Investigate_a_Dataset

December 13, 2018

1 Project: Investigate TMDB movie data

1.1 Table of Contents

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2.1 Introduction

For this Data Analyst project, I selected the TMDb movie dataset from kaggle to investigate. According to kaggle introduction page, the data contains information that are provided from The Movie Database (TMDb). It collects 5000+ movies and their rating and basic move information, including user ratings and revenue data. The potiental problem that can be discussed in the dataset:

2.1.1 The potiental problem that can be discussed in the dataset:

Accroding Kaggle data overview, the dataset provides some metrics that measure how successful these movies are. These metrics include popularity, revenue and vote average. It also contains some basic information corresponding to the movie like cast, director, keywords, runtime, genres, etc. Any of the basic information can be a key to a success movie. More specificly, these factors can be classified to two categrories as follows: Metrics for Evaluating the Success Movie

Metrics for Evaluating the Success Movie

```
popularity
revenue
vote average score
```

Potential Key to Affect the Success of a Movie

```
Budget
Cast
Director
```

```
Tagline
Keywords
Runtime
Genres
Production Companies
Release Date
Vote Average
```

Since the dataset is featured with the rating of movies as mentioned above, it contains plentiful information for exploring the properties that are associated with successful movies, which can be defined by high popularity, high revenue and high rating score movies. Besides, the dataset also contains the movie released year, so it also can let us to explore the trend in these movie metrics. Therefore, the qestions I am going to explore are including three parts:

Research Part 1: General Explore

```
Question 1: Popularity Over Years
Question 2: The distribution of revenue in different popularity levels in recent five years.
Question 3: The distribution of revenue in different score rating levels in recent five years.
```

Research Part 2 : Find the Properties are Associated with Successful Movies

```
Question 1: What kinds of properties are associated with movies that have high popularity?
Question 2: What kinds of properties are associated with movies that have high voting score?
```

Research Part 3 Top Keywords and Genres Trends by Generation

```
Question 1: Number of movie released year by year
Question 2: Keywords Trends by Generation
Question 3: Genres Trends by Generation
```

Data Wrangling

2.1.2 General Dataset Properties

First, let's look what the dataset looks like for preceeding to investigate.

```
In [2]: # Import statements for all of the packages that I plan to use.
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from collections import Counter
        % matplotlib inline
```

Load the data and print out a few lines. Perform operations to inspect data Types and look for instances of missing or possibly errant data.

```
In [3]: df = pd.read_csv("https://d17h27t6h515a5.cloudfront.net/topher/2017/October/59dd1c4c_tmd
        df.head(1)
```

```
Out[3]:        id    imdb_id  popularity     budget     revenue  original_title  \
        0  135397  tt0369610   32.985763  150000000  1513528810  Jurassic World

                                                        cast  \
        0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...

                                 homepage          director            tagline  \
        0  http://www.jurassicworld.com/  Colin Trevorrow  The park is open.

               ...                                                  overview runtime  \
        0      ...       Twenty-two years after the events of Jurassic ...     124

                                            genres  \
        0  Action|Adventure|Science Fiction|Thriller

                                      production_companies release_date vote_count  \
        0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562

           vote_average  release_year    budget_adj   revenue_adj
        0           6.5          2015  1.379999e+08  1.392446e+09

        [1 rows x 21 columns]
```

```
In [4]: #see the column info and null values in the dataset
        df.info()
```

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

```
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

From the table above, there are totally 10866 entries and total 21 columns. And there exists som

Let's see some descriptive statistics for the data set.

In [5]:
```python
df.describe()
```

Out[5]:
```
                  id    popularity        budget       revenue       runtime  \
count   10866.000000  10866.000000  1.086600e+04  1.086600e+04  10866.000000
mean    66064.177434      0.646441  1.462570e+07  3.982332e+07    102.070863
std     92130.136561      1.000185  3.091321e+07  1.170035e+08     31.381405
min         5.000000      0.000065  0.000000e+00  0.000000e+00      0.000000
25%     10596.250000      0.207583  0.000000e+00  0.000000e+00     90.000000
50%     20669.000000      0.383856  0.000000e+00  0.000000e+00     99.000000
75%     75610.000000      0.713817  1.500000e+07  2.400000e+07    111.000000
max    417859.000000     32.985763  4.250000e+08  2.781506e+09    900.000000

         vote_count  vote_average  release_year    budget_adj   revenue_adj
count  10866.000000  10866.000000  10866.000000  1.086600e+04  1.086600e+04
mean     217.389748      5.974922   2001.322658  1.755104e+07  5.136436e+07
std      575.619058      0.935142     12.812941  3.430616e+07  1.446325e+08
min       10.000000      1.500000   1960.000000  0.000000e+00  0.000000e+00
25%       17.000000      5.400000   1995.000000  0.000000e+00  0.000000e+00
50%       38.000000      6.000000   2006.000000  0.000000e+00  0.000000e+00
75%      145.750000      6.600000   2011.000000  2.085325e+07  3.369710e+07
max     9767.000000      9.200000   2015.000000  4.250000e+08  2.827124e+09
```

In [6]:
```python
#Let's take a look at some zero budget and revenue data.

df_budget_zero = df.query('budget == 0')
df_budget_zero.head(3)
```

Out[6]:
```
        id    imdb_id  popularity  budget   revenue    original_title  \
30  280996  tt3168230    3.927333       0  29355203        Mr. Holmes
36  339527  tt1291570    3.358321       0  22354572            Solace
72  284289  tt2911668    2.272044       0     45895  Beyond the Reach

                                                 cast  \
30  Ian McKellen|Milo Parker|Laura Linney|Hattie M...
36  Abbie Cornish|Jeffrey Dean Morgan|Colin Farrel...
72  Michael Douglas|Jeremy Irvine|Hanna Mangan Law...

                      homepage                 director  \
30  http://www.mrholmesfilm.com/           Bill Condon
```

```
36                            NaN           Afonso Poyart
72                            NaN  Jean-Baptiste LÃĩonetti

                                             tagline      ...      \
30                           The man behind the myth      ...
36  A serial killer who can see your future, a psy...      ...
72                                               NaN      ...

                                            overview runtime  \
30  The story is set in 1947, following a long-ret...     103
36  A psychic doctor, John Clancy, works with an F...     101
72  A high-rolling corporate shark and his impover...      95

                genres                               production_companies  \
30       Mystery|Drama  BBC Films|See-Saw Films|FilmNation Entertainme...
36  Crime|Drama|Mystery  Eden Rock Media|FilmNation Entertainment|Flynn...
72            Thriller                                     Furthur Films

  release_date vote_count  vote_average  release_year  budget_adj  \
30      6/19/15        425           6.4          2015         0.0
36       9/3/15        474           6.2          2015         0.0
72      4/17/15         81           5.5          2015         0.0

    revenue_adj
30  2.700677e+07
36  2.056620e+07
72  4.222338e+04

[3 rows x 21 columns]
```

In [7]:
```python
df_revenue_zero = df.query('revenue == 0')
df_revenue_zero.head(3)
```

Out[7]:
```
        id    imdb_id  popularity    budget  revenue          original_title  \
48  265208  tt2231253    2.932340  30000000        0               Wild Card
67  334074  tt3247714    2.331636  20000000        0                Survivor
74  347096  tt3478232    2.165433         0        0  Mythica: The Darkspore

                                                cast  \
48  Jason Statham|Michael Angarano|Milo Ventimigli...
67  Pierce Brosnan|Milla Jovovich|Dylan McDermott|...
74  Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...

                                    homepage        director  \
48                                       NaN      Simon West
67                  http://survivormovie.com/  James McTeigue
74  http://www.mythicamovie.com/#!blank/wufvh   Anne K. Black
```

```
                                      tagline     ...       \
48  Never bet against a man with a killer hand.     ...
67            His Next Target is Now Hunting Him     ...
74                                          NaN     ...

                                          overview runtime  \
48  When a Las Vegas bodyguard with lethal skills ...      92
67  A Foreign Service Officer in London tries to p...      96
74  When Teelaâs sister is murdered and a powerf...     108

                     genres  \
48      Thriller|Crime|Drama
67     Crime|Thriller|Action
74  Action|Adventure|Fantasy

                               production_companies release_date vote_count  \
48  Current Entertainment|Lionsgate|Sierra / Affin...      1/14/15        481
67  Nu Image Films|Winkler Films|Millennium Films|...      5/21/15        280
74                           Arrowstorm Entertainment      6/24/15         27

    vote_average  release_year    budget_adj  revenue_adj
48           5.3          2015  2.759999e+07          0.0
67           5.4          2015  1.839999e+07          0.0
74           5.1          2015  0.000000e+00          0.0

[3 rows x 21 columns]
```

In [8]:
```
df_budget_0count =  df.groupby('budget').count()['id']
df_budget_0count.head(2)
```

Out[8]:
```
budget
0    5696
1       4
Name: id, dtype: int64
```

In [9]:
```
df_revenue_0count =  df.groupby('revenue').count()['id']
df_revenue_0count.head(2)
```

Out[9]:
```
revenue
0    6016
2       2
Name: id, dtype: int64
```

In [10]:
```
df_runtime_0count =  df.groupby('runtime').count()['id']
df_runtime_0count.head(2)
```

Out[10]:
```
runtime
0    31
2     5
Name: id, dtype: int64
```

Cleaning Decision Summary

1. Drop unnecessary columns for answering those questions : homepage, tagline, imdb_id, overview,budget_adj, revenue_adj.
2. Drop duplicates.
3. Drop null values columns that with small quantity of nulls : cast, director, and genres.
4. Replace zero values with null values in the budget and revenue column.
5. Drop zero values columns that with small quantity of zeros : runtime.

2.1.3 Data Cleaning

First, according to the previous decision, let's drop unncessary columns : imdb_id, homepage, tagline, overview.

After discussing the structure of the data and any problems that need to be cleaned, perform those cleaning steps in the second part of this section. Drop extraneous columns

```
In [11]: col = ['imdb_id', 'homepage', 'tagline', 'overview', 'budget_adj', 'revenue_adj']
         df.drop(col, axis=1, inplace=True)

In [17]: # see if these columns are dropped.
         df.head(1)

Out[17]:        id  popularity     budget     revenue original_title  \
         0  135397   32.985763  150000000  1513528810 Jurassic World

                                                          cast          director  \
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow

                                                 keywords  runtime  \
         0  monster|dna|tyrannosaurus rex|velociraptor|island      124

                                        genres  \
         0  Action|Adventure|Science Fiction|Thriller

                                       production_companies release_date  vote_count  \
         0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15        5562

            vote_average  release_year
         0           6.5          2015

In [12]: df.drop_duplicates(inplace=True)

In [20]: cal2 = ['cast', 'director', 'genres']
         df.dropna(subset = cal2, how='any', inplace=True)

