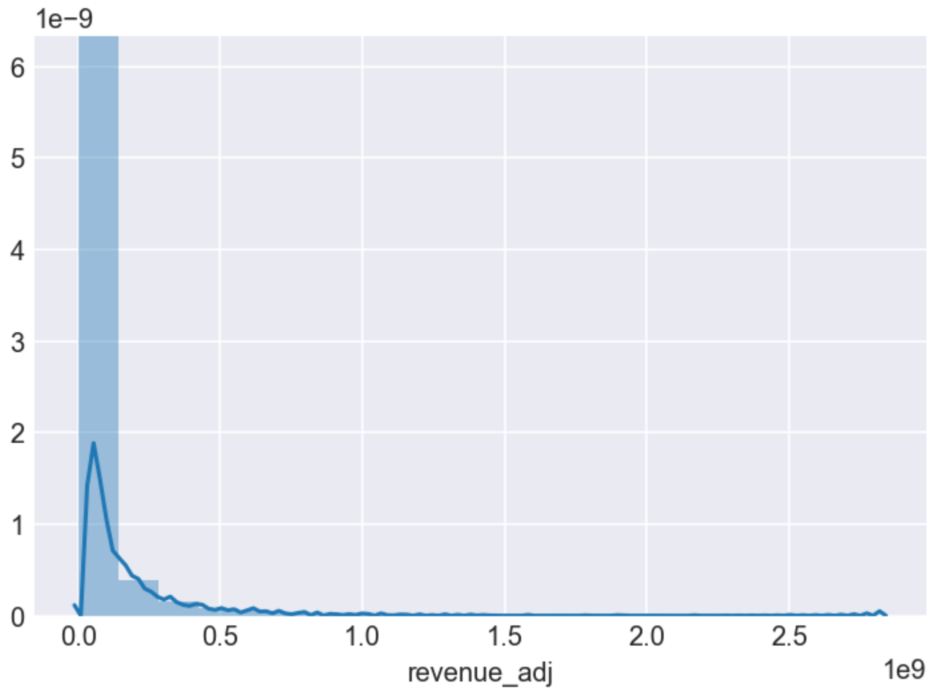
	popularity	cast	director	runtime	genres	production_c
original_title						
The House of the Spirits	0.45	Meryl Streep|Glenn Close|Jeremy Irons|Winona R...	Bille August	140	Romance|Drama	Det Danske Filminstitut|Sp Creek Produc

The max ratio of revenue versus budget is from movie 'The House of the Spirits'. Its budget was 37736749.04 dollor, whereas reveuen was only 9.06 dollor.

Research Question 15: What is the distribution of box office?

In [53]:

```
dis_rev = df_analysis.revenue_adj
sns.distplot(dis_rev, bins=20,hist=True);
```



In [54]:

```
df_analysis.revenue_adj.mean()
```

Out[54]:

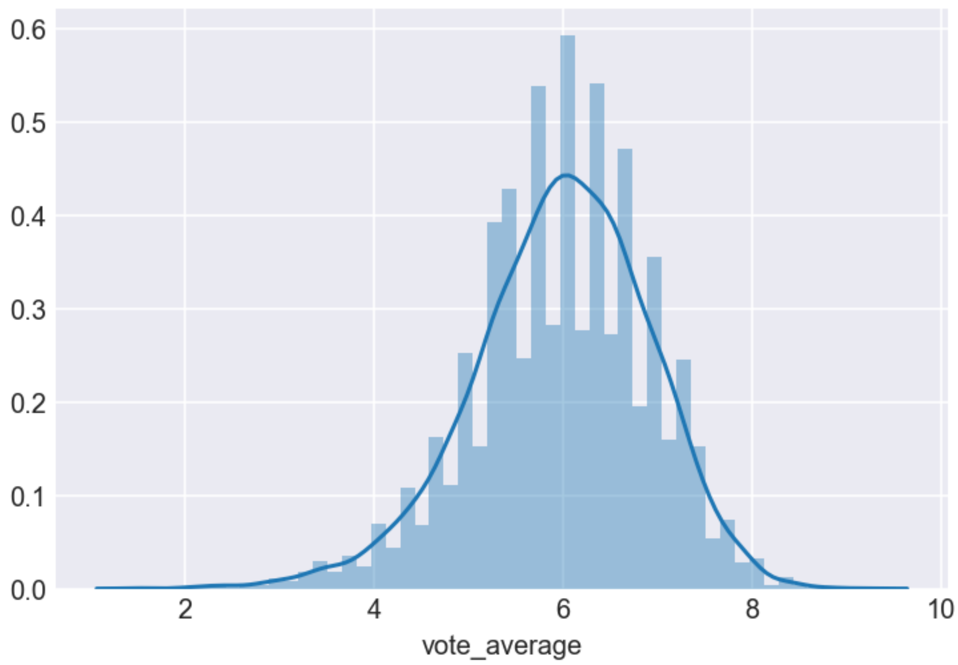
```
51369001.75884257
```

> The box office is right skewed, it is asymmetric with a long tail on the right, with the mean value around 51.37 million.

Researh Question 16: What is the distribution of vote_average?

In [55]:

```
sns.distplot(df_analysis.vote_average);
```



> The vote_average is left skewed, it is asymmetric with a long tail on the left, with the mean value is around 6.

Research Question 17: In which day, month and year does most movies released?

In [56]:

```
# Use groupby function to obtain the total movies number released in each year

r_day = df_analysis.groupby(['release_year']).count()['cast']

# Find out the index which points to the year of which most movies are released

r_day.idxmax()
```

Out[56]:

```
2014
```

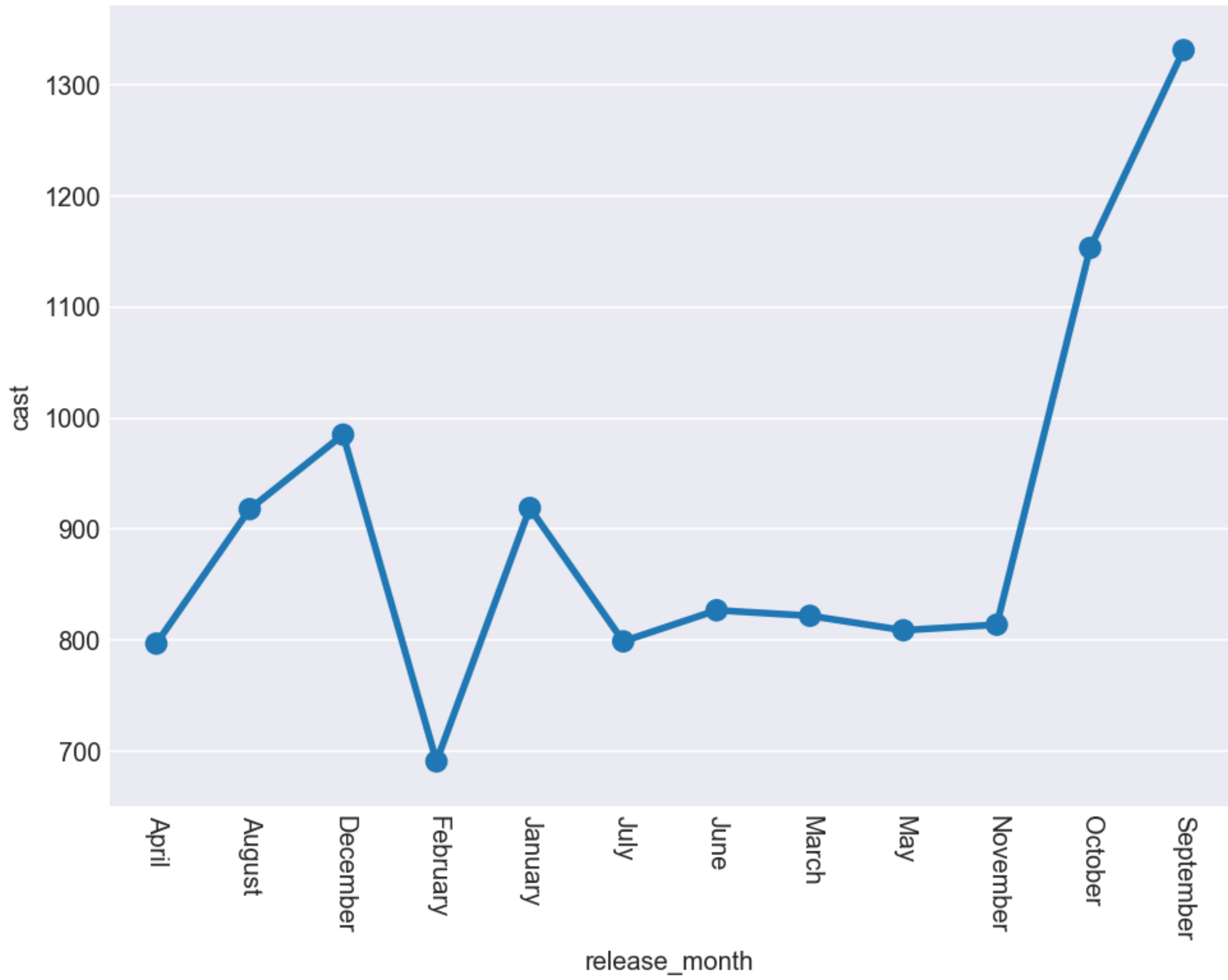
In [57]:

```
print('In 2014, most movies are released in history, and the total number is {}.
'.format(r_day.loc[2014]))
```

```
In 2014, most movies are released in history, and the total number i
s 700.
```