In [13]: df.isnull().sum()

Out[13]: id                          0
         popularity                  0
```

```
budget                    0
revenue                   0
original_title            0
cast                     76
director                 44
keywords               1493
runtime                   0
genres                   23
production_companies   1030
release_date              0
vote_count                0
vote_average              0
release_year              0
dtype: int64
```

In [14]:
```python
#Then, replace zero values with null values in the budget and revenue column.
df['budget'] = df['budget'].replace(0, np.NaN)
df['revenue'] = df['revenue'].replace(0, np.NaN)
# see if nulls are added in budget and revenue columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 15 columns):
id                      10865 non-null int64
popularity              10865 non-null float64
budget                  5169 non-null float64
revenue                 4849 non-null float64
original_title          10865 non-null object
cast                    10789 non-null object
director                10821 non-null object
keywords                9372 non-null object
runtime                 10865 non-null int64
genres                  10842 non-null object
production_companies    9835 non-null object
release_date            10865 non-null object
vote_count              10865 non-null int64
vote_average            10865 non-null float64
release_year            10865 non-null int64
dtypes: float64(4), int64(4), object(7)
memory usage: 1.3+ MB
```

In [15]:
```python
#Finally, drop columns with small quantity of zero values : runtime.
df.query('runtime != 0', inplace=True)
df.query('runtime == 0')
```

Out[15]:
```
Empty DataFrame
Columns: [id, popularity, budget, revenue, original_title, cast, director, keywords, ru
Index: []
```

Cleaning Result Summary:

From the table bellow, we can see that the data in each column are almost clear without too many

In [16]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10834 entries, 0 to 10865
Data columns (total 15 columns):
id                      10834 non-null int64
popularity              10834 non-null float64
budget                  5166 non-null float64
revenue                 4849 non-null float64
original_title          10834 non-null object
cast                    10758 non-null object
director                10792 non-null object
keywords                9357 non-null object
runtime                 10834 non-null int64
genres                  10812 non-null object
production_companies    9822 non-null object
release_date            10834 non-null object
vote_count              10834 non-null int64
vote_average            10834 non-null float64
release_year            10834 non-null int64
dtypes: float64(4), int64(4), object(7)
memory usage: 1.3+ MB
```

In [17]:
```
#And from the table bellow, after transfer all zero values to null values in `budget` a
df.describe()
```

Out[17]:

	id	popularity	budget	revenue	runtime
count	10834.000000	10834.000000	5.166000e+03	4.849000e+03	10834.000000
mean	65750.128854	0.647762	3.075525e+07	8.923886e+07	102.363855
std	91819.986178	1.001204	3.891025e+07	1.620801e+08	30.948225
min	5.000000	0.000065	1.000000e+00	2.000000e+00	2.000000
25%	10586.250000	0.208536	6.000000e+06	7.732325e+06	90.000000
50%	20551.000000	0.384690	1.700000e+07	3.185308e+07	99.000000
75%	75055.000000	0.715448	4.000000e+07	9.996575e+07	112.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year
count	10834.000000	10834.000000	10834.000000
mean	217.962064	5.976343	2001.295274
std	576.370933	0.935047	12.819708
min	10.000000	1.500000	1960.000000
25%	17.000000	5.400000	1995.000000
50%	38.000000	6.000000	2006.000000
75%	146.000000	6.600000	2011.000000
max	9767.000000	9.200000	2015.000000

3

3.1 Exploratory Data Analysis

3.2 Research Part 1: General Explore

```
Question 1: Popularity Over Years.
Question 2: The distribution of popularity in different revenue levels in recent five years.
Question 3: The distribution of score rating in different revenue levels in recent five years.
```

3.3 Research Part 2 : Find the Properties are Associated with Successful Movies

```
Question 1: What kinds of properties are associated with movies that have high popularity?
Question 2: What kinds of properties are associated with movies that have high voting score?
```

3.4 Research Part 3 Top Keywords and Genres Trends by Generation

```
Question 1: Number of movie released year by year.
Question 2: Keywords Trends by Generation.
Question 3: Genres Trends by Generation.
```

4 Research Question 1 (General Explore)

4.1 Question 1: Popularity Over Years

To explore this question, let's take a look of the dataset

```
In [18]: df.head(2)
```

```
Out[18]:        id  popularity       budget       revenue      original_title  \
         0  135397   32.985763  150000000.0  1.513529e+09      Jurassic World
         1   76341   28.419936  150000000.0  3.784364e+08  Mad Max: Fury Road

                                                         cast          director  \
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
         1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...    George Miller

                                                     keywords  runtime  \
         0  monster|dna|tyrannosaurus rex|velociraptor|island      124
         1   future|chase|post-apocalyptic|dystopia|australia      120

                                              genres  \
         0  Action|Adventure|Science Fiction|Thriller
         1  Action|Adventure|Science Fiction|Thriller

                                         production_companies release_date  vote_count  \
         0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15        5562
         1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15        6185
```

```
   vote_average  release_year
0           6.5          2015
1           7.1          2015
```

In [19]:
```python
# computing the mean for popularity
p_mean = df.groupby('release_year').mean()['popularity']
p_mean.tail()
```

Out[19]:
```
release_year
2011    0.678237
2012    0.608985
2013    0.631143
2014    0.890786
2015    1.037783
Name: popularity, dtype: float64
```

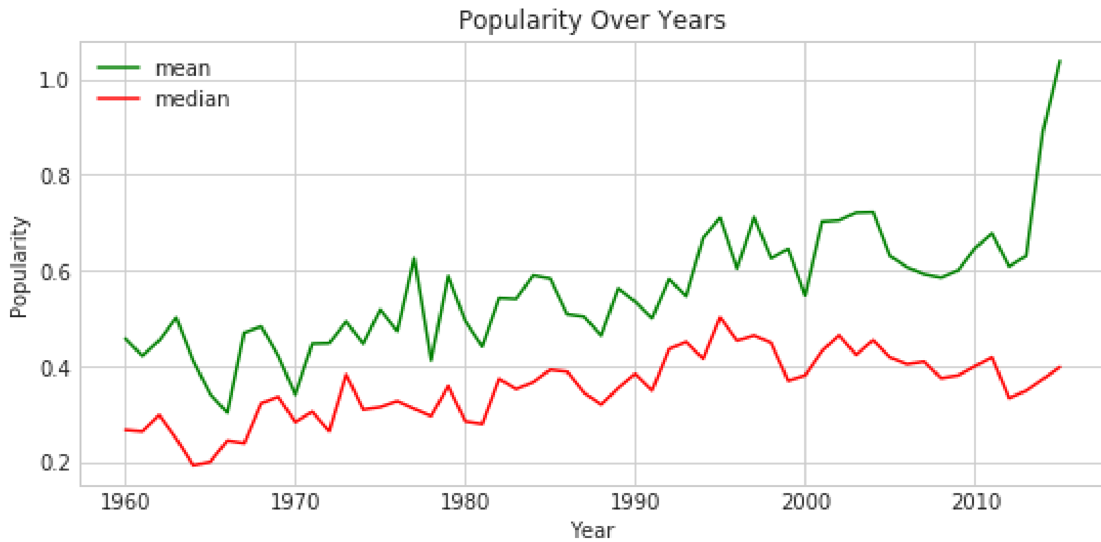
In [20]:
```python
# computing the median for popularity
p_median = df.groupby('release_year').median()['popularity']
p_median.tail()
```

Out[20]:
```
release_year
2011    0.420010
2012    0.334450
2013    0.349973
2014    0.374265
2015    0.399465
Name: popularity, dtype: float64
```

In [21]:
```python
# building the index location for x-axis
index_mean = p_mean.index
index_median = p_median.index
```

In [22]:
```python
#set style
sns.set_style('whitegrid')
#set x, y axis data
#x1, y1 for mean data; x2, y2 for median data
x1, y1 = index_mean, p_mean
x2, y2 = index_median, p_median
#set size
plt.figure(figsize=(9, 4))
#plot line chart for mean and median
plt.plot(x1, y1, color = 'g', label = 'mean')
plt.plot(x2, y2, color = 'r', label = 'median')
#set title and labels
plt.title('Popularity Over Years')
plt.xlabel('Year')
plt.ylabel('Popularity');
#set legend
plt.legend(loc='upper left')
```

Out[22]: <matplotlib.legend.Legend at 0x7f9c796b1978>



From the figure above, we can see that the trend of popularity mean is upward year to year, and the peak is in the 2015, while the trend of popularity median is slightly smoother in recent years. We still can conclude that on average, popularity over years is going up in recent years. The trend is reasonable due to the eaiser access of movie information nowadays. Moreover, in the Internet age, people can easily search and gether movie information, even watch the content through different sources. Maybe it is such the backgroud that boost the movie popularity metrics.

4.2 Question 2: The distribution of popularity in different revenue levels in recent five years.

The movies popularity is growing up in recently years, but how about the popularity in different revenue levels? will popularity be more higher in high revenue level? In this research I don't dicuss the revenue trend since it is affected by many factors like inflation. Although the database contains the adjusted data but I just want the analysis be more simple. Moreever, if I find out the movie revenue trend is growing up, it still can't infer that the trend up is related to popularity just by looking the revenue trend line chart year by yaer.

Hence, it leads me that what to find out the distribution of popularity look like in terms of different revenue levels. Which means I can see the what popularity with which revenue levels. Dou to the revenue data contains wide range, to be more specific, I divided the revenue data into five levels: Low', 'Medium', 'Moderately High', 'High' according to their quartile. Also I choose the recent five years data to dicuss in order to focus on the current data feature.

For the further usage of the level-diveded procedure with quartile, I build a cut_into_quantile function to divided data into four levels according to their quartile: 'Low', 'Medium', 'Moderately High', 'High'.

The cut_into_quantile function- general use.

```
In [24]: # quartile function
         def cut_into_quantile(dfname ,column_name):
         # find quartile, max and min values
             min_value = dfname[column_name].min()
             first_quantile = dfname[column_name].describe()[4]
             second_quantile = dfname[column_name].describe()[5]
             third_quantile = dfname[column_name].describe()[6]
             max_value = dfname[column_name].max()
         # Bin edges that will be used to "cut" the data into groups
             bin_edges = [ min_value, first_quantile, second_quantile, third_quantile, max_value
         # Labels for the four budget level groups
             bin_names = [ 'Low', 'Medium', 'Moderately High', 'High']
         # Creates budget_levels column
             name = '{}_levels'.format(column_name)
             dfname[name] = pd.cut(dfname[column_name], bin_edges, labels=bin_names, include_low
             return dfname
```

Since I want to explore the data by year to year in the question, so to avoide the different level affecting among each year's revenue, I divide revenue levels by with each year's revenue quartile.

```
In [25]: #choose the recent five years
         dfyear =[2011,2012,2013,2014,2015]
         #creat a empty dataframe,df_q2
         df_q2 = pd.DataFrame()

         #for each year, do the following procedure
         for year in dfyear:
             dfn = df.query('release_year == "%s"' % year) # first filter dataframe with the sel
             dfn2 = cut_into_quantile(dfn,'revenue') #apply the cut_into_quantile with the selec
             df_q2 = df_q2.append(dfn2) #append dfn2 to df_q2
         df_q2.info()
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:15: 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/pandas-docs/stable/indexing.html#
  from ipykernel import kernelapp as app


<class 'pandas.core.frame.DataFrame'>
Int64Index: 3096 entries, 3371 to 628
Data columns (total 16 columns):
id                      3096 non-null int64
popularity              3096 non-null float64
budget                  1231 non-null float64
```

```
revenue                 1145 non-null float64
original_title          3096 non-null object
cast                    3057 non-null object
director                3080 non-null object
keywords                2417 non-null object
runtime                 3096 non-null int64
genres                  3086 non-null object
production_companies    2732 non-null object
release_date            3096 non-null object
vote_count              3096 non-null int64
vote_average            3096 non-null float64
release_year            3096 non-null int64
revenue_levels          1145 non-null category
dtypes: category(1), float64(4), int64(4), object(7)
memory usage: 390.2+ KB
```

Now we can see we create a revenue_levels column with the same rows with revenue. Then use the dataset to explore the popularity in each level each year.

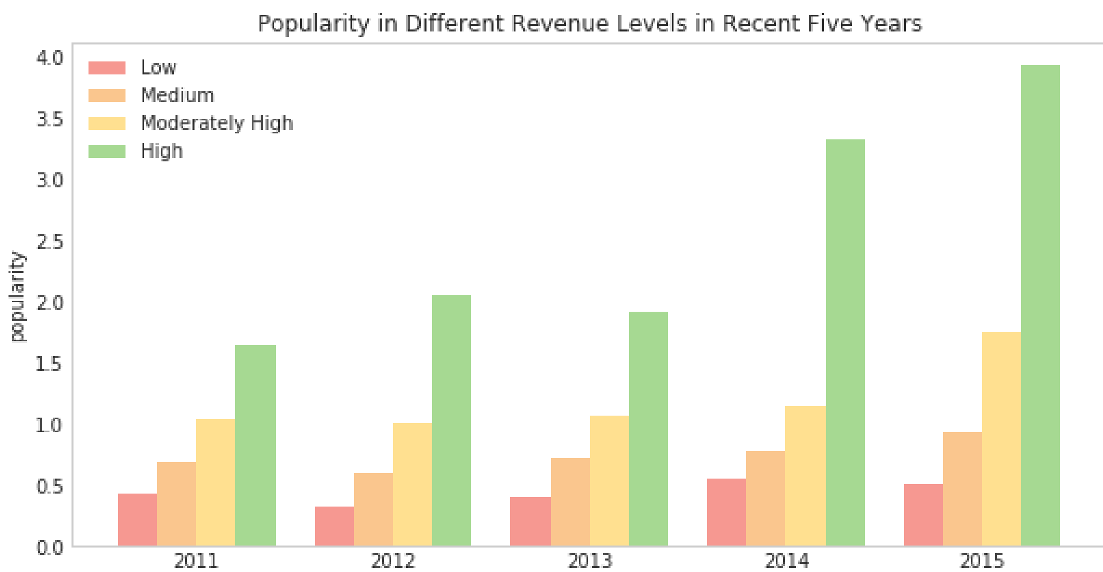
In [26]:
```
# grouping the dataframe I created above with each revenue levels in each year, finding
dfq2_summary = df_q2.groupby(['release_year','revenue_levels']).median()
dfq2_summary.tail(8)
```

Out[26]:
```
                                   id  popularity      budget      revenue  \
release_year revenue_levels
2014         Low             244761.0    0.557453   6000000.0     149337.0
             Medium          234200.0    0.778247   6000000.0    6676471.0
             Moderately High 227159.0    1.142614  21000000.0   53181600.0
             High            157350.0    3.327799  68000000.0  268031828.0
2015         Low             301284.0    0.506000   7500000.0     228615.0
             Medium          272606.5    0.921828  13000000.0   11893552.5
             Moderately High 273980.0    1.750452  19000000.0   61365324.5
             High            253770.0    3.923328  81000000.0  244935102.0

                             runtime  vote_count  vote_average
release_year revenue_levels
2014         Low                95.0       124.0          6.00
             Medium            102.0       209.0          6.30
             Moderately High   106.0       476.0          6.30
             High              113.0      1829.0          6.60
2015         Low                98.5        79.5          5.85
             Medium            105.0       242.5          6.15
             Moderately High   108.0       614.5          6.40
             High              117.0      1576.5          6.50
```

In [27]:
```
# Setting the positions and width for the bars
pos = list(range(len(dfq2_summary.query('revenue_levels =="Low"'))))
width = 0.2
```

```
# Plotting the bars
fig, ax = plt.subplots(figsize=(10,5))

# Create a bar with Low data, in position pos,
plt.bar(pos,
        #using 'Low' data,
        dfq2_summary.query('revenue_levels =="Low"')['popularity'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#EE3224',
        # with label Low
        label= 'Low')

# Create a bar with Medium data,
# in position pos + some width buffer,
plt.bar([p + width for p in pos],
        #using Medium data,
        dfq2_summary.query('revenue_levels =="Medium"')['popularity'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#F78F1E',
        # with label Medium
        label='Medium')

# Create a bar with Moderately High data,
# in position pos + some width buffer,
plt.bar([p + width*2 for p in pos],
        #using Moderately High data,
        dfq2_summary.query('revenue_levels =="Moderately High"')['popularity'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#FFC222',
        # with label Moderately High
        label='Moderately High')

# Create a bar with High data,
# in position pos + some width buffer,
plt.bar([p + width*3 for p in pos],
```

```
        #using High data,
        dfq2_summary.query('revenue_levels =="High"')['popularity'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#4fb427',
        # with label High
        label='High')

ax.set_ylabel('popularity')

ax.set_title('Popularity in Different Revenue Levels in Recent Five Years')

ax.set_xticks([p + 1.5 * width for p in pos])

ax.set_xticklabels([2011,2012,2013,2014,2015])

plt.legend( loc='upper left')
plt.grid()
plt.show()
```



We can see that movies with higher revenue level are with higher popularity in recent five years. We can see that revenue level has postive relation with popularity. The result is reasonable since it makes me think of if movie producer wants to make high revenue movies, the first thing they always is to promote it and make it popular. So according the result from the previous question, I infer that a high revenue movie is always with a higher popularity than movies with lower revenue levels. So if we define success of a movie is it's revenue, one property it has is the high popularity.

But what about the score rating distribution in different revenue levels of movies? Does high revenue level movie has the property of high score rating? Let's explore on the next question.

4.2.1 Question 3: The distribution of revenue in different score rating levels in recent five years.

Use the same procedure on Question 2 to explore this question.

In [28]:
```
# group the dataframe we created above with each revenue levels in each year, find the
dfq2_summary = df_q2.groupby(['release_year','revenue_levels']).mean()
dfq2_summary.tail(4)
```

Out[28]:
```
                                          id  popularity        budget  \
release_year revenue_levels
2015         Low             288091.296296    0.672883  7.802640e+06
             Medium          268269.129630    1.224921  1.779000e+07
             Moderately High 267348.962963    2.017584  2.311923e+07
             High            219819.685185    5.369140  9.754528e+07

                                  revenue     runtime   vote_count  \
release_year revenue_levels
2015         Low             7.311892e+05  101.851852   106.592593
             Medium          1.399316e+07  105.092593   266.703704
             Moderately High 6.356421e+07  107.537037   684.018519
             High            4.173124e+08  117.703704  1952.944444

                             vote_average
release_year revenue_levels
2015         Low                 5.918519
             Medium              6.103704
             Moderately High     6.362963
             High                6.496296
```

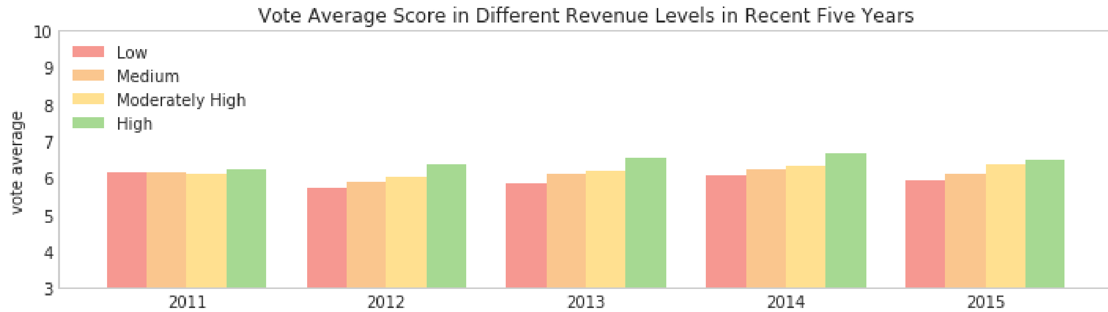
In [38]:
```
# group the dataframe we created above with each revenue levels in each year, find the
dfq2_summary = df_q2.groupby(['release_year','revenue_levels']).mean()
dfq2_summary.tail(4)
```

Out[38]:
```
                                          id  popularity        budget  \
release_year revenue_levels
2015         Low             288091.296296    0.672883  7.802640e+06
             Medium          268269.129630    1.224921  1.779000e+07
             Moderately High 267348.962963    2.017584  2.311923e+07
             High            219819.685185    5.369140  9.754528e+07

                                  revenue     runtime   vote_count  \
```

```
release_year revenue_levels
2015         Low              7.311892e+05  101.851852   106.592593
             Medium           1.399316e+07  105.092593   266.703704
             Moderately High  6.356421e+07  107.537037   684.018519
             High             4.173124e+08  117.703704  1952.944444

                              vote_average
release_year revenue_levels
2015         Low                  5.918519
             Medium               6.103704
             Moderately High      6.362963
             High                 6.496296
```

In [29]:
```
# Setting the positions and width for the bars
pos = list(range(len(dfq2_summary.query('revenue_levels =="Low"'))))
width = 0.2

# Plotting the bars
fig, ax = plt.subplots(figsize=(12,3))

# Create a bar with Low data, in position pos,
plt.bar(pos,
        #using 'Low' data,
        dfq2_summary.query('revenue_levels =="Low"')['vote_average'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#EE3224',
        # with label Low
        label= 'Low')

# Create a bar with Medium data,
# in position pos + some width buffer,
plt.bar([p + width for p in pos],
        #using Medium data,
        dfq2_summary.query('revenue_levels =="Medium"')['vote_average'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#F78F1E',
        # with label Medium
        label='Medium')

# Create a bar with Moderately High data,
```

```python
# in position pos + some width buffer,
plt.bar([p + width*2 for p in pos],
        #using Moderately High data,
        dfq2_summary.query('revenue_levels =="Moderately High"')['vote_average'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#FFC222',
        # with label Moderately High
        label='Moderately High')

# Create a bar with High data,
# in position pos + some width buffer,
plt.bar([p + width*3 for p in pos],
        #using High data,
        dfq2_summary.query('revenue_levels =="High"')['vote_average'],
        # of width
        width,
        # with alpha 0.5
        alpha=0.5,
        # with color
        color='#4fb427',
        # with label High
        label='High')

ax.set_ylabel('vote average')

ax.set_title('Vote Average Score in Different Revenue Levels in Recent Five Years')

ax.set_xticks([p + 1.5 * width for p in pos])

ax.set_xticklabels([2011,2012,2013,2014,2015])

plt.ylim(3, 10)

plt.legend(loc='upper left')
plt.grid()
plt.show()
```



From the chart above, we can see that there is no big difference of movie rating between each revenue level. So it can be concluded that the high revenue movies don't have the significant high score rating.