In [58]:

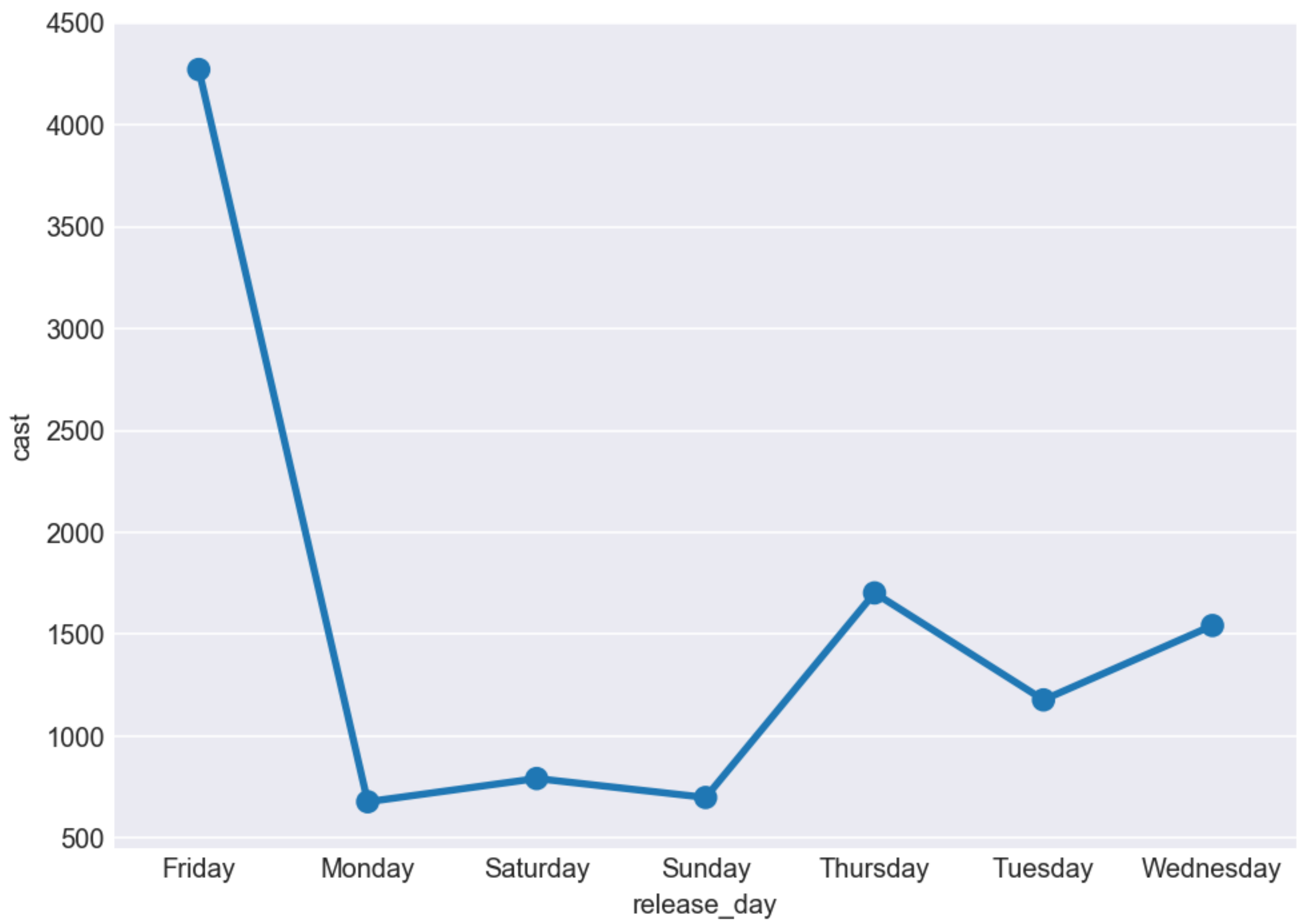
```
# Extract month from datetime column (release_date)

mon_data = df_analysis.release_date.dt.strftime("%B")

# make a copy of data_analysis

df_mon = df_analysis.copy()

# Add a new column of month

df_mon['release_month'] = mon_data

# Use groupby function to obtain the total numbers of movies released in each mo
nth.

count_mon = df_month.groupby(['release_month'], as_index = False)['cast'].count(
)


# Use factor plots which is easy to separate plots by categorical classes

sns.factorplot( x = 'release_month', y= 'cast', data = count_mon, size =5, aspec
t=1.4);


plt.xticks(rotation=-90);
```



According to analysis, in September most movies were released.

In [59]:

```
# Extract week day from datetime column (release_date)

d_data = df_analysis.release_date.dt.strftime("%A")

# make a copy of data_analysis

df_d = df_analysis.copy()

# Add a new column of month

df_d['release_day'] = d_data

# Use groupby function to obtain the total numbers of movies released in each we
ek day.

count_mon = df_d.groupby(['release_day'], as_index = False)['cast'].count()


# Use factor plots which is easy to separate plots by categorical classes

sns.factorplot( x = 'release_day', y= 'cast', data = count_mon, size =5, aspect=
1.4);
```

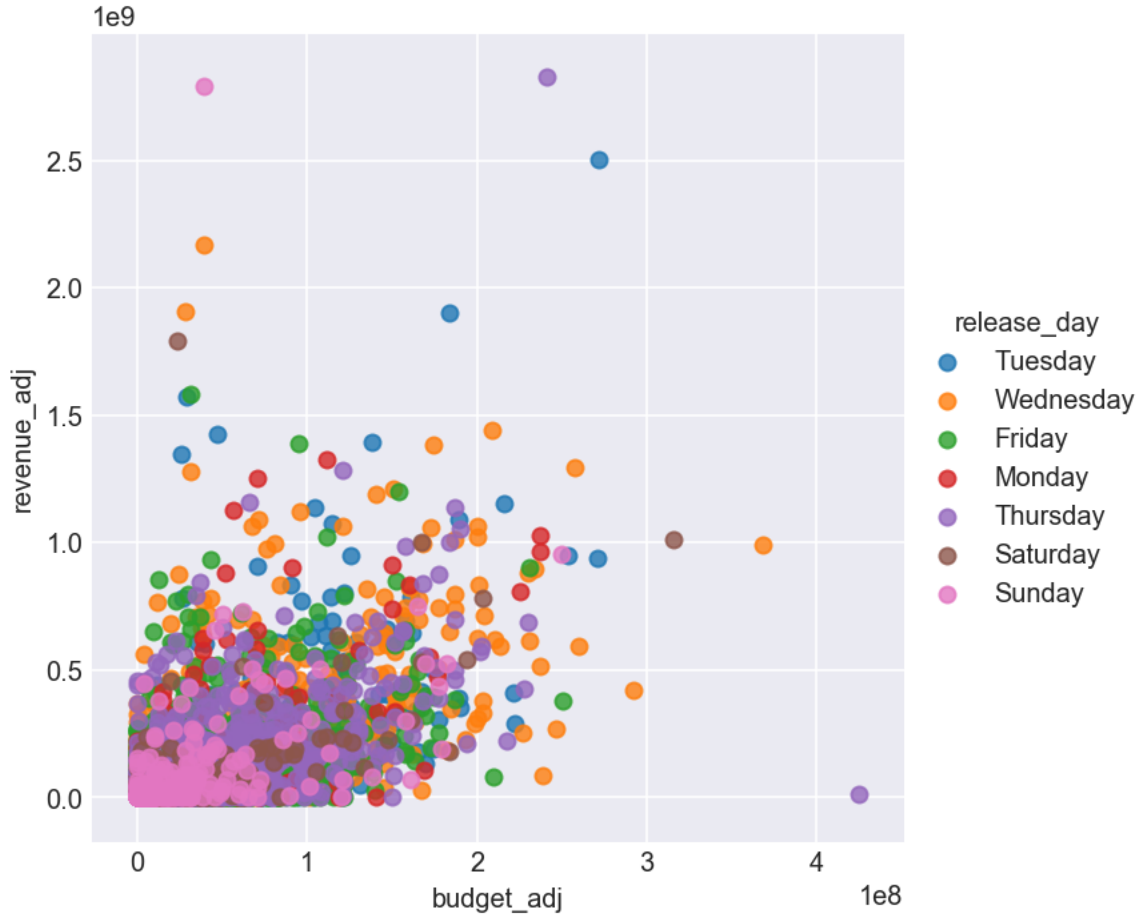


According to analysis, on Friday most movies were released.

Research Question 18: What is the relationsip of budget and revenue?

In [60]:

```
sns.lmplot(x='budget_adj', y='revenue_adj', data=df_d, fit_reg=False, hue='relea
se_day');
```



There is positive correlation between budget and revenue.