4.2.2 Part 1 Question Explore Summary

```
1.Movie popularity trend is growing from 1960, I infer that it is with the background that nowa
2.Movies with higher revenue level are with higher popularity in recent five years. In other wo
3.Movies with higher revenue level don't have the significant high score rating than other reve
```

4.2.3 Research Question 2 (Find the Properties are Associated with Successful Movies)

Question 1: What kinds of properties are associated with movies that have high popularity? What's the budget level movie are associated with movies that have high popularity? What's the runtime level are associated with movies that have high popularity on average? What's casts, directors, keywords, genres and production companies are associated with high popularity?

Question 2: What kinds of properties are associated with movies that have high voting score? What's the budget level are associated with movies that have high voting score? What's the runtime level are associated with movies that have high voting score? What's the directors, keywords, genres are associated with voting score?

4.2.4 Function and research sample prepare

In the dataset, the potential properties associated with movies can be runtime, budget, cast, director, keywords, genres, production companies. These data are including two types: quantitative data and categorical data. Both runtime and budget data are quantitative data; the others are categorical data.

For quantitative data, since the data is quantitative, I can devide the data into various levels and find the properties in all range of movies success, I choose to use the whole dataset and then divided runtime and budget into four levels according to their quartile: 'Low', 'Medium', 'Moderately High', 'High' in all time range. And then find out what's the runtime and budget level with higher degree of movies popularity/voting score.

For categorical data, which are cast, director, keywords and genres, since we are not necessary to discuss all the range of of movies success(which is also difficult to dicuss), I just focus on the high popularity or high rating, so I filter the top 100 popular/ high voting score movies data in each year, and then count the number of occurrences in every category every year to find their properties. Forthermore, in case that the top frequent occurrences are also appeared in the worst popular/ high voting score movies, I also filter the worst 100 popular/ high voting score movies in every year and then compare the result to top 100's. If the top frequent occurrences also appear in the worst movies, I am going to include these factors as properties associated with top movies as well as worst movies. Besides, these data are contain the pipe (|) characters so first I have to spilt them.

4.2.5 The function is the same I ued in the Part 1 Question. So I just past it again below.

A)The cut_into_quantile function- general use. The function is the same I ued in the Part 1 Question. So I just past it again below.

```
In [30]: # quartile function
         def cut_into_quantile(dfname ,column_name):
         # find quartile, max and min values
             min_value = dfname[column_name].min()
             first_quantile = dfname[column_name].describe()[4]
             second_quantile = dfname[column_name].describe()[5]
             third_quantile = dfname[column_name].describe()[6]
             max_value = dfname[column_name].max()
         # Bin edges that will be used to "cut" the data into groups
             bin_edges = [ min_value, first_quantile, second_quantile, third_quantile, max_value
         # Labels for the four budget level groups
             bin_names = [ 'Low', 'Medium', 'Moderately High', 'High']
         # Creates budget_levels column
             name = '{}_levels'.format(column_name)
             dfname[name] = pd.cut(dfname[column_name], bin_edges, labels=bin_names, include_low
             return dfname
```

B) Split pipe (|) characters and then count their number of appeared times, then find the top three factor.

```
In [31]: # split pipe characters and count their number of appeared times
         #argument:dataframe_col is the target dataframe&column; num is the number of the top fa
         def find_top(dataframe_col, num=3):
             # split the characters in the input column
             #and make it to a list
             alist = dataframe_col.str.cat(sep='|').split('|')
             #transfer it to a dataframe
             new = pd.DataFrame({'top' :alist})
             #count their number of appeared times and
             #choose the top3
             top = new['top'].value_counts().head(num)
             return top
```

4.2.6 B. Sample prepare-- Filter Top 100 and Worst 100 movies in each year as the research sample.

A) Select Top 100 popular movies in every year.

In [32]:
```
# Select Top 100 popular movies.
# fisrt sort it by release year ascending and popularity descending
df_top_p = df.sort_values(['release_year','popularity'], ascending=[True, False])
#group by year and choose the top 100 high
df_top_p = df_top_p.groupby('release_year').head(100).reset_index(drop=True)
#check, it must start from 1960, and with high popularity to low
df_top_p.head(2)
```

Out[32]:
```
    id  popularity     budget     revenue         original_title  \
0  539    2.610362   806948.0  32000000.0                 Psycho
1  966    1.872132  2000000.0   4905000.0  The Magnificent Seven

                                                cast           director  \
0  Anthony Perkins|Vera Miles|John Gavin|Janet Le...  Alfred Hitchcock
1  Yul Brynner|Eli Wallach|Steve McQueen|Charles ...      John Sturges

                                         keywords  runtime  \
0                   hotel|clerk|arizona|shower|rain      109
1  horse|village|friendship|remake|number in title      128

                       genres                     production_companies  \
0     Drama|Horror|Thriller                        Shamley Productions
1  Action|Adventure|Western  The Mirisch Corporation|Alpha Productions

  release_date  vote_count  vote_average  release_year
0      8/14/60        1180           8.0          1960
1     10/23/60         224           7.0          1960
```

B) Select Top 100 high revenue movies in every year.

In [89]:
```
# Select Top 100 high revenue movies.
# fisrt sort it by release year ascending and revenue descending
df_top_r = df.sort_values(['release_year','revenue'], ascending=[True, False])
#group by year and choose the top 100 high
df_top_r = df_top_r.groupby('release_year').head(100).reset_index(drop=True)
#check, it must start from 1960, and with high revenue to low
df_top_r.head(2)
```

Out[89]:
```
    id  popularity      budget     revenue original_title  \
0  967    1.136943  12000000.0  60000000.0      Spartacus
1  539    2.610362    806948.0  32000000.0         Psycho

                                                cast           director  \
0  Kirk Douglas|Laurence Olivier|Jean Simmons|Cha...    Stanley Kubrick
1  Anthony Perkins|Vera Miles|John Gavin|Janet Le...  Alfred Hitchcock

                                            keywords  runtime  \
0  gladiator|roman empire|gladiator fight|slavery...      197
```

```
1                     hotel|clerk|arizona|shower|rain      109

                  genres production_companies release_date  vote_count  \
0   Action|Drama|History     Bryna Productions      10/6/60         211
1  Drama|Horror|Thriller   Shamley Productions      8/14/60        1180

   vote_average  release_year budget_levels   runtime_levels
0           6.9          1960        Medium             High
1           8.0          1960           Low  Moderately High
```

C) Select Top 100 high score rating movies in every year.

In [34]:
```python
# Select Top 100 high scorer ating movies.
# fisrt sort it by release year ascending and high scorer ating descending
df_top_s = df.sort_values(['release_year','vote_average'], ascending=[True, False])
#group by year and choose the top 100 high
df_top_s = df_top_s.groupby('release_year').head(100).reset_index(drop=True)
#check, it must start from 1960, and with high scorer ating to low
df_top_s.head(2)
```

Out[34]:
```
    id  popularity     budget     revenue original_title  \
0  539    2.610362   806948.0  32000000.0         Psycho
1  284    0.947307  3000000.0  25000000.0  The Apartment

                                                cast          director  \
0  Anthony Perkins|Vera Miles|John Gavin|Janet Le...  Alfred Hitchcock
1  Jack Lemmon|Shirley MacLaine|Fred MacMurray|Ra...      Billy Wilder

                                            keywords  runtime  \
0                     hotel|clerk|arizona|shower|rain      109
1  new york|new year's eve|lovesickness|age diffe...      125

                  genres                production_companies release_date  \
0  Drama|Horror|Thriller                 Shamley Productions      8/14/60
1   Comedy|Drama|Romance  United Artists|The Mirisch Company      6/15/60

   vote_count  vote_average  release_year
0        1180           8.0          1960
1         235           7.9          1960
```

D) To compare to results, I also create three subdataset for the last 100 movies.

In [35]:
```python
# the last 100 popular movies in every year
df_low_p = df.sort_values(['release_year','popularity'], ascending=[True, True])
df_low_p = df_low_p.groupby('release_year').head(100).reset_index(drop=True)
# the last 100 high revenue movies in every year
df_low_r = df.sort_values(['release_year','revenue'], ascending=[True, True])
df_low_r = df_low_r.groupby('release_year').head(100).reset_index(drop=True)
```

```
# the last 100 score rating movies in every year
df_low_s = df.sort_values(['release_year','vote_average'], ascending=[True, True])
df_low_s = df_low_s.groupby('release_year').head(100).reset_index(drop=True)
```

4.3 Question 1: What kinds of properties are associated with movies that have high popularity?

1. What's the budget level movie are associated with movies that have high popularity?
2. What's the runtime level are associated with movies that have high popularity on average?
3. What's casts, directors, keywords, genres and production companies are associated with high popularity?

4.4 1.1 What's the budget level movie are associated with movies that have high popularity?

First, divided budget data into four levels with it's quartile: 'Low', 'Medium', 'Moderately High', 'High' and create a level column.

In [36]:
```
# use cut_into_quantile function to build a level column
df = cut_into_quantile(df,'budget')
df.head(1)
```

Out[36]:
```
       id  popularity       budget       revenue  original_title  \
0  135397   32.985763  150000000.0  1.513529e+09  Jurassic World

                                                cast          director  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow

                                          keywords  runtime  \
0  monster|dna|tyrannosaurus rex|velociraptor|island      124

                                     genres  \
0  Action|Adventure|Science Fiction|Thriller

                                production_companies release_date  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15        5562

   vote_average  release_year budget_levels
0           6.5          2015          High
```

From the table above, I built a budget_levels columns.

In [37]:
```
# Find the mean and median popularity of each level with groupby
result_mean = df.groupby('budget_levels')['popularity'].mean()
result_mean
```

Out[37]:
```
budget_levels
Low                0.507000
Medium             0.726641
```

```
Moderately High    0.986812
High               1.821742
Name: popularity, dtype: float64
```

In [38]:
```
result_median = df.groupby('budget_levels')['popularity'].median()
result_median
```

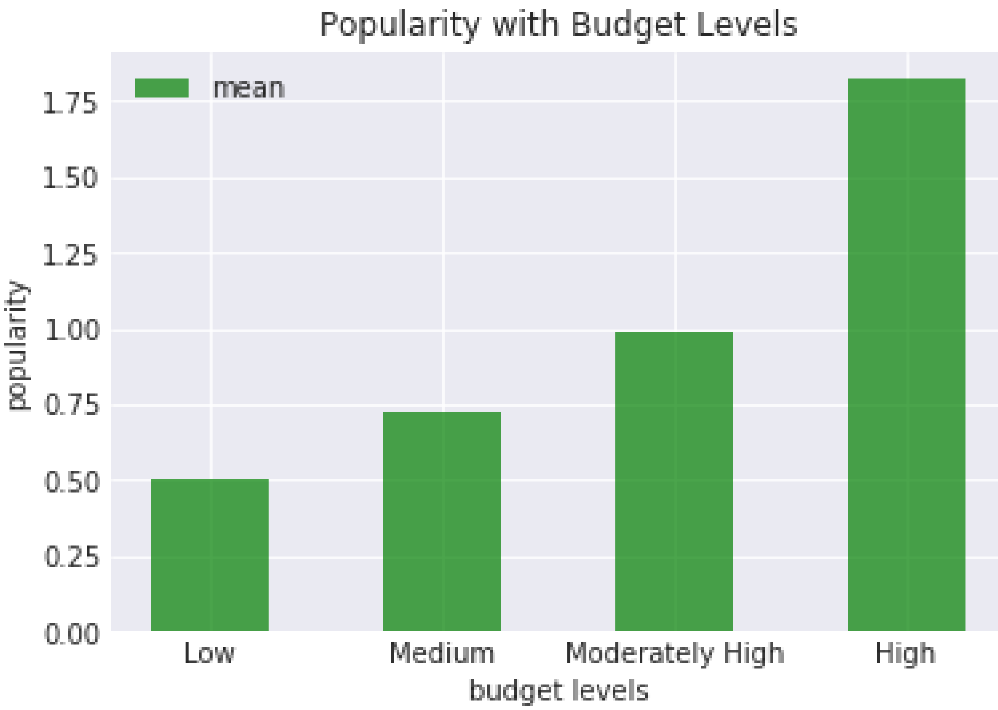
Out[38]:
```
budget_levels
Low                0.361715
Medium             0.506031
Moderately High    0.733917
High               1.232098
Name: popularity, dtype: float64
```

In [39]:
```
#Visualing
# the x locations for the groups
ind = np.arange(len(result_mean))
# the width of the bars
width = 0.5
ind
```

Out[39]:
```
array([0, 1, 2, 3])
```

In [40]:
```
# plot bars
#set style
sns.set_style('darkgrid')
bars = plt.bar(ind, result_mean, width, color='g', alpha=.7, label='mean')

# title and labels
plt.ylabel('popularity')
plt.xlabel('budget levels')
plt.title('Popularity with Budget Levels')
locations = ind  # xtick locations345...
labels = result_median.index
plt.xticks(locations, labels)
# legend
plt.legend()
```

Out[40]:
```
<matplotlib.legend.Legend at 0x7f9c794b6898>
```



From the figure above, we can see that movies with higher popularity are with higher budget level. The result is reasonable since movies with higher popularity may has a higher promoting advertising cost. And with the high promotion level people always have more probability to get know these movies.

4.5 1.2 What's the runtime level are associated with movies that have high popularity on average?

Divided runtime data into four levels with it's quartile: 'Short', 'Medium', 'Moderately Long', 'Long'.

```
In [42]: df = cut_into_quantile(df,'runtime')
         df.head(1)
```

```
Out[42]:        id  popularity       budget       revenue  original_title  \
         0  135397   32.985763  150000000.0  1.513529e+09  Jurassic World

                                                       cast         director  \
         0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow

                                                   keywords  runtime  \
         0  monster|dna|tyrannosaurus rex|velociraptor|island      124

                                              genres  \
         0  Action|Adventure|Science Fiction|Thriller
```

```
                              production_companies release_date  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15        5562

   vote_average  release_year budget_levels runtime_levels
0           6.5          2015          High           High
```

In [43]:
```python
# Find the mean popularity of each level with groupby
result_mean = df.groupby('runtime_levels')['popularity'].mean()
result_mean
```

Out[43]:
```
runtime_levels
Low                  0.410934
Medium               0.549395
Moderately High      0.653673
High                 1.014841
Name: popularity, dtype: float64
```

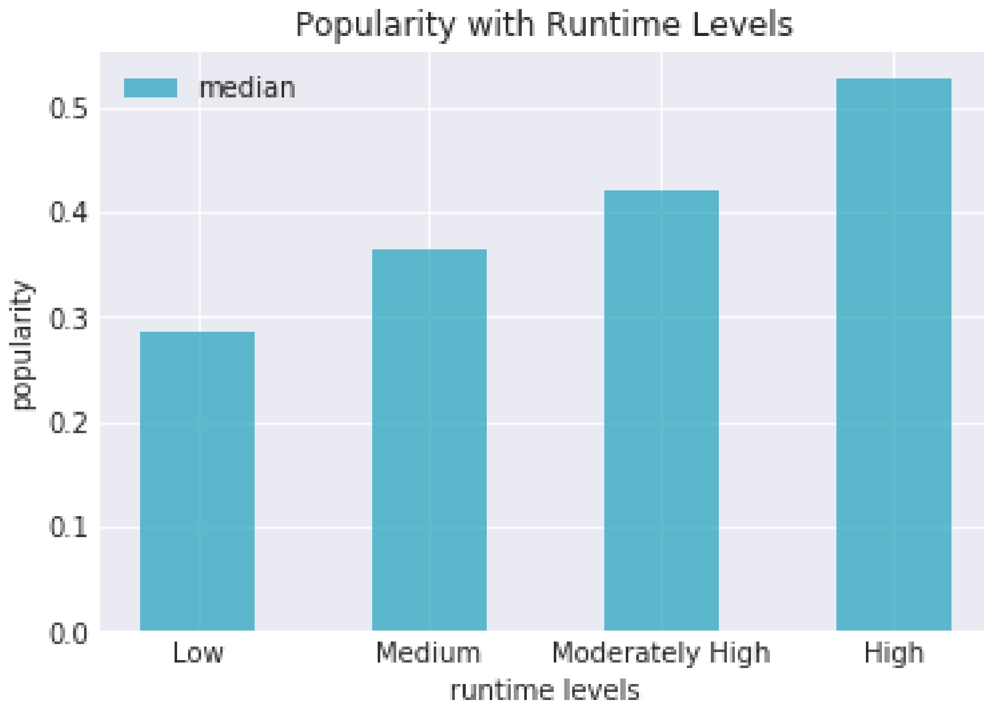
In [44]:
```python
# Find the median popularity of each level with groupby
result_median = df.groupby('runtime_levels')['popularity'].median()
result_median
```

Out[44]:
```
runtime_levels
Low                  0.284617
Medium               0.364854
Moderately High      0.419636
High                 0.526297
Name: popularity, dtype: float64
```

In [45]:
```python
ind = np.arange(len(result_median))  # the x locations for the groups
width = 0.5       # the width of the bars
```

In [46]:
```python
# plot bars
bars = plt.bar(ind, result_median, width, color='#1ea2bc', alpha=.7, label='median')

# title and labels
plt.ylabel('popularity')
plt.xlabel('runtime levels')
plt.title('Popularity with Runtime Levels')
locations = ind  # xtick locations345...
labels = result_median.index
plt.xticks(locations, labels)
# legend
plt.legend()
```

Out[46]:
```
<matplotlib.legend.Legend at 0x7f9c794a0a20>
```



We can see that the higher popularity movies has longer run time.

4.6 1.3 What's casts, directors, keywords, genres and production companies are associated with high popularity?

First, choose the dataset-df_top_p. It is the dataframe about top 100 popular movies in each year.

```
In [50]: df_top_p.head(2)
```

```
Out[50]:     id  popularity     budget     revenue          original_title  \
         0  539    2.610362   806948.0  32000000.0                  Psycho
         1  966    1.872132  2000000.0   4905000.0  The Magnificent Seven

                                                      cast          director  \
         0  Anthony Perkins|Vera Miles|John Gavin|Janet Le...  Alfred Hitchcock
         1  Yul Brynner|Eli Wallach|Steve McQueen|Charles ...      John Sturges

                                               keywords  runtime  \
         0                  hotel|clerk|arizona|shower|rain      109
         1  horse|village|friendship|remake|number in title      128

                                genres                        production_companies  \
         0     Drama|Horror|Thriller                         Shamley Productions
         1  Action|Adventure|Western  The Mirisch Corporation|Alpha Productions
```

```
  release_date  vote_count  vote_average  release_year
0      8/14/60        1180           8.0          1960
1     10/23/60         224           7.0          1960
```

Then, find the three highest occurrences in each category among the top 100 popular movies. And store the result table into variables in order to create a summary table.

```
In [51]: # find top three cast
         a = find_top(df_top_p.cast)
         # find top three director
         b = find_top(df_top_p.director)
         # find top three keywords
         c = find_top(df_top_p.keywords)
         # find top three genres
         d = find_top(df_top_p.genres)
         # find top three production companies
         e = find_top(df_top_p.production_companies)
```

Use the result above to create a summary dataframe.

```
In [52]: df_popular = pd.DataFrame({'popular_cast': a.index, 'popular_director': b.index, 'popul
         df_popular
```

```
Out[52]:      popular_cast  popular_director popular_genres popular_keywords  \
         0  Robert De Niro       Woody Allen          Drama    based on novel
         1    Bruce Willis  Steven Spielberg         Comedy               sex
         2   Michael Caine   Martin Scorsese       Thriller          dystopia

              popular_producer
         0        Warner Bros.
         1  Universal Pictures
         2  Paramount Pictures
```

Finally, find the three highest occurrences in each category among the 100 unpopular movies.

```
In [54]: # call the dataset wiht the 100 unpopular movies in each year
         df_low_p.head(2)
```

```
Out[54]:      id  popularity     budget    revenue        original_title  \
         0  18973    0.055821  3000000.0  7100000.0           Cinderfella
         1  39890    0.065808        NaN        NaN  The City of the Dead

                                                       cast              director  \
         0  Jerry Lewis|Ed Wynn|Judith Anderson|Henry Silv...        Frank Tashlin
         1  Christopher Lee|Dennis Lotis|Patricia Jessel|T...  John Llewellyn Moxey

                                                   keywords  runtime          genres  \
         0                                              NaN       91  Comedy|Romance
```

```
1  witch|burning of witches|witch burning|witchcraft       76          Horror

                          production_companies release_date  vote_count  \
0  Paramount Pictures|Jerry Lewis Productions     12/18/60          13
1                      Vulcan Productions Inc.       9/9/60          13

   vote_average  release_year
0           7.2          1960
1           6.1          1960
```