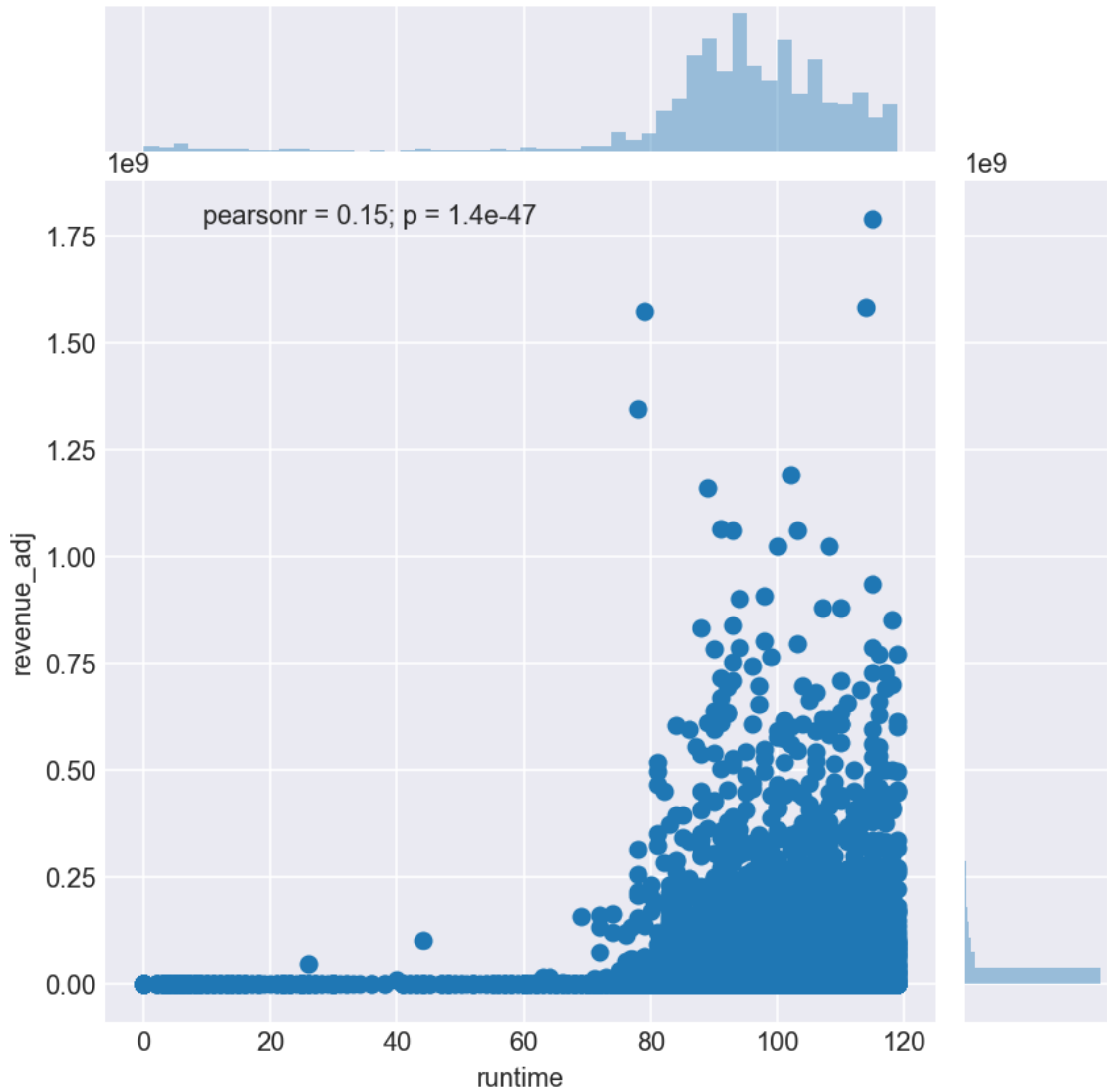
Research Question 19: Does the lenghth of movie affect its revenue? Group the movie by the lengh intervals, eg, below 120 mins, between 120 to 180 mins, above 180min, then compare the mean revenue of each group of movies.

In [61]:

```
time_low = df_mon.query('runtime < 120')
time_mid = df_mon.query('runtime >= 120 & runtime < 180')
time_high = df_mon.query('runtime >= 180')
```

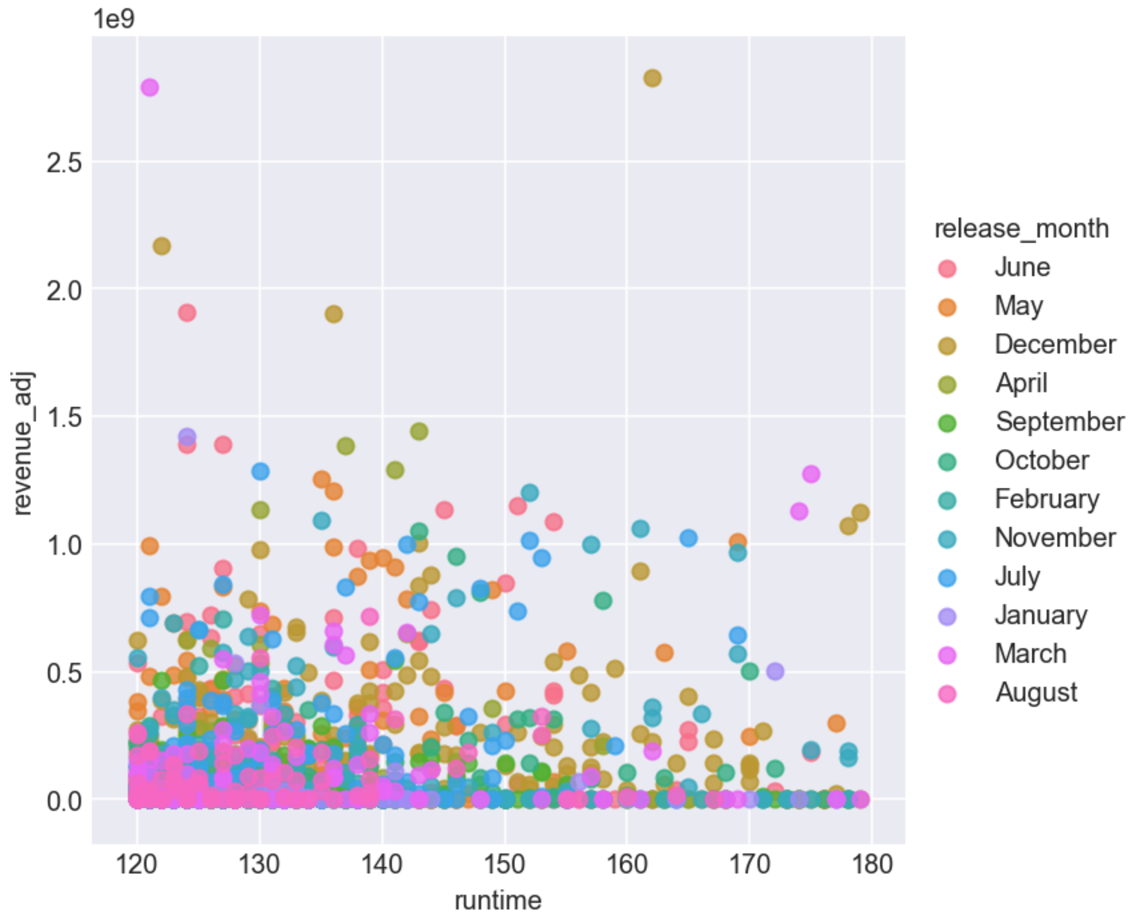
In [62]:

```
sns.jointplot(x='runtime', y='revenue_adj', data=time_low);
```



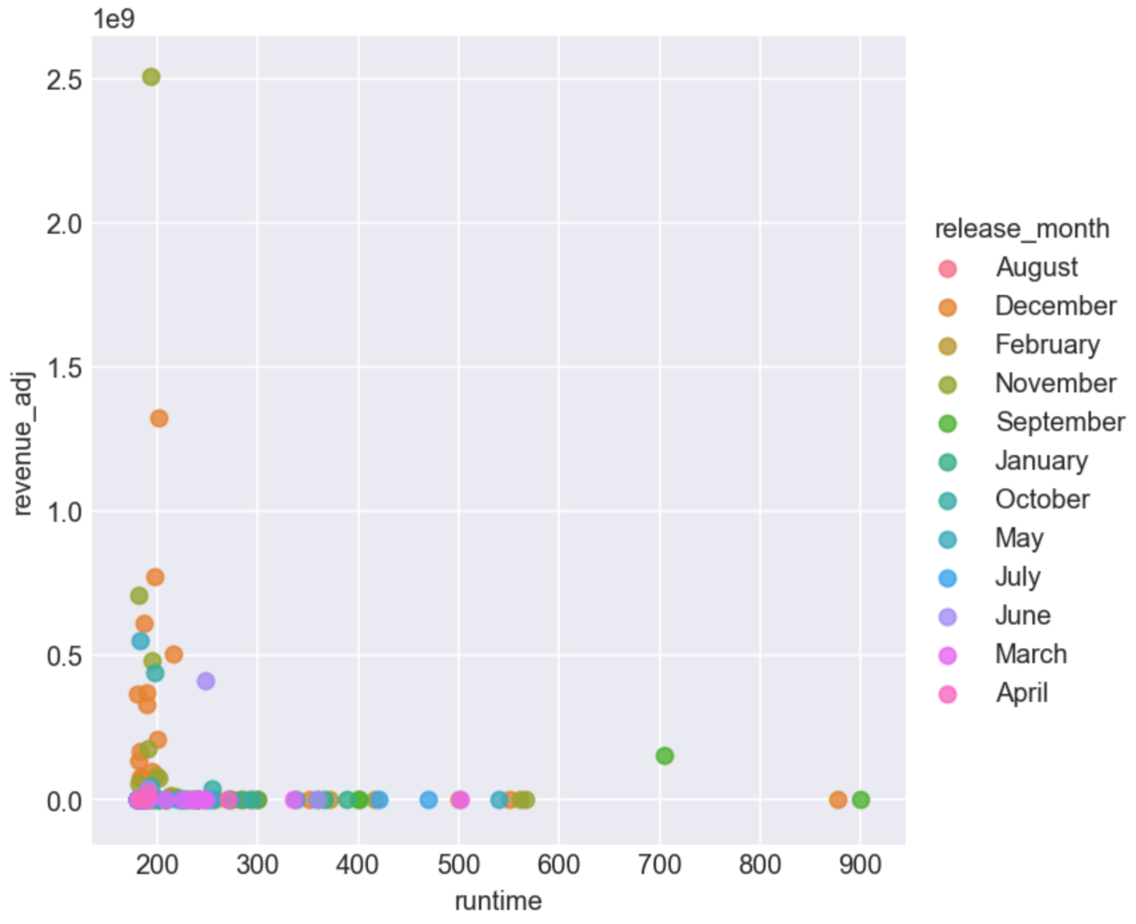
In [81]:

```
sns.lmplot(x='runtime', y='revenue_adj', data=time_mid,
           fit_reg=False,
           hue='release_month');
```