In [55]:
```
# find top three cast among the among the 100 unpopular movies
na = find_top(df_low_p.cast)
# find top three director among the among the 100 unpopular movies
nb = find_top(df_low_p.director)
# find top three keywords among the among the 100 unpopular movies
nc = find_top(df_low_p.keywords)
# find top three genres among the among the 100 unpopular movies
nd = find_top(df_low_p.genres)
# find top three production companiess among the among the 100 unpopular movies
ne = find_top(df_low_p.production_companies)
```

In [56]:
```
df_unpopular = pd.DataFrame({'unpopular_cast': na.index, 'unpopular_director': nb.index
df_unpopular
```

Out[56]:
```
   unpopular_cast unpopular_director unpopular_genres unpopular_keywords  \
0  Clint Eastwood        Woody Allen            Drama   independent film
1   Michael Caine     Clint Eastwood           Comedy     woman director
2    Sean Connery    Martin Scorsese         Thriller                sex

   unpopular_producer
0  Universal Pictures
1        Warner Bros.
2  Paramount Pictures
```

Now, we get the two table that list the properties occurred the most among the top 100 popular movies each year, among the top 100 unpopular movies each year respectively.

Now we can campare the two tables and find out What's casts, directors, keywords, genres and production companies are associated with high popularity.

In [78]:
```
# compare
df_popular
```

Out[78]:
```
     popular_cast  popular_director popular_genres popular_keywords  \
0  Robert De Niro       Woody Allen          Drama   based on novel
1    Bruce Willis  Steven Spielberg         Comedy              sex
2   Michael Caine    Clint Eastwood       Thriller         dystopia
```

```
     popular_producer
0        Warner Bros.
1  Universal Pictures
2  Paramount Pictures
```

From the tabbles above, we can find that cast Michael Caine is appeared in both popular and unpopular movies; director Woody Allen and Clint Eastwood are appeared in both popular and unpopular movies; all three genres Drama, Comedy, Thriller are appeared in both popular and unpopular movies; sex is appeared in both popular and unpopular movies; all three producer Universal Pictures, Warner Bros, Paramount Pictures are appeared in both popular and unpopular movies. The summary are as follows:

```
Cast associated with high popularity movies: Robert De Niro and Bruce Willis. It's really reason
Director associated with high popularity movies: Steven Spielberg. It's no doubt that he got the
Both of the most popular and unpopular movies are associated three mainly genres: Drama, Comedy,
Keywords associated with high popularity movies: based on novel and dystopia. It' also no doubt
Producer associated with high popularity movies and unpopularity movies: Warner Bros., Universal
```

4.6.1 Question 2: What kinds of properties are associated with movies that have high voting score?

1. What's the budget level are associated with movies that have high voting score?
2. What's the runtime level are associated with movies that have high voting score?
3. What's the directors, keywords, genres are associated with voting score?

Use the same procedure with Research 2, Question 1 to answer these questions.

4.7 2.1 What's the budget level are associated with movies that have high voting score?

First, use the dataframe with budget level I have created in the previous question. Then find the mean and median of vote_average group by different budget level.

```
In [57]: # Find the mean and median voting score of each level with groupby
         result_mean = df.groupby('budget_levels')['vote_average'].mean()
         result_mean
```

```
Out[57]: budget_levels
         Low                 5.950444
         Medium              6.017976
         Moderately High     6.065580
         High                6.104504
         Name: vote_average, dtype: float64
```

```
In [58]: result_median = df.groupby('budget_levels')['vote_average'].median()
         result_median
```

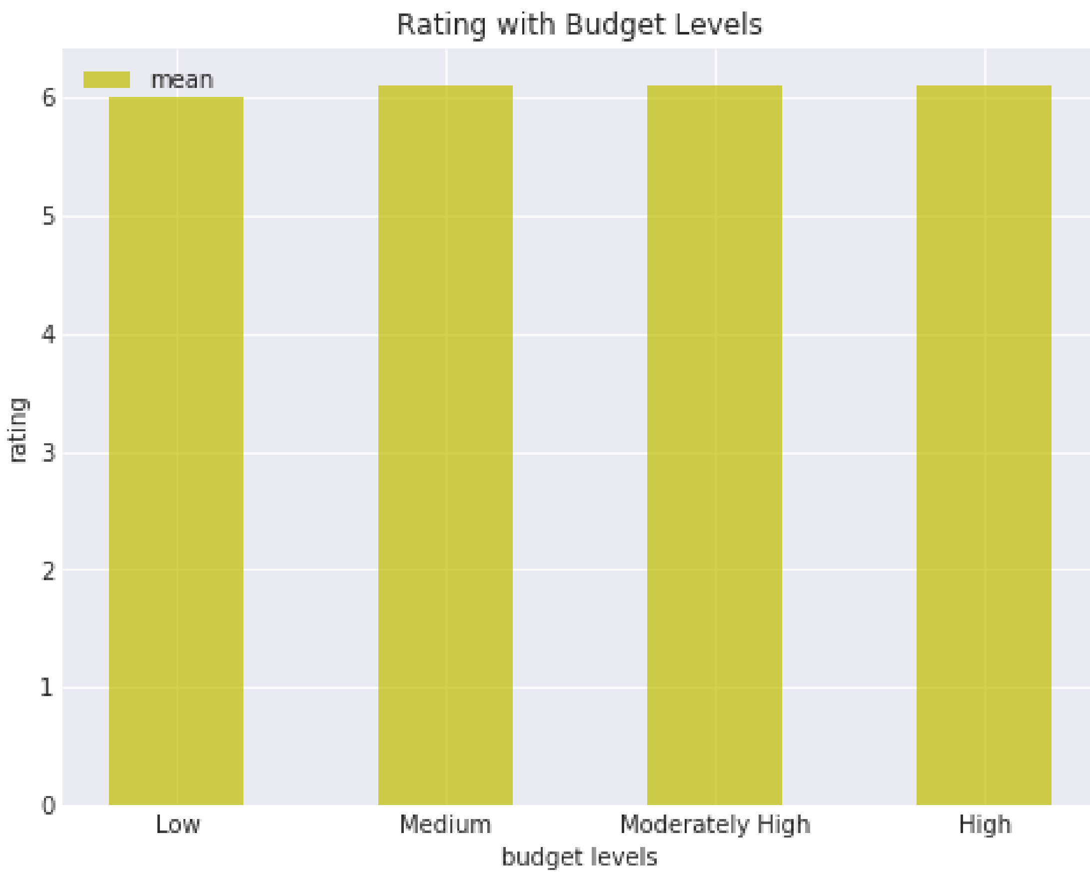
```
Out[58]: budget_levels
         Low                 6.0
```

```
Medium              6.1
Moderately High     6.1
High                6.1
Name: vote_average, dtype: float64
```

Let's use the mean table above to visualize it.

```
In [59]: # plot bars
         #set style
         sns.set_style('darkgrid')
         ind = np.arange(len(result_mean))  # the x locations for the groups
         width = 0.5       # the width of the bars

         # plot bars
         plt.subplots(figsize=(8, 6))
         bars = plt.bar(ind, result_median, width, color='y', alpha=.7, label='mean')

         # title and labels
         plt.ylabel('rating')
         plt.xlabel('budget levels')
         plt.title('Rating with Budget Levels')
         locations = ind  # xtick locations345...
         labels = result_median.index
         plt.xticks(locations, labels)
         # legend
         plt.legend( loc='upper left')
```

```
Out[59]: <matplotlib.legend.Legend at 0x7f9c792e3668>
```



We can see that there is no big difference in average voting score at different budget levels. So from the result, maybe high budget of a movie is not necessary to a good quality of movie!

4.8 2.2 What's the runtime level are associated with movies that have high voting score?

First, use the dataframe with runtime level I have created in the previous question. Then find the mean and median of vote_average group by different runtime level.

```
In [60]: # Find the mean popularity of each level with groupby
         result_mean = df.groupby('runtime_levels')['vote_average'].mean()
         result_mean
```

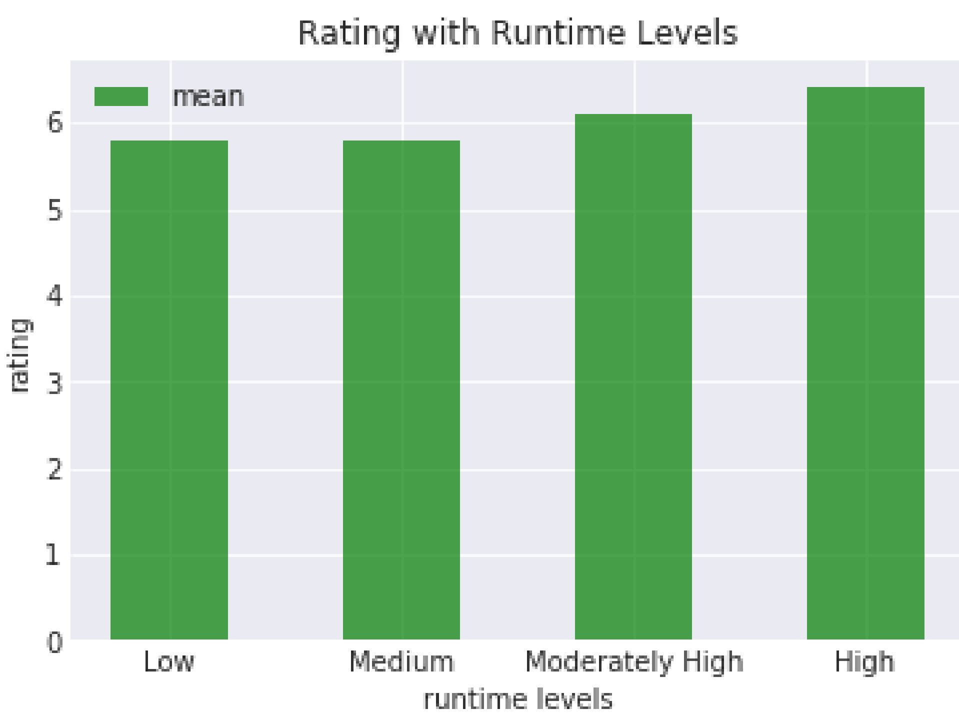
```
Out[60]: runtime_levels
         Low                5.759877
         Medium             5.729687
         Moderately High    6.048664
         High               6.403831
         Name: vote_average, dtype: float64
```

```
In [61]: result_median = df.groupby('runtime_levels')['vote_average'].median()
         result_median
```

```
Out[61]: runtime_levels
         Low                 5.8
         Medium              5.8
         Moderately High     6.1
         High                6.4
         Name: vote_average, dtype: float64
```

```
In [62]: sns.set_style('darkgrid')
         ind = np.arange(len(result_mean))  # the x locations for the groups
         width = 0.5       # the width of the bars

         # plot bars
         bars = plt.bar(ind, result_median, width, color='g', alpha=.7, label='mean')

         # title and labels
         plt.ylabel('rating')
         plt.xlabel('runtime levels')
         plt.title('Rating with Runtime Levels')
         locations = ind  # xtick locations345...
         labels = result_median.index
         plt.xticks(locations, labels)
         # legend
         plt.legend()
```

```
Out[62]: <matplotlib.legend.Legend at 0x7f9c79276390>
```



We can see that there is no big difference in average voting score in different runtime levels. So from the result, maybe long runtime of a movie is not necessary to a good quality of movie!