In [67]:

```
sns.lmplot(x='runtime', y='revenue_adj', data=time_high,
           fit_reg=False,
           hue='release_month');
```



There is a strong positive correlation between revenue and runtime below 120 mins as well as in the range of 120 and 180 mins; no apprent correlation was noticed between revenue and runtime above 180 mins.

Research Question 20: Which genres are most popular from year to year?

In [68]:

```python
# Put unique in a list

year_list = df_analysis.release_year.sort_values(ascending=True).unique().tolist
()


# Create an empty dataframe for later analysis

pop_gen = pd.DataFrame(index = year_list, columns = ['genre'])

# Use loop to add row and values in dataframe

for ye in year_list:

    year = df.query('release_year == @ye')['popularity']

    ind_pop = year.idxmax()

    pop_gen.loc[ye] = df.iloc[ind_pop]['genres']


# Print out the result

print(pop_gen)
```

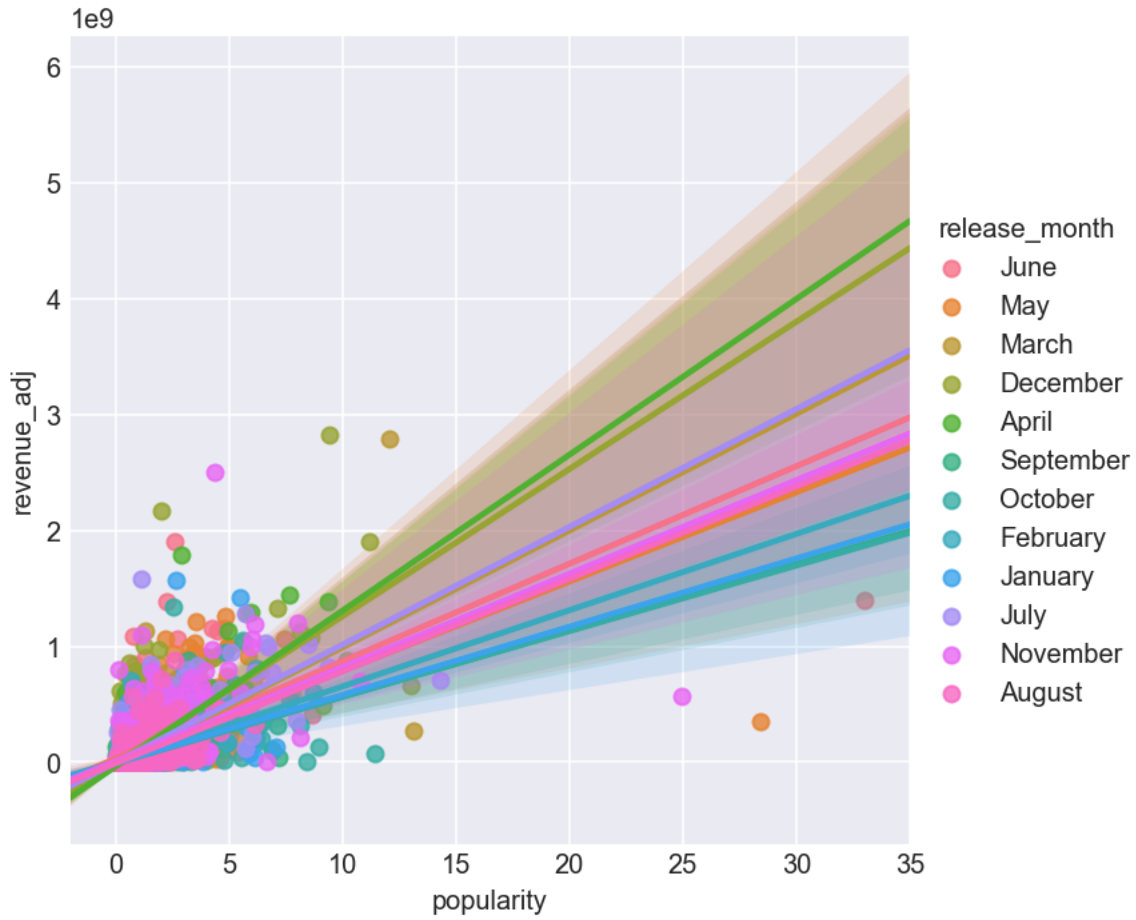
```
                                               genre
1960                           Action|Adventure|Western
1961                              Comedy|Drama|Romance
1962                       Adventure|Drama|History|War
1963                                  Animation|Family
1964                                 Drama|Comedy|War
1965                        Drama|Family|Music|Romance
1966                            Drama|Science Fiction
1967                              Comedy|Drama|Romance
1968                 Adventure|Science Fiction|Mystery
1969                       History|Drama|Western|Crime
1970                 Adventure|Science Fiction|Mystery
1971                                    Family|Fantasy
1972                         Drama|Adventure|Thriller
1973                            Drama|Horror|Thriller
1974                   Crime|Drama|Mystery|Thriller
1975                        Horror|Thriller|Adventure
1976                                             Drama
1977                  Adventure|Action|Science Fiction
1978                                   Horror|Thriller
1979                                         Drama|War
1980                                   Horror|Thriller
1981                                    Romance|Comedy
1982        Science Fiction|Adventure|Family|Fantasy
1983                     Action|Crime|Drama|Thriller
1984                                  Adventure|Action
```

```
1985                                     Comedy|Drama
1986                        Adventure|Action|Fantasy
1987                                        Drama|War
1988          Fantasy|Drama|Comedy|Romance|Family
1989                                Adventure|Action
1990                                      Drama|Crime
1991                 Action|Thriller|Science Fiction
1992       Animation|Family|Comedy|Adventure|Fantasy
1993                       Fantasy|Animation|Family
1994                                      Drama|Crime
1995                         Animation|Comedy|Family
1996                       Adventure|Action|Thriller
1997                         Drama|Romance|Thriller
1998       Action|Thriller|Science Fiction|Adventure
1999                          Action|Science Fiction
2000                                Mystery|Thriller
2001                       Adventure|Fantasy|Family
2002                       Adventure|Fantasy|Family
2003                         Fantasy|Action|Thriller
2004                           Action|Crime|Thriller
2005                              Action|Crime|Drama
2006                       Adventure|Fantasy|Action
2007                Adventure|Fantasy|Family|Mystery
2008                                Animation|Family
2009        Action|Adventure|Fantasy|Science Fiction
2010  Action|Thriller|Science Fiction|Mystery|Adventure
2011              Action|Adventure|Science Fiction
2012                           Fantasy|Action|Horror
2013                Science Fiction|Thriller|Drama
2014                Adventure|Drama|Science Fiction
2015      Action|Adventure|Science Fiction|Thriller
```

Research Question 21: What kinds of properties are associated with movies that have high revenues?

In [69]:

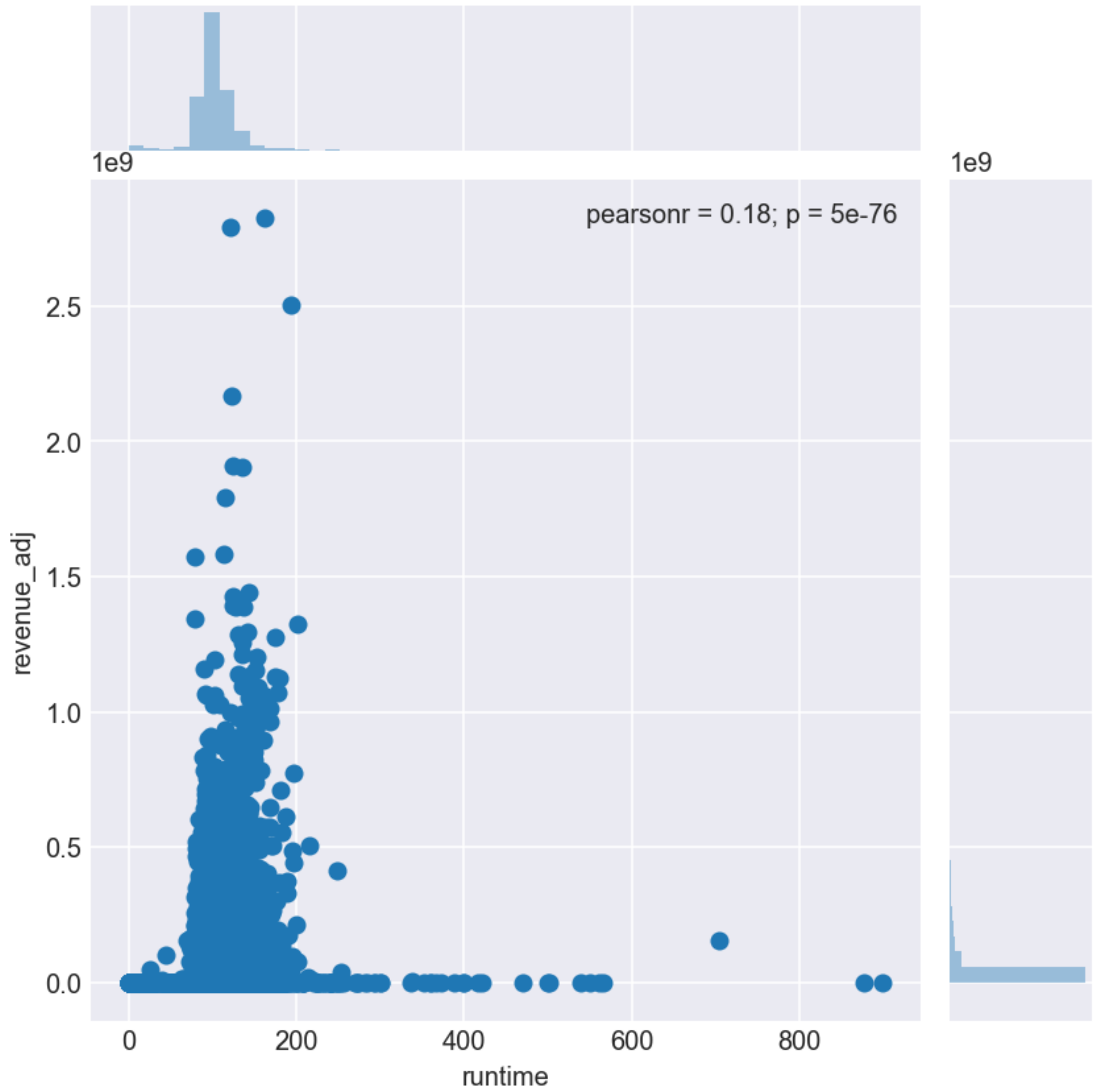
```
# Relationship of popularity and revenue

sns.lmplot(x = 'popularity', y = 'revenue_adj', hue = 'release_month', data = df
_mon);
```



Popularity and reveune are positively correlated, which means high popularity associated with high reveune.

In [70]:

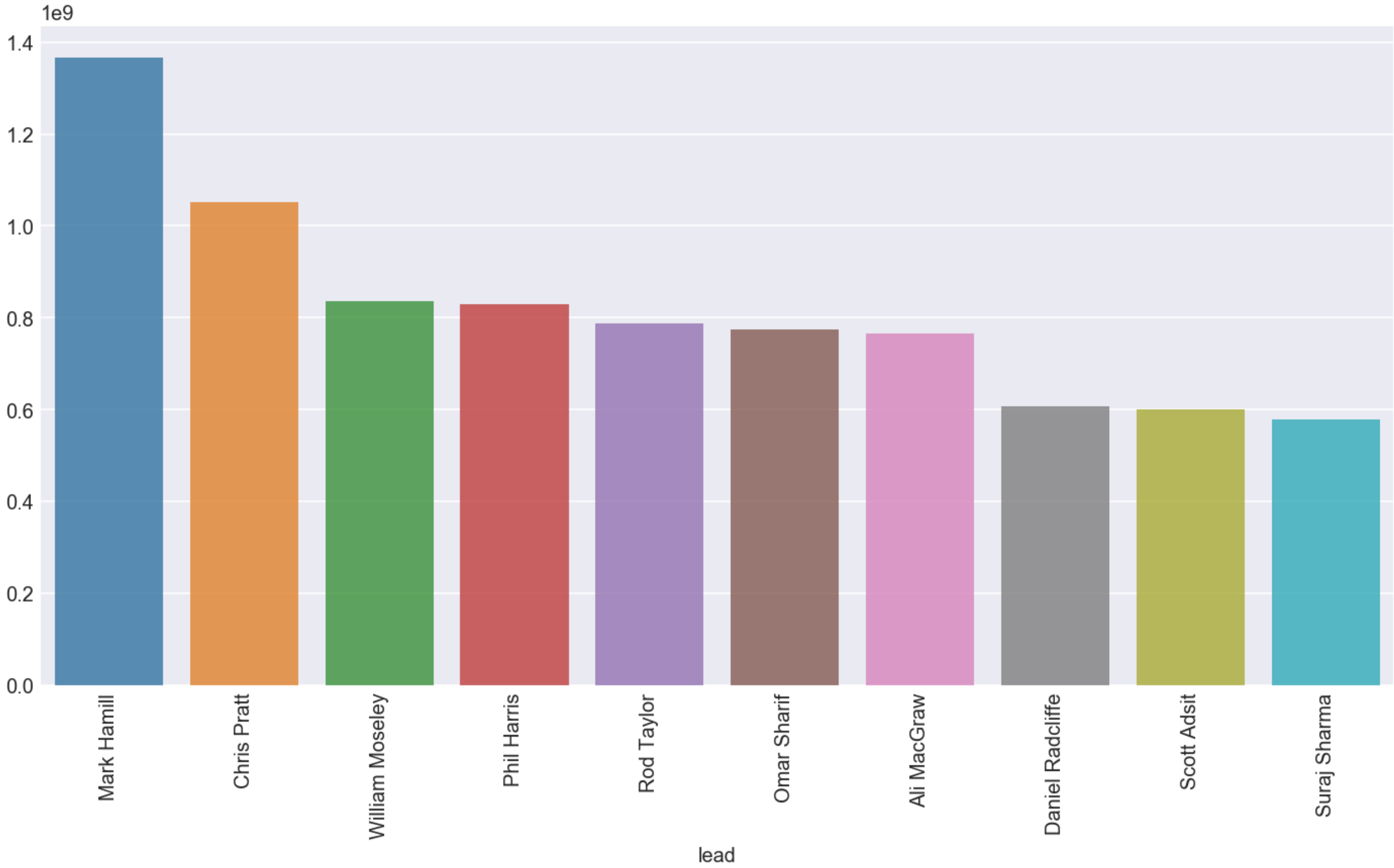
```
# Relationship of runtime and revenue

sns.jointplot(x='runtime', y='revenue_adj', data=df_analysis);
```



As shown above, revenue regariding runtime is right skewed. Runtime between 120 and 180 mins are most profitable, with around 150 mins are highest. Runtime being too short or too long would lead to low revenue.

In [71]:

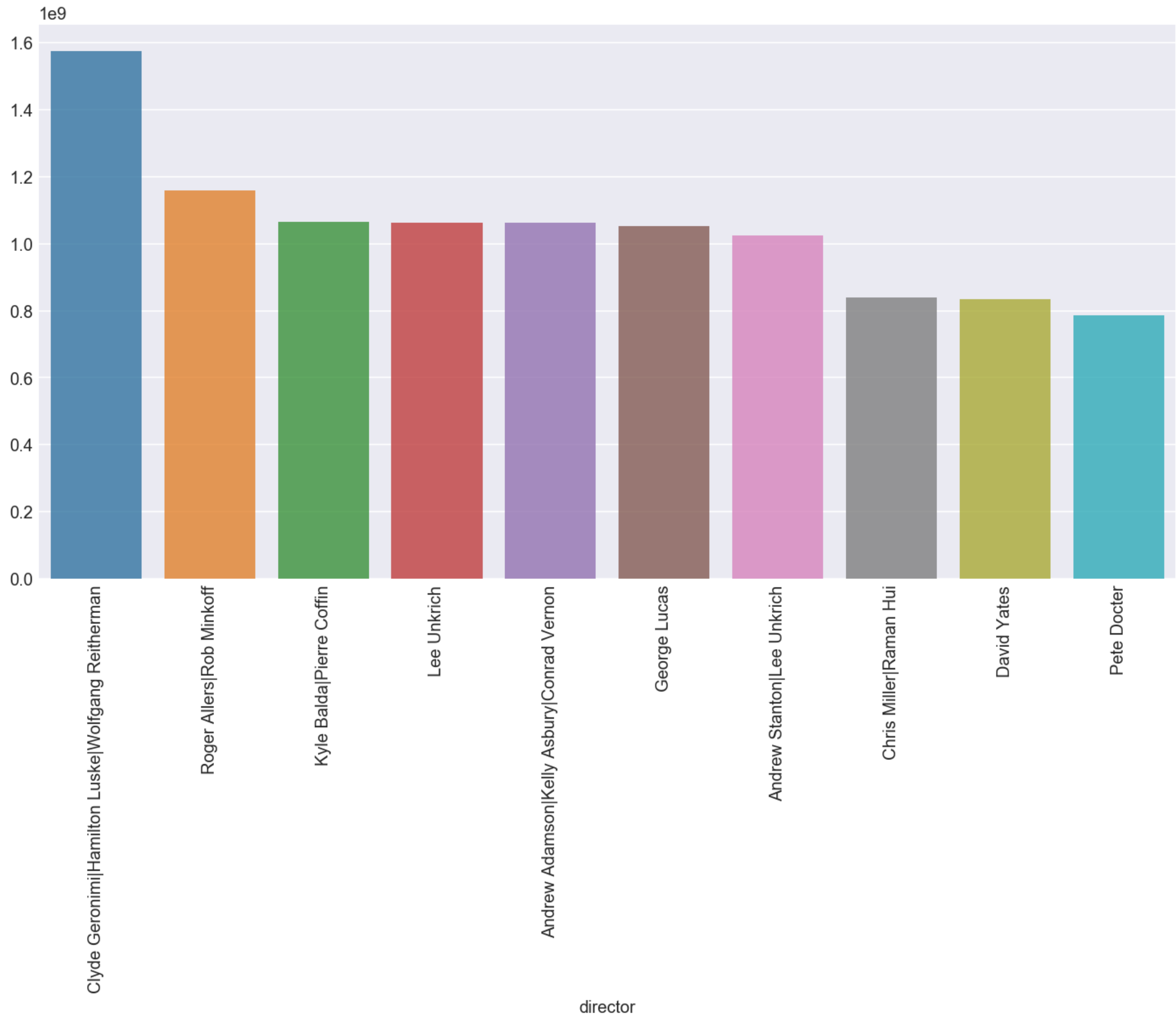
```
# Investigate leading actor's average contirbution on each single movie
# Find out the corresponding average value

lead_rev = df_analysis.groupby(['lead'])['revenue_adj'].sum()/df_analysis.groupb
y(['lead'])['revenue_adj'].count()

# Select the top 10 leading actors to plot

lead_rev = lead_rev.nlargest(n = 10)
plt.subplots(figsize = (12,6))
plt.xticks(rotation=90)
sns.barplot(lead_rev.index,lead_rev.tolist(), alpha = 0.8);
```