4.9 2.3 What's the directors, keywords, genres are associated with voting score?

First, choose the dataset-df_top_s. It is the dateframe about top 100 high voting score movies in each year.

In [64]:
```
df_top_s.head(2)
```

Out[64]:
```
    id  popularity     budget     revenue original_title  \
0  539    2.610362   806948.0  32000000.0         Psycho
1  284    0.947307  3000000.0  25000000.0  The Apartment

                                                cast          director  \
0  Anthony Perkins|Vera Miles|John Gavin|Janet Le...  Alfred Hitchcock
1  Jack Lemmon|Shirley MacLaine|Fred MacMurray|Ra...      Billy Wilder

                                            keywords  runtime  \
0                  hotel|clerk|arizona|shower|rain      109
1  new york|new year's eve|lovesickness|age diffe...      125

                   genres               production_companies release_date  \
0  Drama|Horror|Thriller                 Shamley Productions      8/14/60
1   Comedy|Drama|Romance  United Artists|The Mirisch Company      6/15/60

   vote_count  vote_average  release_year
0        1180           8.0          1960
1         235           7.9          1960
```

Then, find the three highest occurrences in each category among the top 100 high voting score movies. And store the result table into variables in order to create a summary table.

In [65]:
```
# find top three director
a = find_top(df_top_s.director)
# find top three keywords
b = find_top(df_top_s.keywords)
# find top three genres
c = find_top(df_top_s.genres)
```

Use the result above to create a summary table.

In [66]:
```
#create a summary dataframe.
df_high_score = pd.DataFrame({'high_score_director': a.index, 'high_score_keywords': b.
df_high_score
```

Out[66]:
```
  high_score_director high_score_genres high_score_keywords
0         Woody Allen             Drama      based on novel
1     Martin Scorsese            Comedy    independent film
2      Clint Eastwood          Thriller      woman director
```

Finally, find the three highest occurrences in each category of the worst 100 rating score movies.

In [67]:
```
# call the dataset wiht the 100 low rating movies in each year
df_low_s.head(2)
```

Out[67]:
```
      id  popularity  budget  revenue   original_title  \
0  24014    0.875173     NaN      NaN  Let's Make Love
1   6643    0.421043     NaN      NaN   The Unforgiven

                                                cast      director  \
0  Marilyn Monroe|Yves Montand|Tony Randall|Frank...  George Cukor
1  Burt Lancaster|Audrey Hepburn|Audie Murphy|Joh...   John Huston

                         keywords  runtime                 genres  \
0                         musical      114         Comedy|Romance
1  indian|texas|farm|siblings|saddle      125  Action|Drama|Western

                                production_companies release_date  vote_count  \
0  Twentieth Century Fox Film Corporation|The Com...      10/7/60          15
1                                  James Productions       1/1/60          17

   vote_average  release_year
0           4.9          1960
1           4.9          1960
```

In [68]:
```
# find top three director among the among the 100 low rating movies
na = find_top(df_low_s.director)
# find top three keywords among the among the 100 low rating movies
nb = find_top(df_low_s.keywords)
# find top three genres among the among the 100 low rating movies
nc = find_top(df_low_s.genres)
```

Use the result above to create a summary table.

In [69]:
```
df_low_score = pd.DataFrame({'low_score_director': na.index, 'low_score_keywords': nb.i
df_low_score
```

Out[69]:

	low_score_director	low_score_genres	low_score_keywords
0	Woody Allen	Comedy	sex
1	John Landis	Drama	independent film
2	John Carpenter	Thriller	female nudity

In [70]:
```
# compare
df_high_score
```

Out[70]:

	high_score_director	high_score_genres	high_score_keywords
0	Woody Allen	Drama	based on novel
1	Martin Scorsese	Comedy	independent film
2	Clint Eastwood	Thriller	woman director

After summing up both tables above, we can find that:

```
Martin Scorsese and Clint Eastwood have made top quality movies on average over the past years f
The top quality movies have the keywords with based on novel and woman director over the past ye
```

4.10 Part 2 Question Explore Summary

```
For the properties are associated with high popularity movies, they are high budget levels and l

Each level in both runtime and budget don't have obvious different high rating score. In other w
```

4.11 Research Part 3 Top Keywords and Genres Trends by Generation

```
Question 1: Number of movie released year by year
Question 2: Keywords Trends by Generation
Question 3: Genres Trends by Generation </b>
```

In question 1, I am going to find out the number of movie released year by year. In question 2 and 3, I am going to find out what's the keyword and genre appeared most by generation? To do this:

```
Step one: group the dataframe into five generations: 1960s, 1970s, 1980s, 1990s and 2000s
Step two: use the find_top function to count out the most appeared keyword and genre in each gen
```

4.12 Question 1: Number of movie released year by year

First, use group by release year and count the number of movie released in each year.

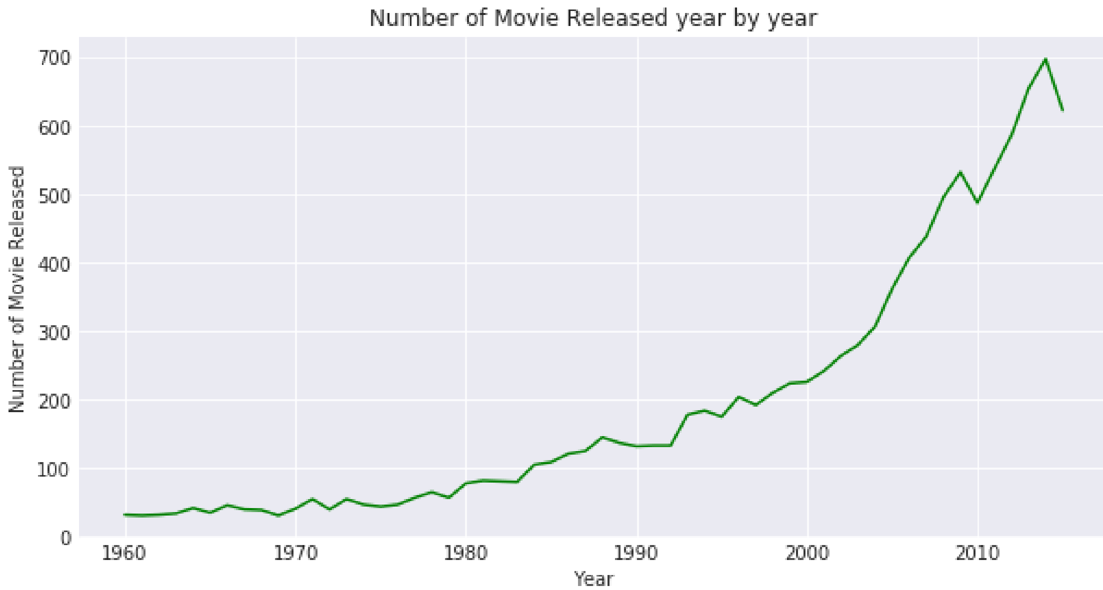
```
In [80]: movie_count = df.groupby('release_year').count()['id']
         movie_count.head()
```

```
Out[80]: release_year
         1960    32
         1961    31
         1962    32
         1963    34
         1964    42
         Name: id, dtype: int64
```

Then visualize the result.

```
In [81]: #set style
         sns.set_style('darkgrid')
         #set x, y axis data
         # x is movie release year
         x = movie_count.index
         # y is number of movie released
         y = movie_count
         #set size
```

```
plt.figure(figsize=(10, 5))
#plot line chart
plt.plot(x, y, color = 'g', label = 'mean')
#set title and labels
plt.title('Number of Movie Released year by year')
plt.xlabel('Year')
plt.ylabel('Number of Movie Released');
```



We can see that the number of movie released are increasing year by year. And the it is the accelerated growth since the curve is concave upward.

4.13 Question 2: Keywords Trends by Generation

First, sort the movie release year list to group the dataframe into generation.

```
In [83]: # sort the movie release year list.
         dfyear= df.release_year.unique()
         dfyear= np.sort(dfyear)
         dfyear
```

```
Out[83]: array([1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970,
                1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981,
                1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992,
                1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003,
                2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014,
                2015])
```

Then, build the generation catagory of 1960s, 1970s, 1980s, 1990s and 2000s.

```
In [84]: # year list of 1960s
         y1960s =dfyear[:10]
         # year list of 1970s
         y1970s =dfyear[10:20]
         # year list of 1980s
         y1980s =dfyear[20:30]
         # year list of 1990s
         y1990s = dfyear[30:40]
         # year list of afer 2000
         y2000 = dfyear[40:]
```

Then for each generation dataframe, use the find_top to find out the most appeared keywords, then combine this result to a new datafram.

```
In [85]: # year list of each generation
         times = [y1960s, y1970s, y1980s, y1990s, y2000]
         #generation name
         names = ['1960s', '1970s', '1980s', '1990s', 'after2000']
         #creat a empty dataframe,df_r3
         df_r3 = pd.DataFrame()
         index = 0
         #for each generation, do the following procedure
         for s in times:
             # first filter dataframe with the selected generation, and store it to dfn
             dfn = df[df.release_year.isin(s)]
             #apply the find_top function with the selected frame, using the result create a dat
             dfn2 = pd.DataFrame({'year' :names[index],'top': find_top(dfn.keywords,1)})
              #append dfn2 to df_q2
             df_r3 = df_r3.append(dfn2)
             index +=1
         df_r3
```

```
Out[85]:                    top       year
         based on novel      16      1960s
         based on novel      23      1970s
         nudity              39      1980s
         independent film    80      1990s
         woman director     352  after2000
```