The leading actor has great impact on the reveune, eg, the top 10 leading actor contribute from around 0.65 to 1.4 billion per movie averagely.

In [72]:

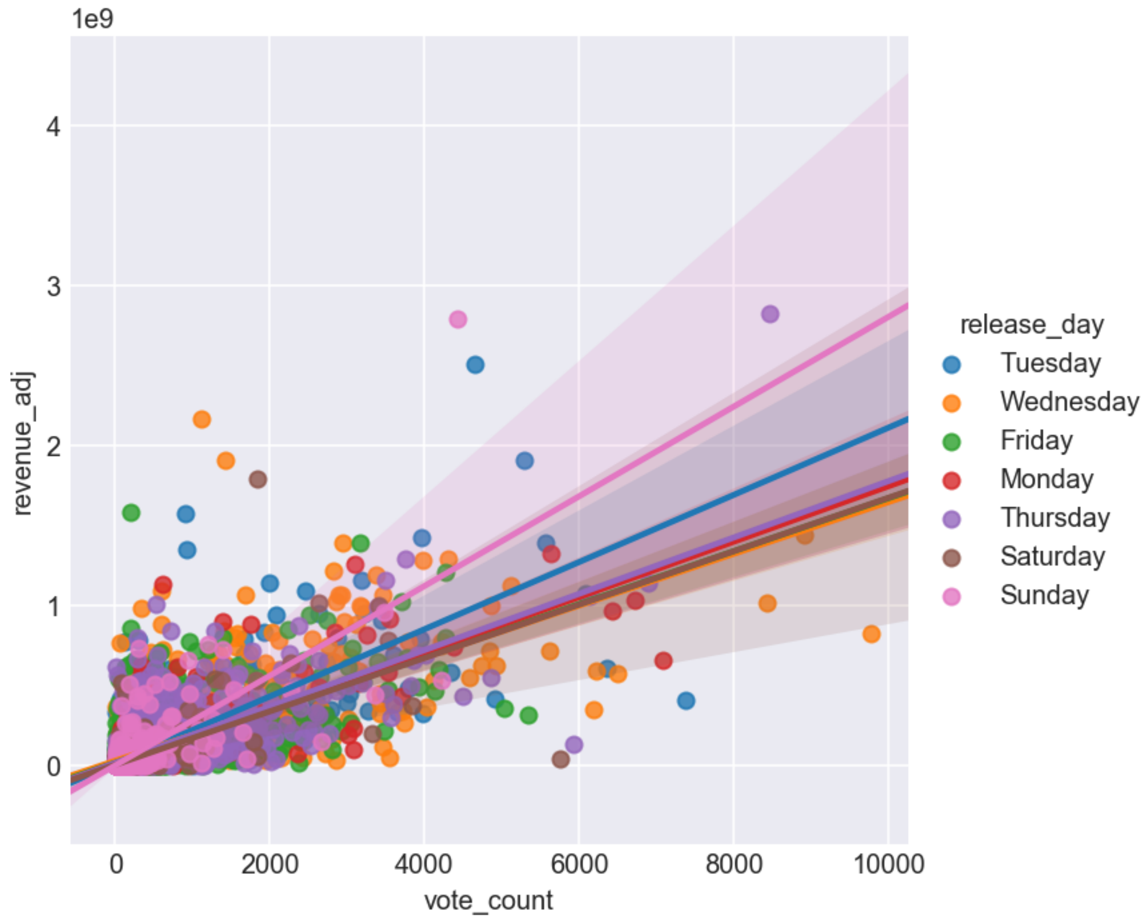
```
# Investigate director's average contirbution on each single movie
# Find out the corresponding average value

dre_rev = df_analysis.groupby(['director'])['revenue_adj'].sum()/df_analysis.gro
upby(['director'])['revenue_adj'].count()

# Select the top 10 director to plot

dre_rev = dre_rev.nlargest(n = 10)
plt.subplots(figsize = (12,6))
plt.xticks(rotation=90)
sns.barplot(dre_rev.index,dre_rev.tolist(), alpha = 0.8);
```



The director has great impact on the reveune, eg, the top 10 leading actor contribute from around 0.8 to 1.6 billion per movie averagely.

In [73]:

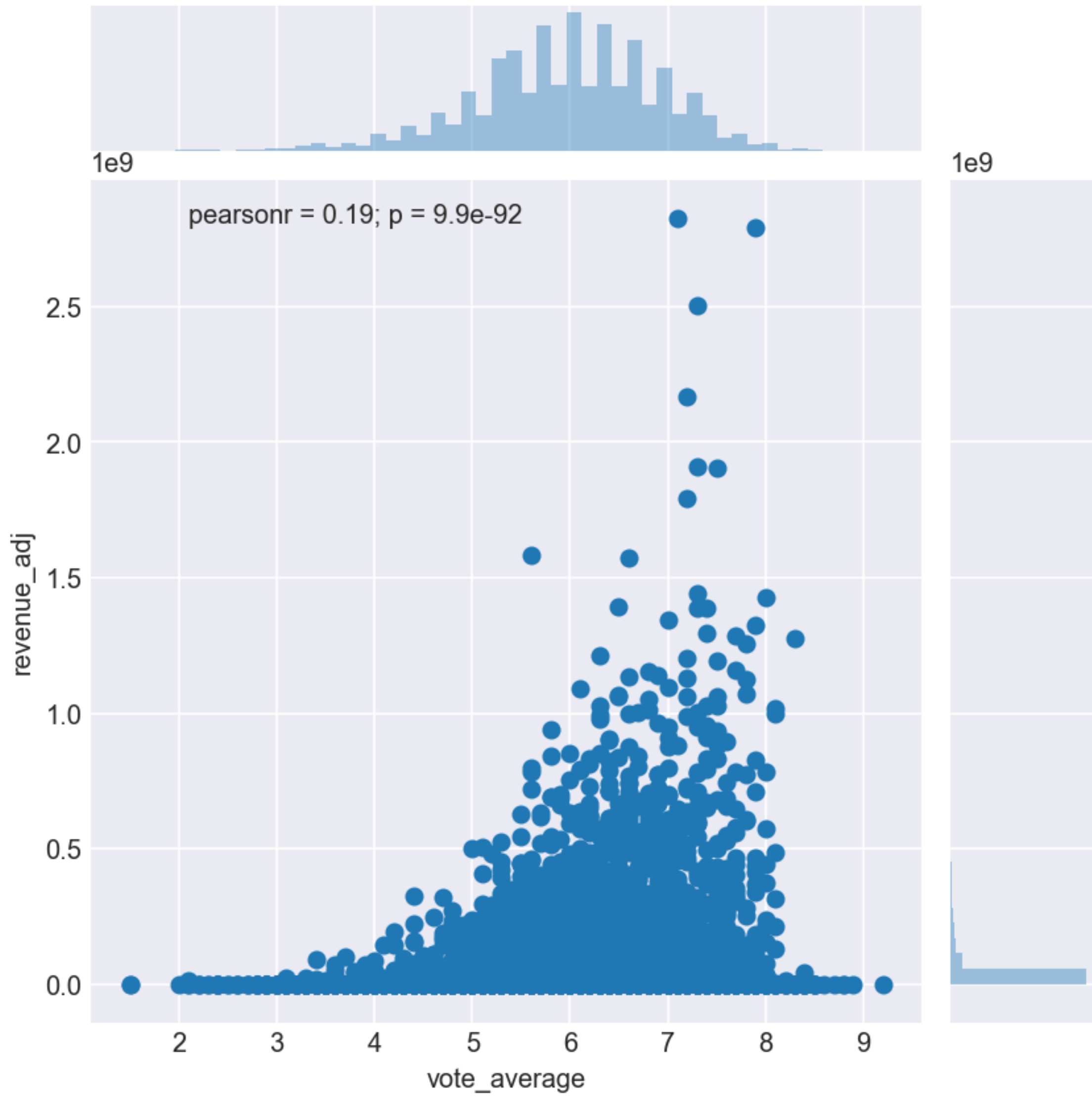
```
# Relationship of vote_count and revenue

sns.lmplot(x='vote_count', y='revenue_adj', hue = 'release_day', data=df_d);
```



Vote_counts and reveune are positively correlated, which means high vote_counts associated with high reveune.

In [74]:

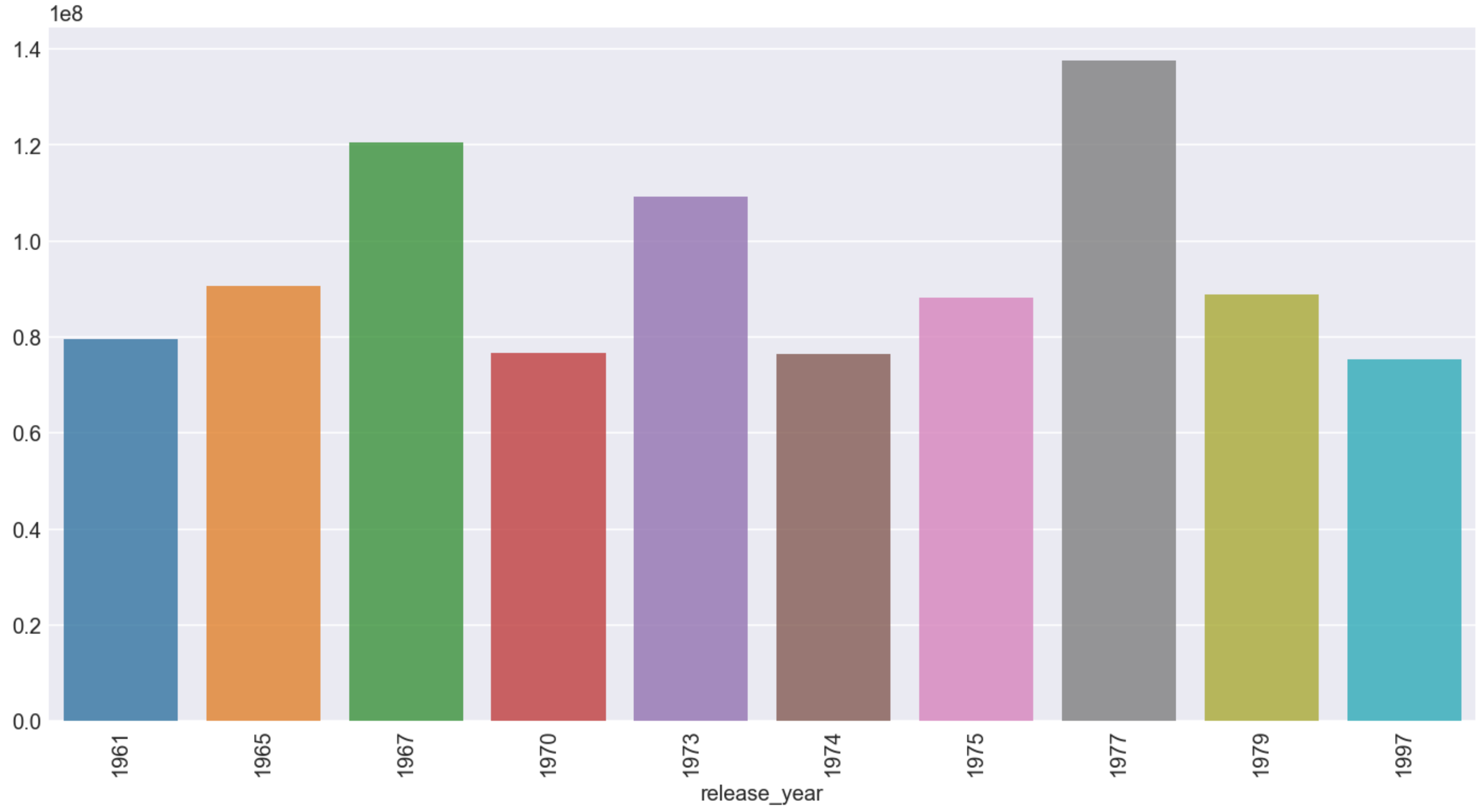
```
# Relationship of vote_average and revenue

sns.jointplot(x='vote_average', y='revenue_adj', data=df_analysis);
```



As shown above, the distribution of revenue regarding to vote_average is left skewed. When vote_average is between 5 and 8 points is most profitable with 7 at the highest. Vote_average being too small or too big would lead to low revenue.

In [75]:

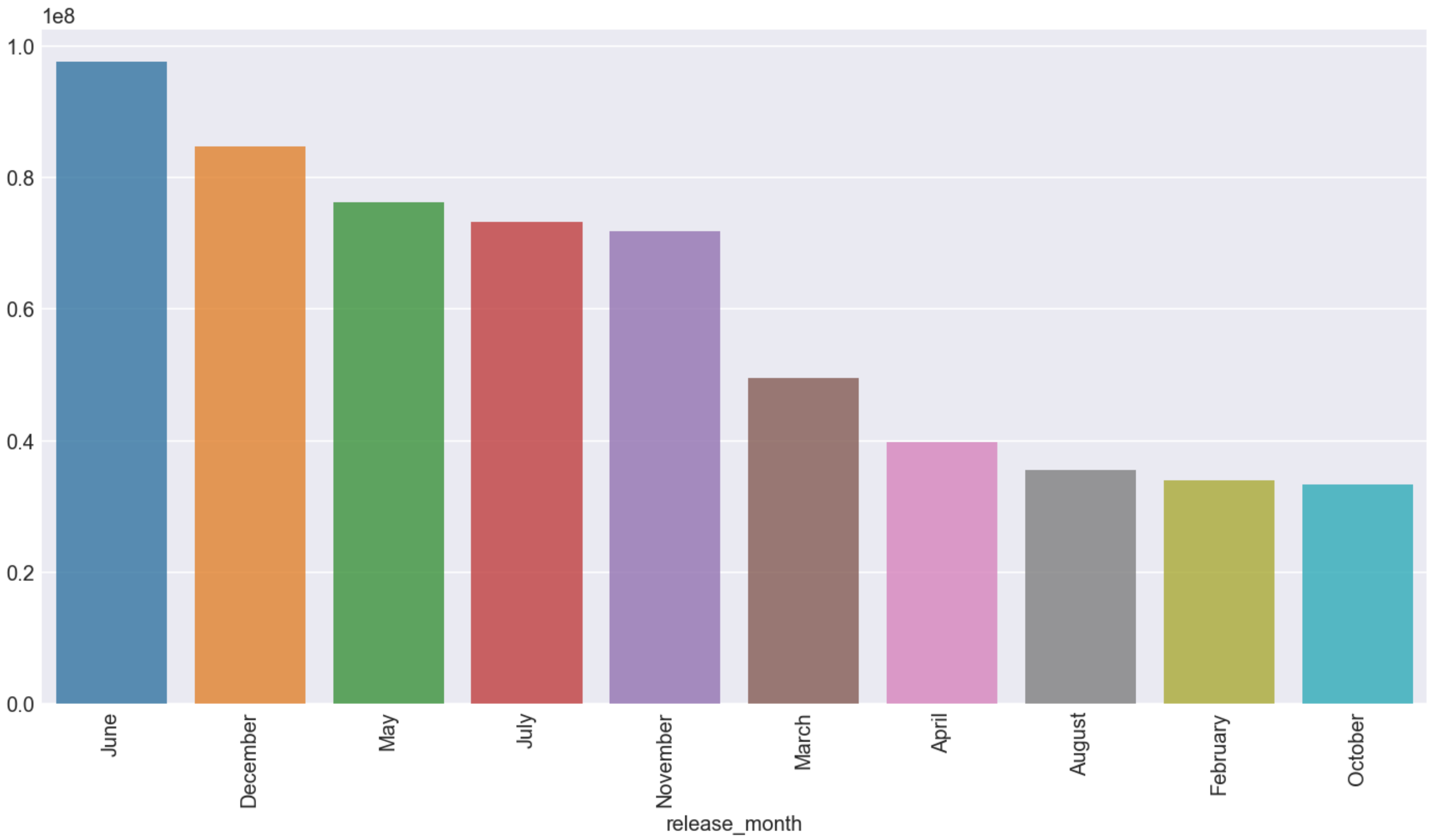
```
# Investigate relationship of release year and revenue
# Find out the corresponding average value

reyr_rev = df_analysis.groupby(['release_year'])['revenue_adj'].sum()/df_analysi
s.groupby(['release_year'])['revenue_adj'].count()

# Select the top 10 director to plot

reyr_rev = reyr_rev.nlargest(n = 10)
plt.subplots(figsize = (12,6))
plt.xticks(rotation=90)
sns.barplot(reyr_rev.index,reyr_rev.tolist(), alpha = 0.8);
```



The release year is important determinant for reveune, as shown above in the top 10 release year, average revenue per movie ranging from around 80 million to 0.14 billion.

In [76]:

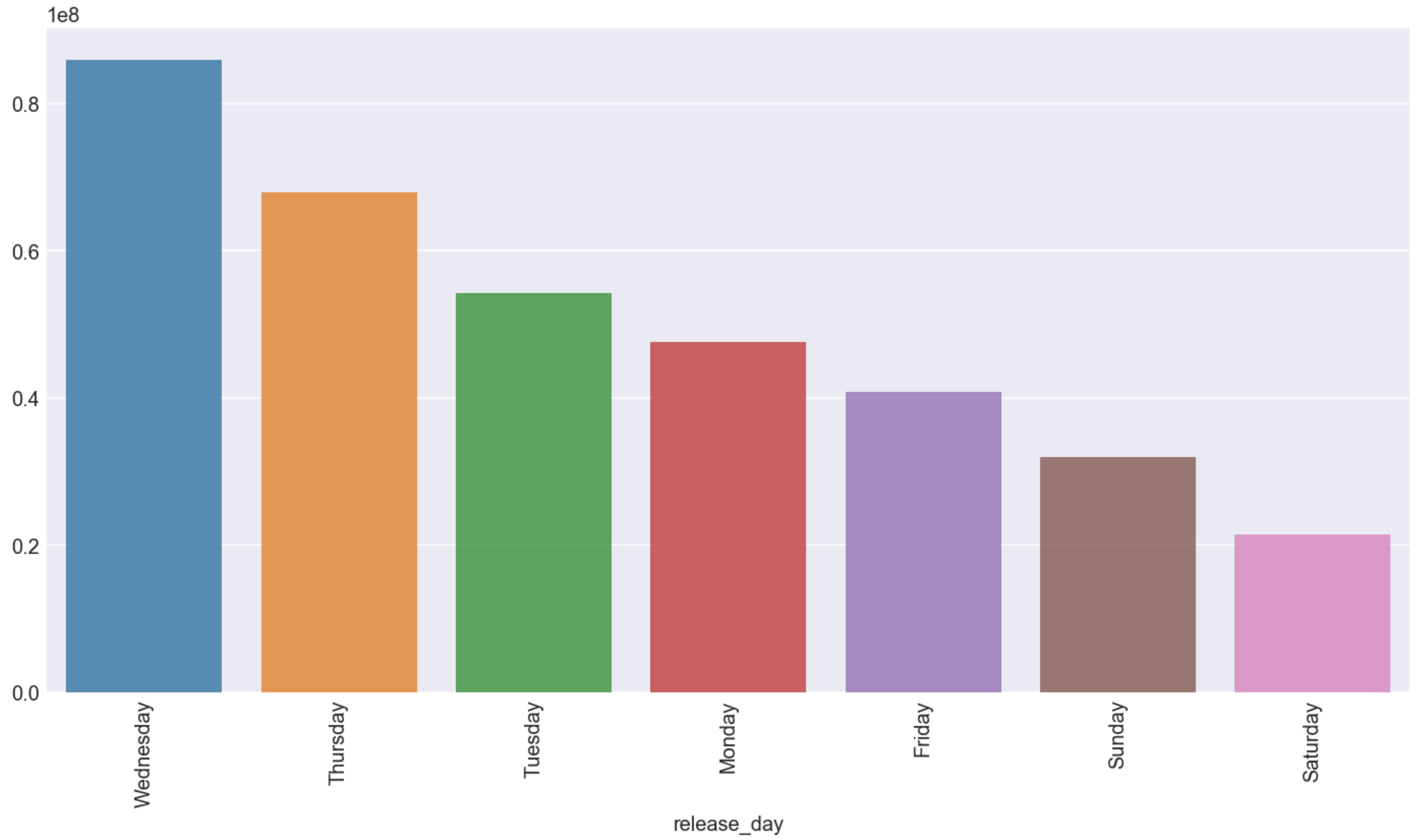
```
# Investigate relationship of release month and revenue
# Find out the corresponding average value

remon_rev = df_mon.groupby(['release_month'])['revenue_adj'].sum()/df_mon.groupb
y(['release_month'])['revenue_adj'].count()

# Select the top 10 director to plot

remon_rev = remon_rev.nlargest(n = 10)
plt.subplots(figsize = (12,6))
plt.xticks(rotation=90)
sns.barplot(remon_rev.index,remon_rev.tolist(), alpha = 0.8);
```



The release month is important determinant for reveune, as shown above in the top 10 release month, average revenue per movie ranging from around 35 million to 0.1 billion.

In [77]:

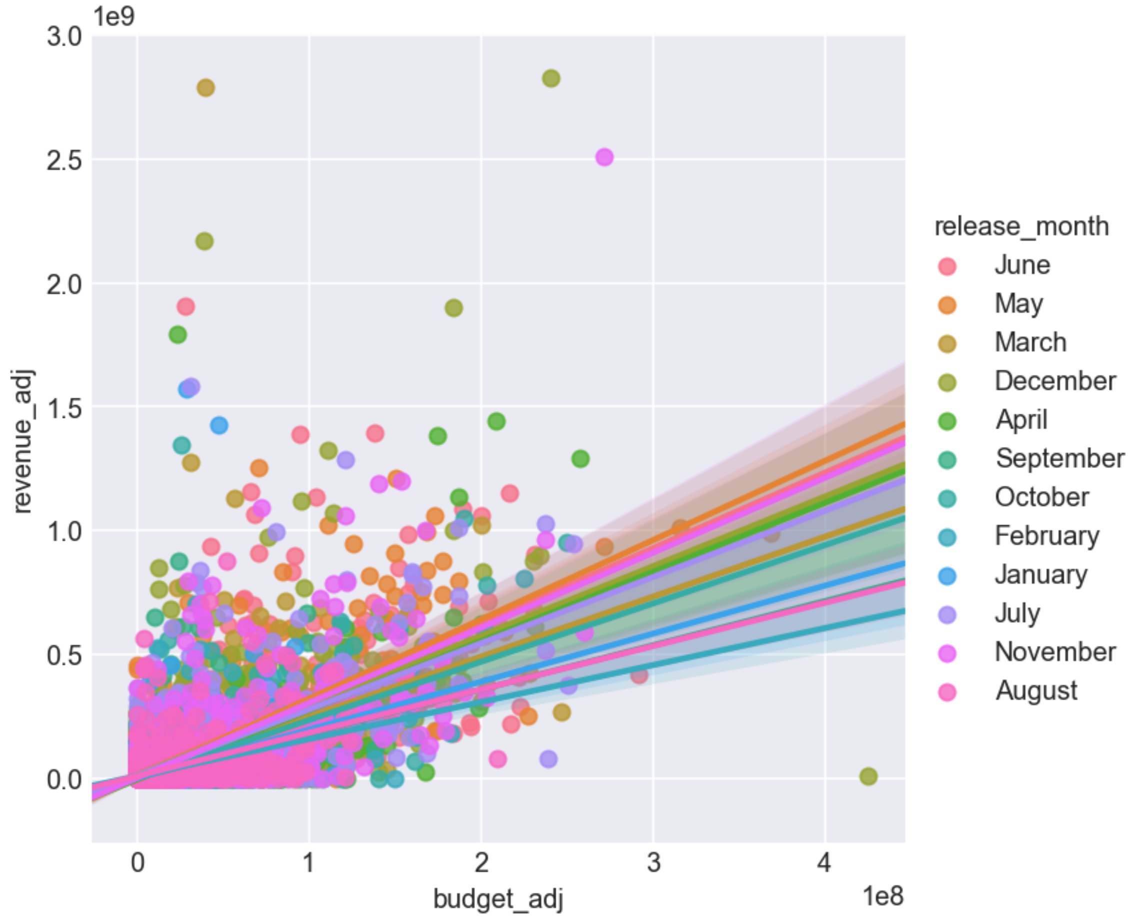
```
# Investigate relationship of release day and revenue
# Find out the corresponding average value

reday_rev = df_d.groupby(['release_day'])['revenue_adj'].sum()/df_d.groupby(['re
lease_day'])['revenue_adj'].count()

# Select the top 10 director to plot

reday_rev = reday_rev.nlargest(n = 10)
plt.subplots(figsize = (12,6))
plt.xticks(rotation=90)
sns.barplot(reday_rev.index,reday_rev.tolist(), alpha = 0.8);
```



The release day is important determinant for reveune, as shown above in the top 10 release day, average revenue per movie ranging from around 20 to 90 million.

In [78]:

```
# Relationship of budget and revenue

sns.lmplot(x='budget_adj', y='revenue_adj', hue = 'release_month', data=df_mon);
```



Budget and reveune are positively correlated, which means high budgets associated with high reveune.

Conclusions

> In current study, a good amount of profound analysis has been carried out. Prior to each step, deailed instructions was given and interpretions was also provided afterwards. The dataset included 10866 pieces of film information ranging from 1960 to 2015, which consisted most of the main stream movies. Based on such substantial data, the analysis would be more reliable as opposed to small scale analysis. The limitations of current study were NaN values, which could affect the process of analysis. Luckily, those NaN values were all of category type, thus it has limited impact on arithmetic computing.
>
> However, it might matter when comparing category column with numerical column for analysis. The stragety appiled in current study is to keep those NaN value, but convert them as 'No record' which is a string type of data. Among the 19 questions, only 2 questions were affected by the NaN value, thus most of the analysis are highly reliable.

In [79]:

```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_TMDb_Movie_Data_20180108.ipynb']
)
```

Out[79]:

```
0
```