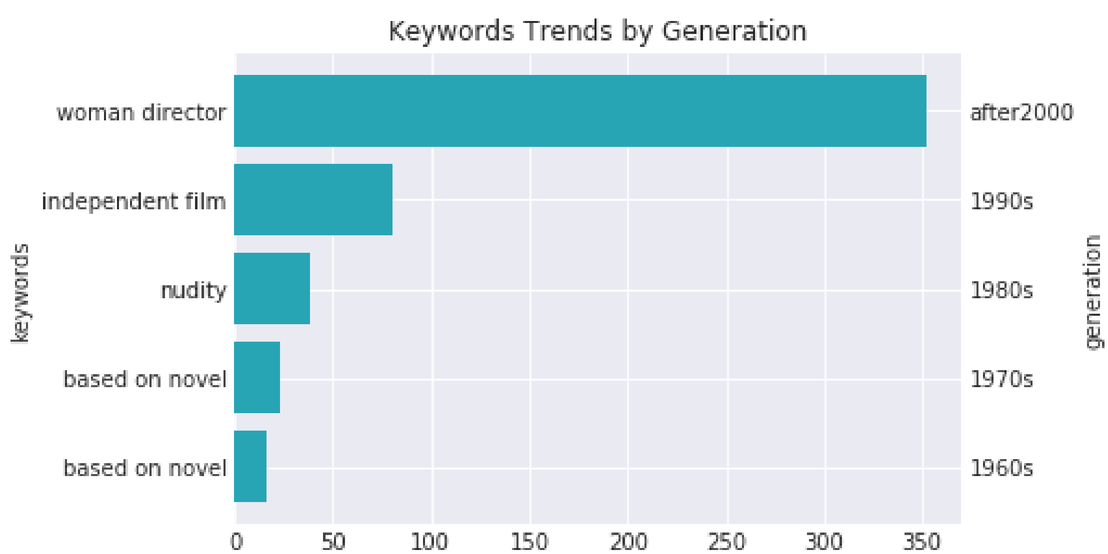
Now, we get the keywords of most filmed movies in each generation. We can see that in 1960s and 1970s, the top keywords was based on novel, which means movies with the keyword based on novel are released most according the dataset. In 1980s, the top keyword was nudity, what a special trend! In 1990s, independent film became the top keyword. And after 2000, the movie with the feature woman director were released most. It's sounds great!

Now let's visualize the result.

```
In [86]: # Setting the positions
         generation = ['1960s', '1970s', '1980s', '1990s', 'after2000']
```

```
keywords = df_r3.index
y_pos = np.arange(len(generation))
fig, ax = plt.subplots()
# Setting y1: the keywords number
y1 = df_r3.top
# Setting y2 again to present the right-side y axis labels
y2 = df_r3.top
#plot the bar
ax.barh(y_pos,y1, color = '#007482')
#set the left side y axis ticks position
ax.set_yticks(y_pos)
#set the left side y axis tick label
ax.set_yticklabels(keywords)
#set left side y axis label
ax.set_ylabel('keywords')

#create another axis to present the right-side y axis labels
ax2 = ax.twinx()
#plot the bar
ax2.barh(y_pos,y2, color = '#27a5b4')
#set the right side y axis ticks position
ax2.set_yticks(y_pos)
#set the right side y axis tick label
ax2.set_yticklabels(generation)
#set right side y axis label
ax2.set_ylabel('generation')
#set title
ax.set_title('Keywords Trends by Generation')
```

```
Out[86]: Text(0.5,1,'Keywords Trends by Generation')
```



One more thing, we can see that the number of the keywords appeared changes from 16 to 347 by generation, and it is resonable since the trend is consistent with the number of movie released.

5 Question 3: Genres Trends by Generation

Use the same procedure as Question 2, first use the find_top to find out the most appeared genres, then combine this result to a new datafram.

In [87]:
```
# year list of each generation
times = [y1960s, y1970s, y1980s, y1990s, y2000]
#generation name
names = ['1960s', '1970s', '1980s', '1990s', 'after2000']
#creat a empty dataframe,df_r3
df_r3 = pd.DataFrame()
index = 0
#for each generation, do the following procedure
for s in times:
    # first filter dataframe with the selected generation, and store it to dfn
    dfn = df[df.release_year.isin(s)]
    #apply the find_top function with the selected frame, using the result create a dat
    dfn2 = pd.DataFrame({'year' :names[index],'top': find_top(dfn.genres,1)})
     #append dfn2 to df_q2
    df_r3 = df_r3.append(dfn2)
    index +=1
df_r3
```

Out[87]:

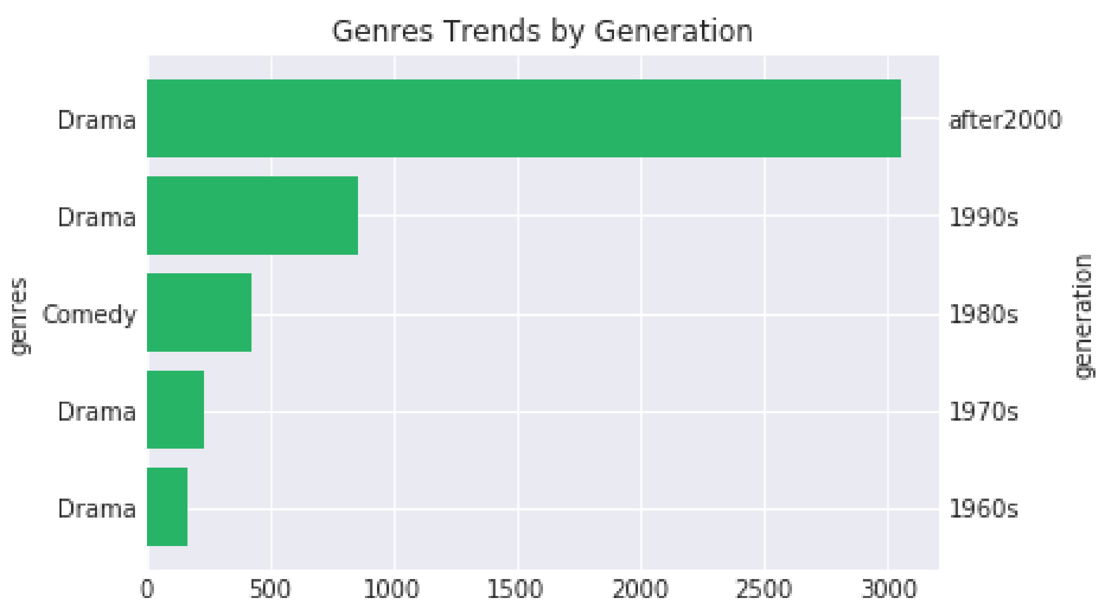
	top	year
Drama	168	1960s
Drama	239	1970s
Comedy	428	1980s
Drama	862	1990s
Drama	3059	after2000

Visualize the result.

In [88]:
```
# Setting the positions
generation = ['1960s', '1970s', '1980s', '1990s', 'after2000']
genres = df_r3.index
y_pos = np.arange(len(generation))
fig, ax = plt.subplots()
# Setting y1: the genre number
y1 = df_r3.top
# Setting y2 again to present the right-side y axis labels
y2 = df_r3.top
#plot the bar
ax.barh(y_pos,y1, color = '#007482')
#set the left side y axis ticks position
```

```
ax.set_yticks(y_pos)
#set the left side y axis tick label
ax.set_yticklabels(genres)
#set left side y axis label
ax.set_ylabel('genres')

#create another axis to present the right-side y axis labels
ax2 = ax.twinx()
#plot the bar
ax2.barh(y_pos,y2, color = '#27b466')
#set the right side y axis ticks position
ax2.set_yticks(y_pos)
#set the right side y axis tick label
ax2.set_yticklabels(generation)
#set right side y axis label
ax2.set_ylabel('generation')
#set title
ax.set_title('Genres Trends by Generation')
```

Out[88]: Text(0.5,1,'Genres Trends by Generation')



We can see that the genre Drama are the most filmed in almost all generation. Only the 1980s are dominated by the comedy type.

6 Part 3 Question Explore Summary

1. The number of movie released are increasing year by year. And the it is in the accelerated growth trend.

2. In 1960s and 1970s, the top keywords was based on novel, which means movies with the keyword based on novel are released most according the dataset. In 1980s, the top keyword was nudity. In 1990s, independent film became the top keyword. And after 2000, the movie with the feature woman director were released most.

3. The genre Drama are the most filmed in almost all generation. Only the 1980s are dominated by the comedy type.

6.1 Conclusions:

The goal in the research is primary to explore three parts questions:

Part one: General Explore

```
At part one, I explored some general questions. The result turned out that the movie popularity
```

Part two: Find the Properties are Associated with Successful Movies

```
At this part, I first found out the properties that are associated with high popularity movies.

And the I found out the properties that are associated with high high voting score. Each level i
```

Part three: Top Keywords and Genres Trends by Generation

```
In this part, I explored the number of movie released trend year by year. Then explored the keyw

The number of movie released are increasing year by year. And the it is in the accelerated growt

To sum up, I did find a lot of interesting information among the dataset, just hope that I can d
```

7 Limitation

1. Data quality: althought I assume the zero values in revenue and budget column are missing, there are still a lot of unreasonable small/big value in the both of the columns. Also, the metrics about rating or popularity are not defined clearly, and the basis of them may be changing year by year.
2. Although the the popularity doesn't have the upperbound , it actually have the high probability of having outliers. But I choose to retain the data to keep the data originalty. Maybe there are still the reason that I should take it into account.
3. Units of revenue and budget column: I am not sure that the budgets and revenues all in US dollars?
4. The inflation effect: I used the revenue and budget data to explore, but I didn't use the adjusted data, although it is provided the adjusted data based on the year 2010.
5. In my reseach one, although I discussed the distribution of popularity in different revenue levels in recent five years, but I just cut the revenue levels based on it's quantile. I didn't find out the whole revenue distributin in the fisrt, so there may be exist risks that the high revenue level still cover a wide of range, and may affect the final result. Besides, in the part, I just discuss data in the recent five year, maybe in other year there are some different distribution.

6. In research two, I dicussed the properties are associated with successful movies. The successful I defined here are high popularity and high voting score. But I didn't find the properties of high revenue since I just assume the high revenue level are with higher popularity, which is I found in research one, so it makes me just leave out the finding the properties of high revenue movie. But I think there must be some other factor that are associated with high revenue movies.
7. In research two, I dicussed the budget level and runtime level properties, but I just cut both of them based on the whole time quantile data not year by year. Also, to cut them into four levels based on quantile still rough.
8. The categorical data, when I analysed them, I just split them one by one, and count them one by one. But the thing is, there must be some effect when these words combine. For example, the keyword based on novel is popular, but what truly keyword that makes the movie sucess maybe the based on novel&adventure.
9. I didn't count number of votes into consideration, so the rating score may be a bias whe the vote number is few.

In [90]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[90]: 0

In [ ]: