# Investigate_a_Dataset

August 29, 2018

# 1 Project: Investigate a TMDb Movie Dataset

## 1.1 Table of Contents


## Introduction

I selected TMDb movie dataset for this Data Analyst project. The original data from Kaggle was cleaned and considered for this analysis. AS per TMDb, it is a community built movie and TV database. This data set contains information about 10,000 movies, including user ratings and revenue data.

### 1.1.1 Details about Dataset

TMDb movie dataset mainly contains attributes related to measure the successful movie and properties associated with success of movie. The attributes to measure the successful of movie are popularity,revenue and vote average. The metrics associated with the movie success are budget,cast,director,tagline,runtime,genres,production company and release date.

As per TMDb, the popularity is an cumulative factor considering Number of votes for the day, views for the day, users who marked it as a "favourite" for the day, users who added it to their "watchlist" for the day, release date, total votes and previous days score.

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.

After eyeing through the dataset, the following questions came into my mind. In this report,the answers for that questions were explored through systematic data analysis process.

### 1.1.2 Research Questions to Explore

### 1.1.3 Research Part 1: General Exploration

Analysis 1: Budget/Revenue Trend over the Period of Time
Analysis 2: Popularity Trend over the Period of Time
Analysis 3: Average Vote Trend over the Period of Time
Analysis 4: Number of Movies Released Over the Time
Analysis 5: Runtime Distribution of Movies
### Research Part 2a (Quantitative Analyses): Properties associated with High Revenue Movies
Research Question 1 (Which Revenue Level receives the highest popularity?)
Research Question 2 (Which Budget Level Receives the Highest Popularity?)
Research Question 3 (Which Runtime Level Receives the Highest Popularity?
Research Question 4 (Which Runtime Level Receives the Highest Avergae Voting?
### Research Part 2b (Categorical Analyses): Properties associated with High Revenue Movies
Research Question 1 (Which Movies are Top 10 highest popularity?)
Research Question 2: (What kind of Genres are top in High Revenue movies?)
Research Question3: (Which Production Companies are top in Best Revenue movies?)
Research Question 4: (Which Actors are top in Best Revenue movies?)
Research Question 5: (Which directors are top in Best Revenue movies?)
Research Question 6: (Which keywords are top in Best Revenue movies?)ű
Research Question 7: (Which Genres are top during 60s and 2Ks Best Revenue movies?)ű
Research Question 8: (Which Keywords are top during 60s and 2Ks Best Revenue movies?)ű

In [327]:
```
# importing all packages related to this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as matplotlib
import seaborn as sns
% matplotlib inline
```

## Data Wrangling

### 1.1.4 Loading Dataset

First, we will read the data set for proceeding to investigate

In [328]:
```
# Loading data and print out a few lines.
df = pd.read_csv('tmdb-movies.csv')
df.head()
```

Out[328]:
```
       id    imdb_id  popularity     budget     revenue  \
0  135397  tt0369610   32.985763  150000000  1513528810
1   76341  tt1392190   28.419936  150000000   378436354
2  262500  tt2908446   13.112507  110000000   295238201
3  140607  tt2488496   11.173104  200000000  2068178225
4  168259  tt2820852    9.335014  190000000  1506249360
```

```
              original_title  \
0             Jurassic World
1         Mad Max: Fury Road
2                  Insurgent
3  Star Wars: The Force Awakens
4                  Furious 7

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                            homepage          director  \
0                      http://www.jurassicworld.com/   Colin Trevorrow
1                        http://www.madmaxmovie.com/     George Miller
2     http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
4                           http://www.furious7.com/         James Wan

                        tagline      ...       \
0            The park is open.      ...
1           What a Lovely Day.      ...
2     One Choice Can Destroy You      ...
3  Every generation has a story.      ...
4          Vengeance Hits Home      ...

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic ...     124
1  An apocalyptic story set in the furthest reach...     120
2  Beatrice Prior must confront her inner demons ...     119
3  Thirty years after defeating the Galactic Empi...     136
4  Deckard Shaw seeks revenge against Dominic Tor...     137

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                      Action|Crime|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
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
```

```
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

The above dataset looks perfect interms of formatting and column index names. There are some odd characters in the 'cast' column. I am going to leave them as it is. It also shows 21 columns in the dataset

### 1.1.5 Exploring Dataset

In [329]:
```
#   shape of the dataset
df.shape
```

Out[329]: (10866, 21)

The dataset contains total of 10866 rows and 21 columns

In [330]:
```
# exploring data
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
```

The above information indicates types and number of non-null for all column index. After exploring the dataset, From the table above, there are totally 10866 entries and total 21 columns. And there exists some null value in the cast, director, overview and genres columns. But some columns are with a lot of null value rows like homepage, tagline, keywords and production_companies, especially the homepage and tagline columns are not required for this analysis,so I decided to drop homepage, tagline and keywords along with imdb_id. Column indexes such as cast, director and genres are having few missing nonnull values. I decided to drop small quantity of null values in columns cast, director and genres

In [331]:
```
df.describe()
```

Out[331]:

| | 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 |

The above table shows the descriptive statistics information of the dataset. The popularity shows the outlier information. AS per TMDb, the popularity is the cumulative number of favourites and number of watched list etc, since it has no upperbond, I decided to retain the original data. This table shows lot of "0" for budget, revenue, runtime, budget_adj and revenue_adj. Are those movies not released? But there is no minimum zero value in release year. So, I assume these values are missing values and not "real" values. In order to confirm this, I decided to find how many zeroes in those column indexes.

In [332]:
```
# finding how many zeroes in budget
```

```
df_budget_zero = df['budget'].value_counts()
df_budget_zero.head(2)
```

Out[332]:
```
0           5696
20000000     190
Name: budget, dtype: int64
```

In [333]:
```
# filtering the zero in budget
df_budget_zero = df.query('budget == 0')
df_budget_zero.head()
```

Out[333]:
```
        id    imdb_id  popularity  budget   revenue  \
30  280996  tt3168230    3.927333       0  29355203
36  339527  tt1291570    3.358321       0  22354572
72  284289  tt2911668    2.272044       0     45895
74  347096  tt3478232    2.165433       0         0
75  308369  tt2582496    2.141506       0         0

                     original_title  \
30                       Mr. Holmes
36                           Solace
72                Beyond the Reach
74          Mythica: The Darkspore
75  Me and Earl and the Dying Girl

                                                 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...
74  Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...
75  Thomas Mann|RJ Cyler|Olivia Cooke|Connie Britt...

                                             homepage  \
30                        http://www.mrholmesfilm.com/
36                                                 NaN
72                                                 NaN
74          http://www.mythicamovie.com/#!blank/wufvh
75  http://www.foxsearchlight.com/meandearlandthed...

                  director  \
30             Bill Condon
36           Afonso Poyart
72  Jean-Baptiste LÃľonetti
74           Anne K. Black
75     Alfonso Gomez-Rejon

                                              tagline      ...       \
30                              The man behind the myth      ...
```

```
36  A serial killer who can see your future, a psy...       ...
72                                              NaN       ...
74                                              NaN       ...
75          A Little Friendship Never Killed Anyone.       ...

                                          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
74  When Teelaâs sister is murdered and a powerf...     108
75  Greg is coasting through senior year of high s...     105

                      genres  \
30             Mystery|Drama
36       Crime|Drama|Mystery
72                  Thriller
74  Action|Adventure|Fantasy
75              Comedy|Drama

                                 production_companies release_date vote_count  \
30  BBC Films|See-Saw Films|FilmNation Entertainme...      6/19/15        425
36  Eden Rock Media|FilmNation Entertainment|Flynn...       9/3/15        474
72                                      Furthur Films      4/17/15         81
74                            Arrowstorm Entertainment      6/24/15         27
75                                  Indian Paintbrush      6/12/15        569

    vote_average  release_year  budget_adj   revenue_adj
30           6.4          2015         0.0  2.700677e+07
36           6.2          2015         0.0  2.056620e+07
72           5.5          2015         0.0  4.222338e+04
74           5.1          2015         0.0  0.000000e+00
75           7.7          2015         0.0  0.000000e+00

[5 rows x 21 columns]
```

In order to confirm zeroes in budget, i quickly checked Mr. Holmes budget in the internet wikipedia and there is information for budget. So, I decided to assume missing values for all zero values in budget column and replace with "NaN"

In [334]:
```
# finding how many zeroes in revenue
df_revenue_zero = df['revenue'].value_counts()
df_revenue_zero.head(2)
```

Out[334]:
```
0           6016
12000000      10
Name: revenue, dtype: int64
```

In [335]:
```
# filtering the zero in revenue
df_revenue_zero = df.query('revenue == 0')
df_revenue_zero.head()
```

Out[335]:
```
        id    imdb_id  popularity    budget  revenue  \
48  265208  tt2231253    2.932340  30000000        0
67  334074  tt3247714    2.331636  20000000        0
74  347096  tt3478232    2.165433         0        0
75  308369  tt2582496    2.141506         0        0
92  370687  tt3608646    1.876037         0        0

                     original_title  \
48                        Wild Card
67                         Survivor
74          Mythica: The Darkspore
75  Me and Earl and the Dying Girl
92        Mythica: The Necromancer

                                                 cast  \
48  Jason Statham|Michael Angarano|Milo Ventimigli...
67  Pierce Brosnan|Milla Jovovich|Dylan McDermott|...
74  Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...
75  Thomas Mann|RJ Cyler|Olivia Cooke|Connie Britt...
92  Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...

                                             homepage             director  \
48                                                NaN           Simon West
67                         http://survivormovie.com/       James McTeigue
74          http://www.mythicamovie.com/#!blank/wufvh        Anne K. Black
75  http://www.foxsearchlight.com/meandearlandthed...  Alfonso Gomez-Rejon
92          http://www.mythicamovie.com/#!blank/y9ake        A. Todd Smith

                                     tagline     ...       \
48  Never bet against a man with a killer hand.     ...
67           His Next Target is Now Hunting Him     ...
74                                          NaN     ...
75     A Little Friendship Never Killed Anyone.     ...
92                                          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
75  Greg is coasting through senior year of high s...     105
92  Mallister takes Thane prisoner and forces Mare...       0

                     genres  \
48      Thriller|Crime|Drama
67     Crime|Thriller|Action
74  Action|Adventure|Fantasy
75              Comedy|Drama
92  Fantasy|Action|Adventure
```

```
                                    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
75                                 Indian Paintbrush      6/12/15        569
92  Arrowstorm Entertainment|Camera 40 Productions...     12/19/15         11

    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
75           7.7          2015  0.000000e+00          0.0
92           5.4          2015  0.000000e+00          0.0

[5 rows x 21 columns]
```

Similarly in order to confirm zeroes in revenue, i quickly checked wild card budget in the internet wikipedia and there is information for revenue. So, I decided to assume missing values for all zero values in budget column and replace with "NaN".

In [336]:
```
#count zero values in runtime data using groupby
df_runtime_count =  df.groupby('runtime').count()
df_runtime_count.head(2)
```

Out[336]:
```
         id  imdb_id  popularity  budget  revenue  original_title  cast  \
runtime
0        31       31          31      31       31              31    31
2         5        5           5       5        5               5     1

         homepage  director  tagline  keywords  overview  genres  \
runtime
0               6        29        5        15        29      30
2               2         5        0         3         5       4

         production_companies  release_date  vote_count  vote_average  \
runtime
0                          13            31          31            31
2                           2             5           5             5

         release_year  budget_adj  revenue_adj
runtime
0                  31          31           31
2                   5           5            5
```

In [337]:
```
# filtering the zero in revenue
df_runtime_zero = df.query('runtime == 0')
df_runtime_zero.head()
```

Out[337]:

```
         id    imdb_id  popularity  budget  revenue  \
92   370687  tt3608646    1.876037       0        0
334  361931  tt5065822    0.357654       0        0
410  339342  tt2948712    0.097514       0        0
445  353345  tt3800796    0.218528       0        0
486  333653  tt4058368    0.176744       0        0

                   original_title  \
92        Mythica: The Necromancer
334                        Ronaldo
410                 Anarchy Parlor
445  The Exorcism of Molly Hartley
486            If There Be Thorns

                                                  cast  \
92   Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...
334                                  Cristiano Ronaldo
410  Robert LaSardo|Jordan James Smith|Sara Fabel|T...
445  Sarah Lind|Devon Sawa|Gina Holden|Peter MacNei...
486  Heather Graham|Jason Lewis|Rachael Carpani|Mas...

                                  homepage                director  \
92   http://www.mythicamovie.com/#!blank/y9ake          A. Todd Smith
334            http://www.ronaldothefilm.com          Anthony Wonke
410                                      NaN  Kenny Gage|Devon Downs
445                                      NaN       Steven R. Monroe
486                                      NaN           Nancy Savoca

                               tagline     ...       \
92                                 NaN     ...
334  Astonishing. Intimate. Definitive.     ...
410                                NaN     ...
445                                NaN     ...
486                                NaN     ...

                                              overview runtime  \
92   Mallister takes Thane prisoner and forces Mare...       0
334  Filmed over 14 months with unprecedented acces...       0
410  Six young college hopefuls vacationing and par...       0
445  Taking place years after The Haunting of Molly...       0
486  The third installment in V.C. Andrewsâ bests...      0

                       genres  \
92   Fantasy|Action|Adventure
334               Documentary
410                    Horror
445                    Horror
486            TV Movie|Drama
```

```
                                    production_companies release_date  \
92   Arrowstorm Entertainment|Camera 40 Productions...     12/19/15
334  On The Corner Films|We Came, We Saw, We Conque...      11/9/15
410                                                NaN       1/1/15
445                               WT Canada Productions      10/9/15
486                 A+E Studios|Jane Startz Productions       4/5/15

     vote_count  vote_average  release_year  budget_adj  revenue_adj
92           11           5.4          2015         0.0          0.0
334          80           6.5          2015         0.0          0.0
410          15           5.6          2015         0.0          0.0
445          52           5.0          2015         0.0          0.0
486          11           5.4          2015         0.0          0.0

[5 rows x 21 columns]
```

The above table shows 31 rows of runtime has zero values. Because of small number i decided to drop zero values in runtime

### 1.1.6 Data Cleaning

**Summary of Actions**

Drop unnecessary columns: homepage, tagline, imdb_id, overview, budget_adj, revenue_adj.

Drop duplicates

Drop null values with small quantity of null values in column: cast, director and genres

Replace zero values with "NaN" null values in columns: budget, revenue

Drop zero values in column with small quantity: runtime

In [338]:
```
# drop imdb_id, homepage, tagline, overview, budget_adj, revenue_adj.
df.drop(['imdb_id','homepage','tagline','overview','budget_adj','revenue_adj'],axis=1,
df.head()
```

Out[338]:
```
       id  popularity     budget     revenue                original_title  \
0  135397   32.985763  150000000  1513528810                Jurassic World
1   76341   28.419936  150000000   378436354            Mad Max: Fury Road
2  262500   13.112507  110000000   295238201                     Insurgent
3  140607   11.173104  200000000  2068178225  Star Wars: The Force Awakens
4  168259    9.335014  190000000  1506249360                     Furious 7

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

```
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...       J.J. Abrams
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...         James Wan

                                        keywords  runtime  \
0  monster|dna|tyrannosaurus rex|velociraptor|island      124
1   future|chase|post-apocalyptic|dystopia|australia      120
2  based on novel|revolution|dystopia|sequel|dyst...      119
3              android|spaceship|jedi|space opera|3d      136
4                car race|speed|revenge|suspense|car      137

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                      Action|Crime|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
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15        2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15        5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15        2947

   vote_average  release_year
0           6.5          2015
1           7.1          2015
2           6.3          2015
3           7.5          2015
4           7.3          2015
```

In [339]:
```python
#sum of duplicates
sum(df.duplicated())
```

Out[339]:
```
1
```

In [340]:
```python
# Drop Duplicates
df.drop_duplicates(inplace=True)
```

In [341]:
```python
#drop the null values in cast, director, genres columns
cal2 = ['cast', 'director', 'genres']
df.dropna(subset = cal2, how='any', inplace=True)
```

In [342]:
```python
# check if nulls are dropped.
df.isnull().sum()
```

Out[342]:
```
id                          0
popularity                  0
```

```
budget                     0
revenue                    0
original_title             0
cast                       0
director                   0
keywords                1425
runtime                    0
genres                     0
production_companies     959
release_date               0
vote_count                 0
vote_average               0
release_year               0
dtype: int64
```

In [343]:
```
# directly filter the runtime data with nonzero value
df.query('runtime != "0"', inplace=True)
#check
df.query('runtime == "0"')
```

Out[343]:
```
Empty DataFrame
Columns: [id, popularity, budget, revenue, original_title, cast, director, keywords, r
Index: []
```

In [344]:
```
#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)
# check if nulls are added in budget and revenue columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10703 entries, 0 to 10865
Data columns (total 15 columns):
id                      10703 non-null int64
popularity              10703 non-null float64
budget                  5150 non-null float64
revenue                 4843 non-null float64
original_title          10703 non-null object
cast                    10703 non-null object
director                10703 non-null object
keywords                9293 non-null object
runtime                 10703 non-null int64
genres                  10703 non-null object
production_companies    9759 non-null object
release_date            10703 non-null object
vote_count              10703 non-null int64
vote_average            10703 non-null float64
release_year            10703 non-null int64
dtypes: float64(4), int64(4), object(7)
```

```
memory usage: 1.3+ MB
```

In [345]:
```python
# check number of unique values
df.nunique()
```

Out[345]:
```
id                      10703
popularity              10657
budget                    551
revenue                  4697
original_title          10412
cast                    10638
director                 5001
keywords                 8740
runtime                   242
genres                   2019
production_companies     7398
release_date             5869
vote_count               1289
vote_average               70
release_year               56
dtype: int64
```

In [346]:
```python
# column, row information after cleaning data
df.shape
```

Out[346]:
```
(10703, 15)
```

In [347]:
```python
# Descriptive Statistics information after cleaning data
df.describe()
```

Out[347]:
```
                  id    popularity        budget       revenue       runtime  \
count   10703.000000  10703.000000  5.150000e+03  4.843000e+03  10703.000000
mean    64904.988321      0.653818  3.084401e+07  8.933981e+07    102.736896
std     91161.996308      1.005687  3.893782e+07  1.621546e+08     30.079331
min         5.000000      0.000188  1.000000e+00  2.000000e+00      3.000000
25%     10538.500000      0.211533  6.000000e+06  7.779664e+06     90.000000
50%     20235.000000      0.388036  1.750000e+07  3.191160e+07     99.000000
75%     73637.000000      0.722438  4.000000e+07  1.000000e+08    112.000000
max    417859.000000     32.985763  4.250000e+08  2.781506e+09    900.000000

         vote_count  vote_average  release_year
count  10703.000000  10703.000000  10703.000000
mean     220.333178      5.966112   2001.235355
std      579.481969      0.930155     12.825920
min       10.000000      1.500000   1960.000000
25%       17.000000      5.400000   1995.000000
50%       39.000000      6.000000   2006.000000
75%      149.000000      6.600000   2011.000000
max     9767.000000      9.200000   2015.000000
```

From table above shows the final statistics data info after transfer all zero values to null values in `budget` and `revenue` data. Now budget and revenue colums have some value without zero values accumulation. After deleting the zero values from runtime, the minimum value of runtime looks better. Budget and revenue columns minimum values are 1.0 dollar. This looks suspicious. When i lokeed into the data, i noticed small number of data has budget values ranging from 1 dollar to 100 dollar. Because of small quantity, i leave as it is.

## Exploratory Data Analysis

#### 1.1.7 Research Part 1: General Exploration

Analysis 1: Budget/Revenue Trend over the Period of Time
Analysis 2: Popularity Trend over the Period of Time
Analysis 3: Average Vote Trend over the Period of Time
Analysis 4: Number of Movies Released Over the Time
Analysis 5: Runtime Distribution of Movies
### Research Part 2a (Quantitative Analyses): Properties associated with High Revenue Movies
Research Question 1 (Which Revenue Level receives the highest popularity?)
Research Question 2 (Which Budget Level Receives the Highest Popularity?)
Research Question 3 (Which Runtime Level Receives the Highest Popularity?
Research Question 4 (Which Runtime Level Receives the Highest Avergae Voting?
### Research Part 2b (Categorical Analyses): Properties associated with High Revenue Movies
Research Question 1 (Which Movies are Top 10 highest popularity?)
Research Question 2: (What kind of Genres are top in High Revenue movies?)
Research Question3: (Which Production Companies are top in Best Revenue movies?)
Research Question 4: (Which Actors are top in Best Revenue movies?)
Research Question 5: (Which directors are top in Best Revenue movies?)
Research Question 6: (Which keywords are top in Best Revenue movies?)ű
Research Question 7: (Which Genres are top during 60s and 2Ks Best Revenue movies?)ű
Research Question 8: (Which Keywords are top during 60s and 2Ks Best Revenue movies?)ű

### 1.2 Research Part 1: General Exploration

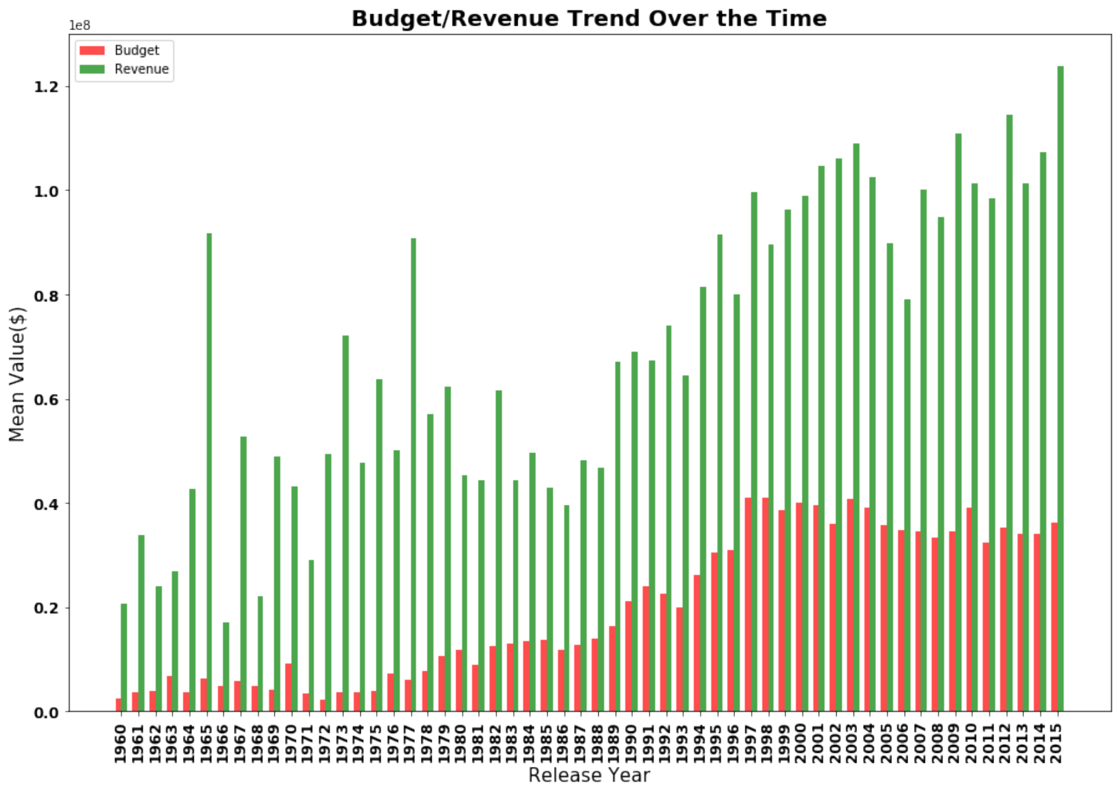
In this part, the general trend of various attributes over the period of time were analysed.

#### 1.2.1 Analysis 1: Budget/Revenue Trend over the Period of Time

Below plot shows the mean Budget and Revenue price trend over the periof of time. Budget increased over the period of time. Particularly from 1995 onwards, budget of the movie were increased double. Similarly revenue also increased over the period of time.

```
In [348]: # plotting parameters
          rc_fonts = {'figure.figsize': (15, 10)}
          matplotlib.rcParams.update(rc_fonts)
          plt.tick_params(labelsize=10)
```

```
plt.xticks(rotation=90,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')

# the width of the bars
width = 0.35

# plot bars
df_budget = df.groupby(['release_year']).mean().budget
df_revenue = df.groupby(['release_year']).mean().revenue
df_release_year = df['release_year'].unique()
df_release_year.sort()
ind = np.arange(len(df_budget))
budget_bars = plt.bar(ind, df_budget, width, color='r', alpha=.7, label='Budget')
revenue_bars = plt.bar(ind + width, df_revenue, width, color='g', alpha=.7, label='Rev

# title and labels
plt.ylabel('Mean Value($)',fontsize=15)
plt.xlabel('Release Year',fontsize=15)
plt.title('Budget/Revenue Trend Over the Time',fontsize=18,weight='bold')
locations = ind + width / 2  # xtick locations
labels = df_release_year  # xtick labels
plt.xticks(locations,labels)
plt.legend(loc='upper left')


# legend
plt.show()
```

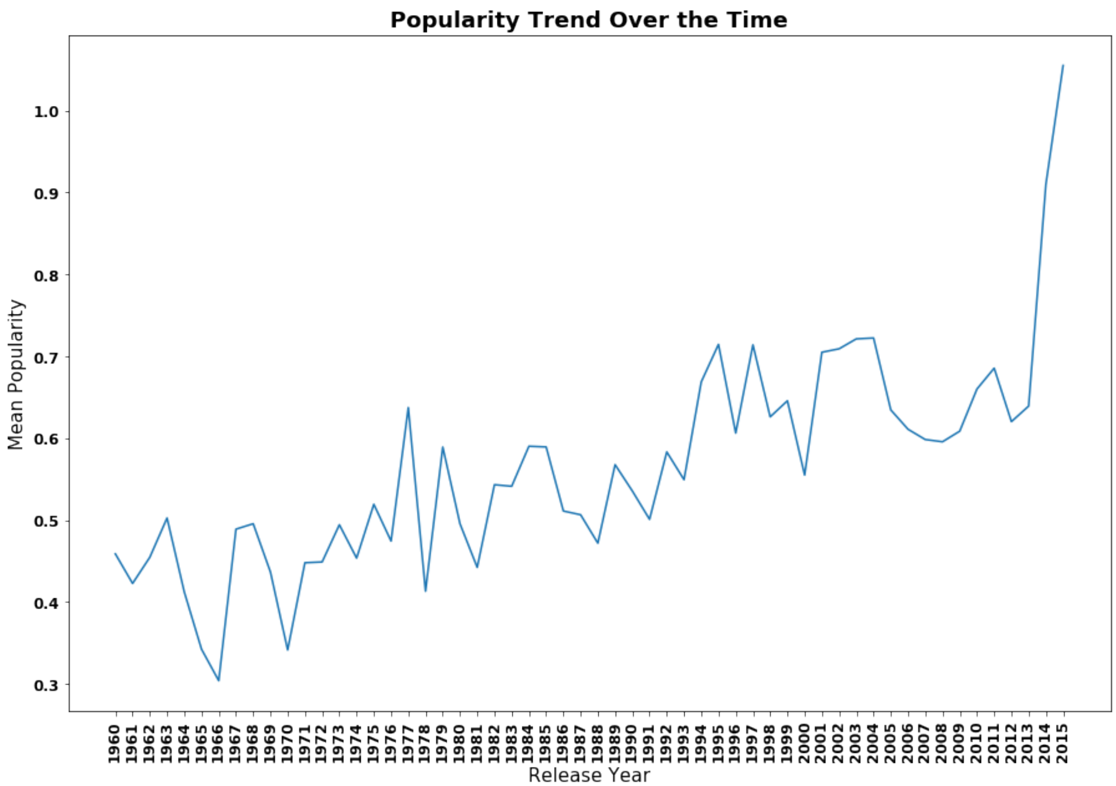



### Analysis 2: Popularity Trend over the Period of Time

The mean popularity trend over the period of time plot is shown below. The popularity score does not have upper limit, hence the mean value is affected by outlier which is reflected in 2015. Overall the mean popularity increases slowly with time. It is due to number of people watching movies and voting from various sources increased over the period of time.

In [349]:
```
# plotting parameters
rc_fonts = {'figure.figsize': (15, 10)}
matplotlib.rcParams.update(rc_fonts)
plt.tick_params(labelsize=10)
plt.xticks(rotation=90)
x = np.array([0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,2
my_xticks= df['release_year'].unique()
my_xticks.sort()
y = df.groupby(['release_year']).mean().popularity

plt.xticks(x, my_xticks,fontsize = 12, weight='bold')
plt.title('Popularity Trend Over the Time',fontsize =18,weight='bold')
plt.ylabel('Mean Popularity',fontsize=15)
plt.xlabel('Release Year',fontsize=15)
plt.xticks(rotation=90,fontsize=12,weight='bold')
```

```
plt.yticks(fontsize=12,weight='bold')


plt.plot(x, y);
```

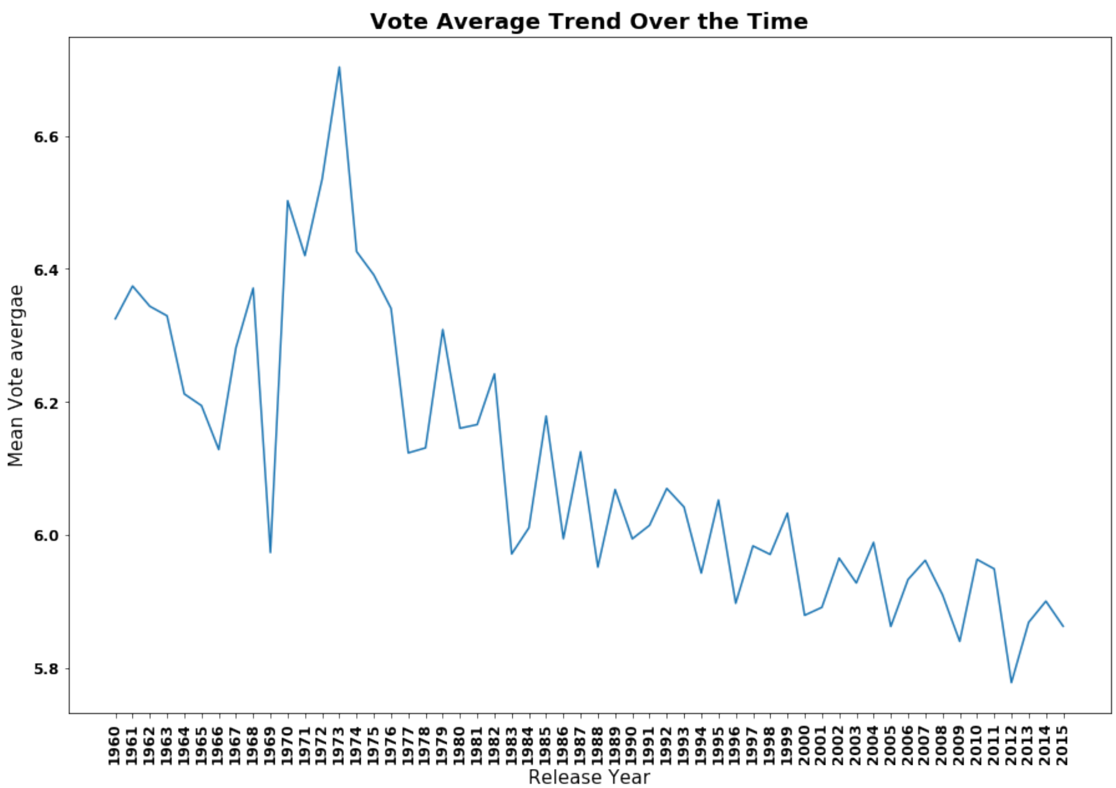



### Analysis 3: Average Vote Trend over the Period of Time

Surprisingly the average vote trend is decreasing slowly over the period of time. AS per IMDb, the vote average is the weighted average and not raw vote average. Various filters are applied to the raw data in order to eliminate and reduce attempts at vote stuffing by people more interested in changing the current rating of a movie than giving their true opinion of it. The Reason for the decreasing trend may be due to applying strict filter to the vote average over the period of time inorder to get accurate average vote

```
In [350]: #  plotting parameters
          rc_fonts = {'figure.figsize': (15, 10)}
          matplotlib.rcParams.update(rc_fonts)
          plt.tick_params(labelsize=10)
          plt.xticks(rotation=90)
          x = np.array([0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,2
          my_xticks= df['release_year'].unique()
          my_xticks.sort()
```

```
plt.xticks(rotation=90,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')


y = df.groupby(['release_year']).mean().vote_average

plt.xticks(x, my_xticks,fontsize = 12, weight='bold')
plt.title('Vote Average Trend Over the Time',fontsize=18,weight='bold')
plt.ylabel('Mean Vote avergae',fontsize = 15)
plt.xlabel('Release Year',fontsize=15)

plt.plot(x, y);
```

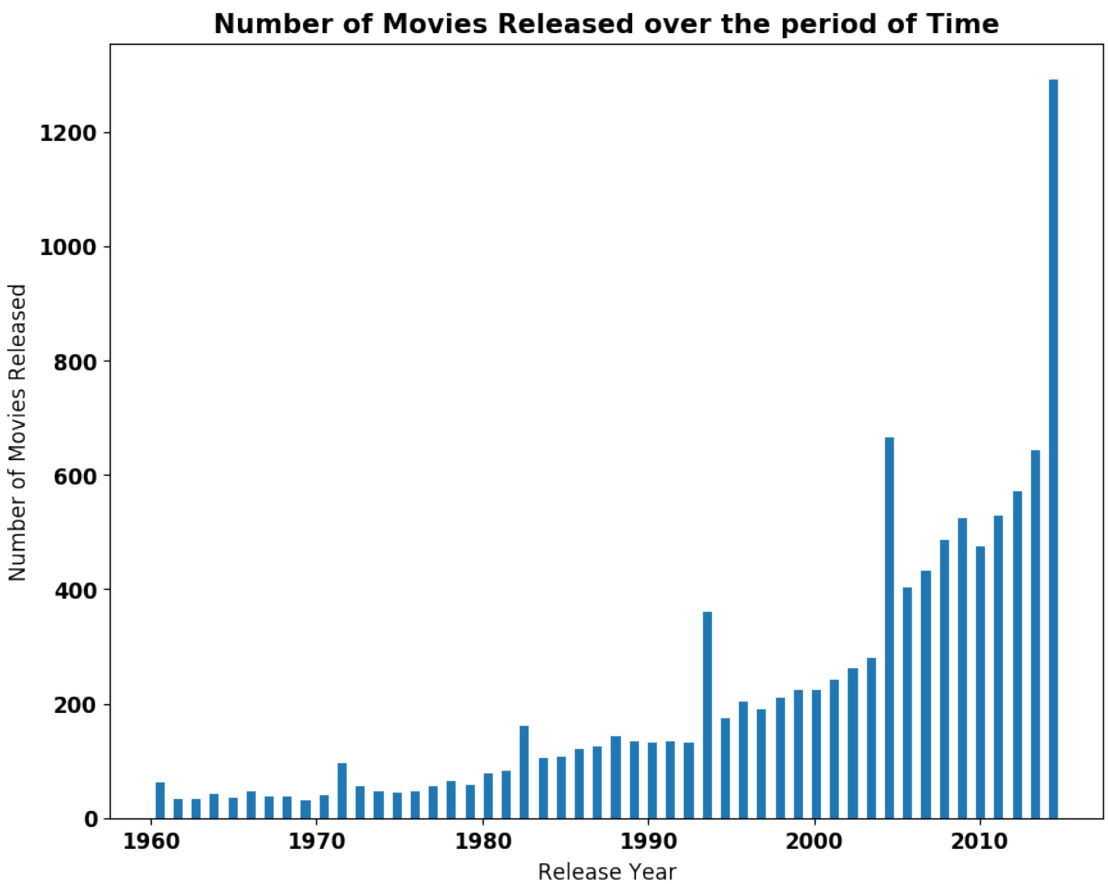



### Analysis 4: Number of Movies Released Over the Time

Below plot indicates the drastic increase in number of movies released over the period of time. During economic downtime, the number of movies released were less and it is reflected in the chart. After 2005, the number of movies released were so high compared to 60s to 90s.This may be due to growth in economy and increase in number of people watching movies through different platforms all over the world.

```
In [351]: #plotting a histogram of runtime of movies
          rc_fonts = {'figure.figsize': (15, 10)}
```

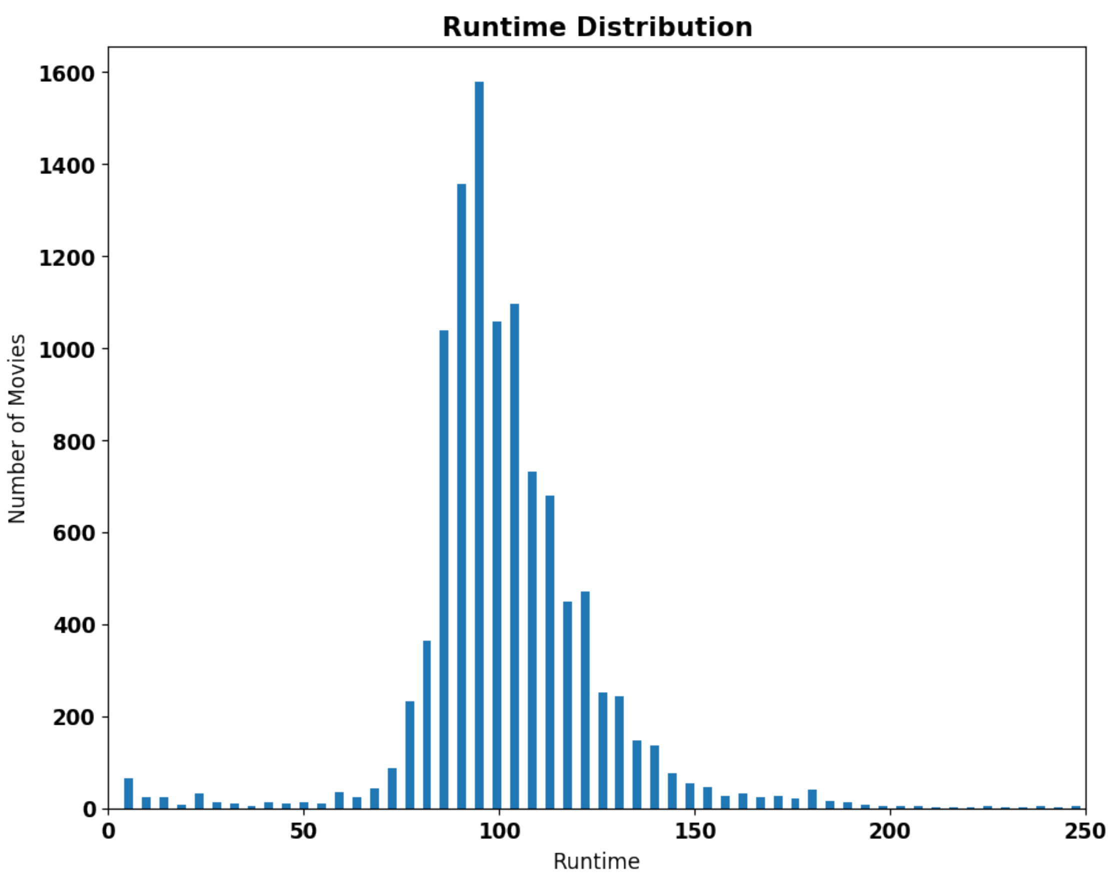
```
#giving the figure size(width, height)
plt.figure(figsize=(10,8), dpi = 100)
#x-axis label name
plt.xlabel('Release Year', fontsize = 12)
#y-axis label name
plt.ylabel('Number of Movies Released', fontsize=12)
#title of the graph
plt.title('Number of Movies Released over the period of Time', fontsize=15, weight='bo

plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')


#giving a histogram plot
plt.hist(df['release_year'], rwidth = 0.5, bins =50)
#displays the plot
plt.show()
```




### Analysis 5: Runtime Distribution of Movies

Below plot shows the bell curve distribution for the runtime. Statistical correlations for runtime are tabulated below. The mean runtime is 103 min which is shown in the plot. Maximum number of movies are produced with mean runtime of 103 min.

```
In [352]: #plotting a histogram of runtime of movies
          rc_fonts = {'figure.figsize': (15, 10)}
          #giving the figure size(width, height)
          plt.figure(figsize=(10,8), dpi = 100)
          #x-axis label name
          plt.xlabel('Runtime', fontsize = 12)
          #y-axis label name
          plt.ylabel('Number of Movies', fontsize=12)
          #title of the graph
          plt.title('Runtime Distribution', fontsize=15, weight='bold')
          plt.xticks(rotation=0,fontsize=12,weight='bold')
          plt.yticks(fontsize=12,weight='bold')
          plt.xlim(0,250)

          #giving a histogram plot
          plt.hist(df['runtime'], rwidth = 0.5, bins =200)
          #displays the plot
          plt.show()
          # descriptive statistical information for runtime
          df['runtime'].describe()
```



```
Out[352]: count    10703.000000
          mean       102.736896
          std         30.079331
          min          3.000000
          25%         90.000000
          50%         99.000000
          75%        112.000000
          max        900.000000
          Name: runtime, dtype: float64
```

## Research Part 2a (Quantitative Analyses): Properties associated with High Revenue Movies

IN order to find the associated properties for high revenue movies, two things need to be considered. One is quantitative analyses and other one is categorical analyses. In quantitative analyses, BUdget and runtime key factors are considered for the quantification of popularity and vote average for the successful movies.

NOw we will see how BUdget and runtime key factors are associated with successful movies.

### Research Question 1 (Which Revenue Level receives the highest popularity?)

In order to determine the differnt revenue levels to categorize, pandas describe function is used to get the statistical properties. min, 25%, 50%, 75%, max revenue values were shown below.

The revenue levers were categorized based on min,25%,50%,75% and max revenue value.

Below chart shows the mean popularity for different Revenue levels. HIgh revenue movies are in high popularity level compared to low reveue movies.

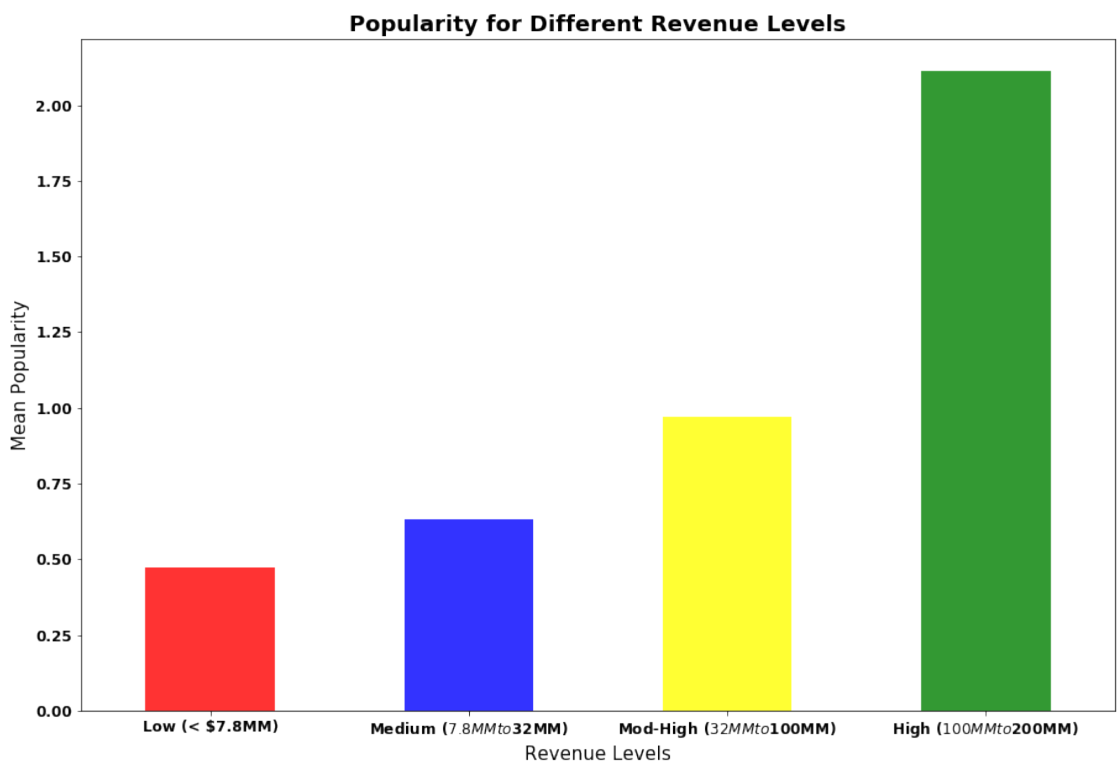
```
In [353]: # View the min, 25%, 50%, 75%, max revenue values with Pandas describe
          df.describe().revenue
```

```
Out[353]: count    4.843000e+03
          mean     8.933981e+07
          std      1.621546e+08
          min      2.000000e+00
          25%      7.779664e+06
          50%      3.191160e+07
          75%      1.000000e+08
          max      2.781506e+09
          Name: revenue, dtype: float64
```

```
In [354]: df.median().revenue
```

Out[354]: 31911598.0

In [355]:
```
# plotting parameters
rc_fonts = {'figure.figsize': (15, 10)}
# Bin edges that will be used to "cut" the data into groups
bin_edges = [2.00, 7.8e+06, 3.2e+07, 1.0e+08, 2.8e+09]

# Labels for the four revenue level groups
bin_names = ['Low (< $7.8MM)', 'Medium ($7.8MM to $32MM)', 'Mod-High ($32MM to $100MM)

# Creates arevenue_levels column
df['Revenue_Levels'] = pd.cut(df['revenue'], bin_edges, labels=bin_names)


#plotting
colors=('red','blue', 'yellow', 'green')
x= df.groupby('Revenue_Levels').mean().popularity
x.plot(kind = 'bar',alpha=0.8,color=colors)
plt.xlabel('Revenue Levels', fontsize=15)
plt.ylabel('Mean Popularity',fontsize=15)
plt.title('Popularity for Different Revenue Levels',fontsize = 18,weight='bold')
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.show()
```



### Research Question 2 (Which Budget Level Receives the Highest Popularity?)

In order to determine the differnt budget levels to categorize, pandas describe function is used to get the statistical properties. min, 25%, 50%, 75%, max budget values were shown below.

The budget levels were categorized based on min,25%,50%,75% and max budget value.

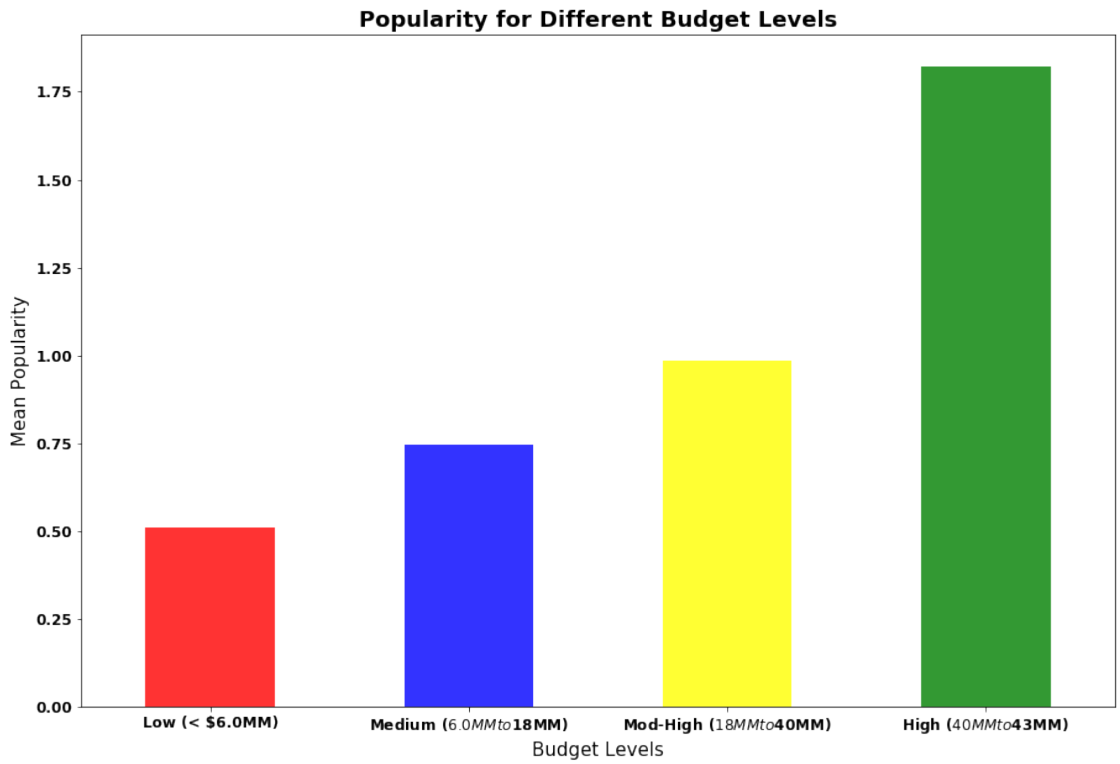
Below chart shows the mean popularity for different budget levels. As in the case of Revenue case, here also, the HIgh budget movies are in high popularity level compared to low budget movies.

In [356]:
```
# View the min, 25%, 50%, 75%, max budget values with Pandas describe
df.describe().budget
```

Out[356]:
```
count    5.150000e+03
mean     3.084401e+07
std      3.893782e+07
min      1.000000e+00
25%      6.000000e+06
50%      1.750000e+07
75%      4.000000e+07
max      4.250000e+08
Name: budget, dtype: float64
```

In [357]:
```
rc_fonts = {'figure.figsize': (15, 10)}



# Bin edges that will be used to "cut" the data into groups
bin_edges = [1.00, 6.0e+06, 1.8e+07, 4.0e+07, 4.3e+08]

# Labels for the four budget level groups
bin_names = ['Low (< $6.0MM)', 'Medium ($6.0MM to $18MM)', 'Mod-High ($18MM to $40MM)'

# Creates budget column
df['Budget_Levels'] = pd.cut(df['budget'], bin_edges, labels=bin_names)

#plotting
colors=('red','blue', 'yellow', 'green')
x= df.groupby('Budget_Levels').mean().popularity
x.plot(kind='bar',alpha=0.8,color = colors)
plt.xlabel('Budget Levels', fontsize=15)
plt.ylabel('Mean Popularity',fontsize=15)
plt.title('Popularity for Different Budget Levels',fontsize = 18,weight='bold')
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')
```

```
plt.xticks(rotation=0,weight='bold')
plt.show()
```




### Research Question 3 (Which Runtime Level Receives the Highest Popularity?

In order to determine the differnt runtime levels to categorize, pandas describe function is used to get the statistical properties. min, 25%, 50%, 75%, max runtime values were shown below.

The runtime levels were categorized based on min,25%,50%,75% and max runtime value.

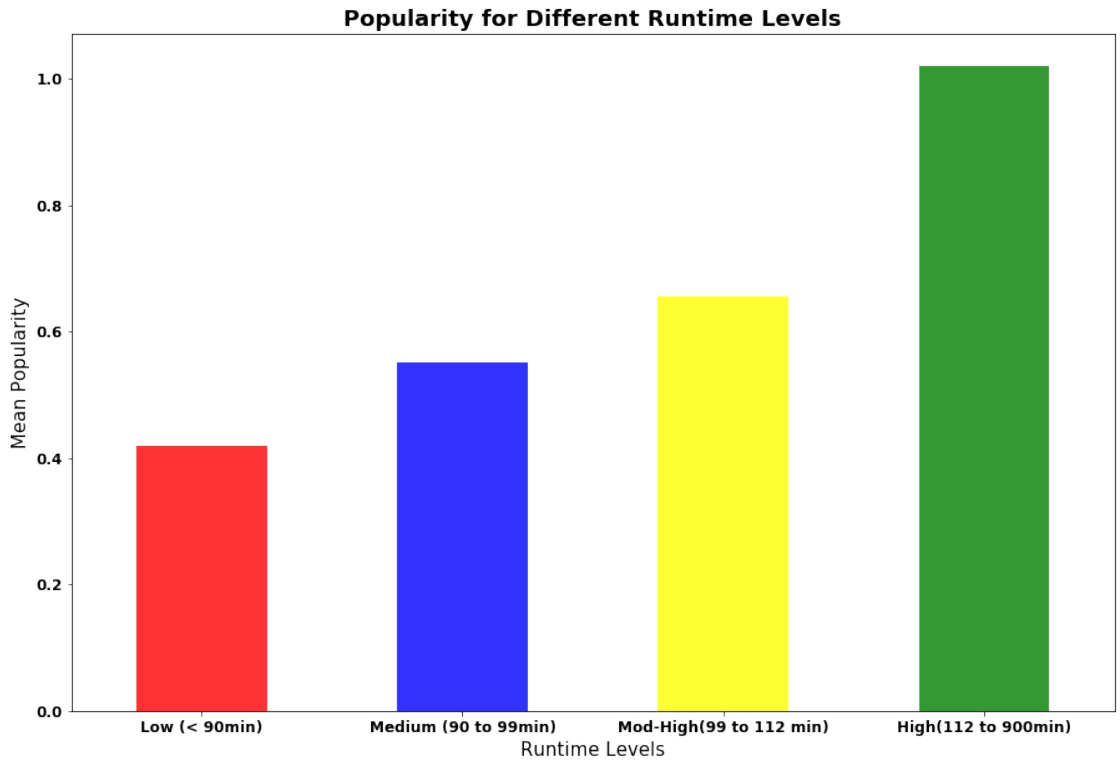
Below chart shows the mean popularity for different runtime levels. As in the case of Revenue, budget cases, here also, the HIgh runtime movies are in high popularity level compared to low runtime movies.

In [358]:
```
# View the min, 25%, 50%, 75%, max runtime values with Pandas describe
df.describe().runtime
```

Out[358]:
```
count    10703.000000
mean       102.736896
std         30.079331
min          3.000000
25%         90.000000
```

```
50%          99.000000
75%         112.000000
max         900.000000
Name: runtime, dtype: float64
```

In [359]:
```
rc_fonts = {'figure.figsize': (15, 10)}

# Bin edges that will be used to "cut" the data into groups
bin_edges = [3.0, 90.0, 99.0, 112, 900.0]

# Labels for the four runtime level groups
bin_names = ['Low (< 90min)', 'Medium (90 to 99min)', 'Mod-High(99 to 112 min)', 'High

# Creates runtime_levels column
df['Runtime_Levels'] = pd.cut(df['runtime'], bin_edges, labels=bin_names)

# plotting
colors=('red','blue', 'yellow', 'green')
x= df.groupby('Runtime_Levels').mean().popularity
x.plot(kind='bar',alpha=0.8,color=colors)
plt.xlabel('Runtime Levels', fontsize=15)
plt.ylabel('Mean Popularity',fontsize=15)
plt.title('Popularity for Different Runtime Levels',fontsize = 18,weight='bold')
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')
plt.xticks(rotation=0,weight='bold')
plt.show()
```



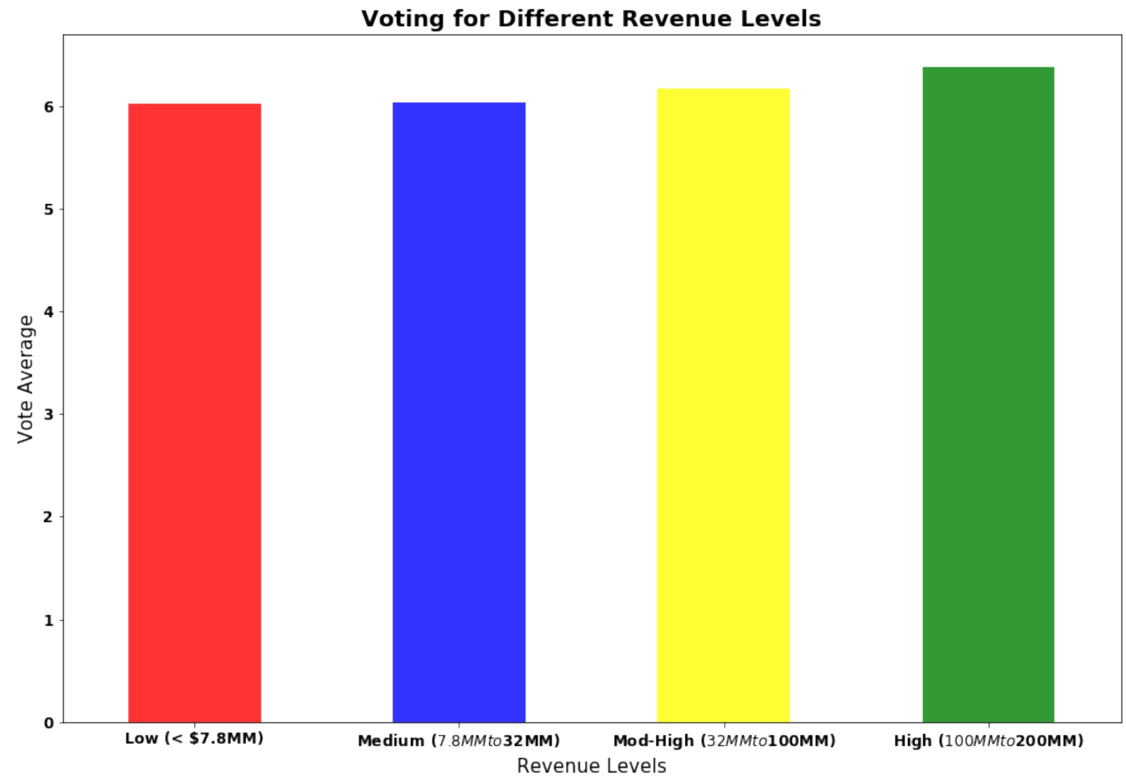

### Research Question 4 (Which Revenue Level Receives the Highest Avergae Voting?

In order to determine the differnt revenue levels to categorize, pandas describe function is used to get the statistical properties. min, 25%, 50%, 75%, max revenue values were shown below.

The revenue levels were categorized based on min,25%,50%,75% and max revenue value.

Below chart shows the mean vote average for different Revenue levels. Surprisingly, all revenue levels are in same vote average. As we discussed earlier, this may be due to implication of strict filter in the voting avergae calculation system over the period of time.

In [360]:
```
# plotting
colors=('red','blue', 'yellow', 'green')
data= df.groupby('Revenue_Levels').mean().vote_average
data.plot(kind='bar',alpha=0.8,color = colors)
plt.xlabel('Revenue Levels', fontsize=15)
plt.ylabel('Vote Average',fontsize=15)
plt.title('Voting for Different Revenue Levels',fontsize=18,weight='bold')
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')
plt.xticks(rotation=0)
plt.show()
```

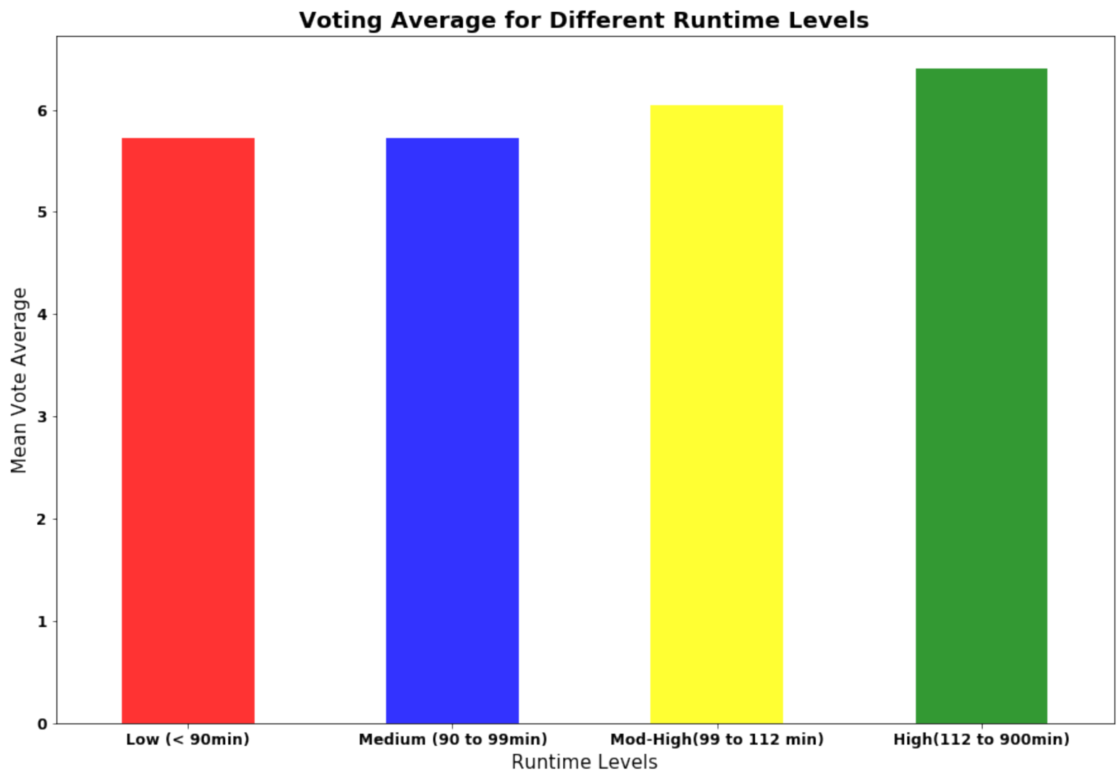



Based on the above analyses, the popular movies are largely associated with high BUd-get movies and the runtime of movies.

### Research Question 4 (Which Runtime Level Receives the Highest Avergae Voting?

```
In [361]: rc_fonts = {'figure.figsize': (15, 10)}

          # Bin edges that will be used to "cut" the data into groups
          bin_edges = [3.0, 90.0, 99.0, 112, 900.0]

          # Labels for the four runtime level groups
          bin_names = ['Low (< 90min)', 'Medium (90 to 99min)', 'Mod-High(99 to 112 min)', 'High

          # Creates runtime_levels column
          df['Runtime_Levels'] = pd.cut(df['runtime'], bin_edges, labels=bin_names)

          # plotting
          colors=('red','blue', 'yellow', 'green')
          x= df.groupby('Runtime_Levels').mean().vote_average
          x.plot(kind='bar',alpha=0.8,color = colors)
          plt.xlabel('Runtime Levels', fontsize=15)
          plt.ylabel('Mean Vote Average',fontsize=15)
          plt.title('Voting Average for Different Runtime Levels',fontsize = 18,weight='bold')
```

```
plt.xticks(rotation=0,fontsize=12,weight='bold')
plt.yticks(fontsize=12,weight='bold')
plt.xticks(rotation=0,weight='bold')
plt.show()
```




The above chart shows voting average for different runtime levels. HIgh runtime has high voting average compared to low runtime movies

```
In [362]: # adding year levels
          # Bin edges that will be used to "cut" the data into groups
          bin_edges = [1960, 1970, 1980, 1990, 2000, 2015]

          # Labels for the four budget level groups
          bin_names = ['60s', '70s', '80s', '90s','2Ks']

          # Creates runtime_levels column
          df['Year_Levels'] = pd.cut(df['release_year'], bin_edges, labels=bin_names)
```

## Research Part 2b (Categorical Analyses): Properties associated with High Revenue Movies

IN this part, we will analyse catregorical keyfactors associated with high revenue movies. The categorical analyses include cast,director, genres, keywords and producer for the successful movies.

NOw we will see how these categorical key factors are associated with successful movies.

### Research Question 1 (Which Movies are Top 10 highest popularity?)

**Collection of Best Movies Dataset**

IN order to find top movies with highest revenue, i decided to extract data having revenue greater than or equal to 90 Million dollar. The reason for that number is from earlier analyses, the high revenue levels are associated with high popularity. Hence i decided to sort out data based on high level (ie > 90 million dollar). Then the dataframe was sorted out based on high popularity

In [363]:
```
# extracting data with revenue >= $90M
profit_movie_data = df[df['revenue'] >= 90000000]

#reindexing new dataframe
profit_movie_data.index = range(len(profit_movie_data))

#initialize dataframe from 1 instead of 0
profit_movie_data.index = profit_movie_data.index + 1
best_movies= profit_movie_data.sort_values(by='popularity', ascending=False)
#print(type(best_movies))
best_movies.head(10)
```

Out[363]:
```
         id  popularity       budget       revenue  \
1    135397   32.985763  150000000.0  1.513529e+09
2     76341   28.419936  150000000.0  3.784364e+08
64   157336   24.949134  165000000.0  6.217525e+08
65   118340   14.311205  170000000.0  7.733124e+08
3    262500   13.112507  110000000.0  2.952382e+08
66   100402   12.971027  170000000.0  7.147666e+08
133      11   12.037933   11000000.0  7.753980e+08
4    140607   11.173104  200000000.0  2.068178e+09
67   131631   10.739009  125000000.0  7.521002e+08
68   122917   10.174599  250000000.0  9.551198e+08

                                original_title  \
1                               Jurassic World
2                           Mad Max: Fury Road
64                                Interstellar
65                     Guardians of the Galaxy
3                                    Insurgent
66         Captain America: The Winter Soldier
133                                  Star Wars
4                 Star Wars: The Force Awakens
67        The Hunger Games: Mockingjay - Part 1
68   The Hobbit: The Battle of the Five Armies
```

```
                                                  cast  \
1    Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
2    Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
64   Matthew McConaughey|Jessica Chastain|Anne Hath...
65   Chris Pratt|Zoe Saldana|Dave Bautista|Vin Dies...
3    Shailene Woodley|Theo James|Kate Winslet|Ansel...
66   Chris Evans|Scarlett Johansson|Sebastian Stan|...
133  Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...
4    Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
67   Jennifer Lawrence|Josh Hutcherson|Liam Hemswor...
68   Martin Freeman|Ian McKellen|Richard Armitage|K...

                    director  \
1            Colin Trevorrow
2              George Miller
64         Christopher Nolan
65                James Gunn
3           Robert Schwentke
66   Joe Russo|Anthony Russo
133             George Lucas
4               J.J. Abrams
67          Francis Lawrence
68             Peter Jackson

                                              keywords  runtime  \
1    monster|dna|tyrannosaurus rex|velociraptor|island      124
2     future|chase|post-apocalyptic|dystopia|australia      120
64   saving the world|artificial intelligence|fathe...      169
65   marvel comic|spaceship|space|scene during end ...      121
3    based on novel|revolution|dystopia|sequel|dyst...      119
66    washington d.c.|future|shield|marvel comic|comic      136
133       android|galaxy|hermit|death star|lightsaber      121
4               android|spaceship|jedi|space opera|3d      136
67     resistance|post-apocalyptic|dystopia|war|sequel      123
68   corruption|elves|dwarves|orcs|middle-earth (to...      144

                                        genres  \
1    Action|Adventure|Science Fiction|Thriller
2    Action|Adventure|Science Fiction|Thriller
64            Adventure|Drama|Science Fiction
65           Action|Science Fiction|Adventure
3          Adventure|Science Fiction|Thriller
66           Action|Adventure|Science Fiction
133          Adventure|Action|Science Fiction
4     Action|Adventure|Science Fiction|Fantasy
67         Science Fiction|Adventure|Thriller
68                           Adventure|Fantasy
```

```
                                   production_companies release_date  \
1    Universal Studios|Amblin Entertainment|Legenda...       6/9/15
2    Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15
64   Paramount Pictures|Legendary Pictures|Warner B...      11/5/14
65   Marvel Studios|Moving Picture Company (MPC)|Bu...      7/30/14
3    Summit Entertainment|Mandeville Films|Red Wago...      3/18/15
66                                      Marvel Studios      3/20/14
133   Lucasfilm|Twentieth Century Fox Film Corporation      3/20/77
4           Lucasfilm|Truenorth Productions|Bad Robot     12/15/15
67                                 Lionsgate|Color Force     11/18/14
68   WingNut Films|New Line Cinema|3Foot7|Metro-Gol...     12/10/14

     vote_count  vote_average  release_year           Revenue_Levels  \
1          5562           6.5          2015  High ($100MM to $200MM)
2          6185           7.1          2015  High ($100MM to $200MM)
64         6498           8.0          2014  High ($100MM to $200MM)
65         5612           7.9          2014  High ($100MM to $200MM)
3          2480           6.3          2015  High ($100MM to $200MM)
66         3848           7.6          2014  High ($100MM to $200MM)
133        4428           7.9          1977  High ($100MM to $200MM)
4          5292           7.5          2015  High ($100MM to $200MM)
67         3590           6.6          2014  High ($100MM to $200MM)
68         3110           7.1          2014  High ($100MM to $200MM)

                Budget_Levels       Runtime_Levels Year_Levels
1       High ($40MM to $43MM)  High(112 to 900min)         2Ks
2       High ($40MM to $43MM)  High(112 to 900min)         2Ks
64      High ($40MM to $43MM)  High(112 to 900min)         2Ks
65      High ($40MM to $43MM)  High(112 to 900min)         2Ks
3       High ($40MM to $43MM)  High(112 to 900min)         2Ks
66      High ($40MM to $43MM)  High(112 to 900min)         2Ks
133  Medium ($6.0MM to $18MM)  High(112 to 900min)         70s
4       High ($40MM to $43MM)  High(112 to 900min)         2Ks
67      High ($40MM to $43MM)  High(112 to 900min)         2Ks
68      High ($40MM to $43MM)  High(112 to 900min)         2Ks
```

The above table shows top 10 movies dataset with revenue greater than or equal to 90 million dollar and high popularity. We will do more analyses based on this extracted dataset

### 1.2.2 Collection of Worst Movies Dataset

IN order to find worst movies with low revenue, i decided to extract data having revenue less than or equal to 7.8 Million dollar. The reason for that number is from earlier analyses, the low revenue levels are associated with low popularity. Hence i decided to sort out data based on low level (ie > 7.8 million dollar).Then the dataframe was sorted out based on low popularity

In [364]:
```python
# extracting data with revenue <= $7.8M
worst_profit_movie_data = df[df['revenue'] <= 7800000]

#reindexing new dataframe
worst_profit_movie_data.index = range(len(worst_profit_movie_data))
#initialize dataframe from 1 instead of 0
worst_profit_movie_data.index = worst_profit_movie_data.index + 1
worst_movies= worst_profit_movie_data.sort_values(by='popularity', ascending=True)

worst_movies.head(10)
```

Out[364]:
```
          id  popularity      budget    revenue  \
859     1392    0.001117    350000.0  3515061.0
594   124067    0.001783         NaN   273747.0
393    33295    0.005391         NaN   887029.0
731   173455    0.006115         NaN   137460.0
858     1843    0.006346         NaN   127067.0
913    15651    0.006681         NaN   312751.0
730   193524    0.015722         NaN   729043.0
1011   36047    0.015997  15000000.0  5217498.0
74    339928    0.017625         NaN   732655.0
496    29047    0.017708     40000.0  1434436.0

                     original_title  \
859              Born into Brothels
594           The Central Park Five
393                More Than a Game
731           Mistaken for Strangers
858                            DiG!
913       For the Bible Tells Me So
730   The Stone Roses: Made of Stone
1011                    The In Crowd
74              Once I Was a Beehive
496     The Kid Stays in the Picture

                                                   cast  \
859           Zana Briski|Avijit|Geeta Masi|Kochi|Mamuni
594   Antron McCray|Kevin Richardson|Yusef Salaam|Ra...
393   LeBron James|Romeo Travis|Sian Cotton|Willie M...
731   Matt Berninger|Tom Berninger|Aaron Dessner|Bry...
858   The Dandy Warhols|The Brian Jonestown Massacre...
913   Imogene Robinson|Victor Robinson|Gene Robinson...
730   Ian Brown|Gary 'Mani' Mounfield|John Squire|Al...
1011  Susan Ward|Lori Heuring|Matthew Settle|Nathan ...
74    Paris Warner|Lisa Clark|Hailey Smith|Clare Nie...
496   Robert Evans|Eddie Albert|Francis Ford Coppola...

                       director  \
```

```
859       Zana Briski|Ross Kauffman
594           Sarah Burns|Ken Burns
393               Kristopher Belman
731                   Tom Berninger
858                    Ondi Timoner
913             Daniel G. Karslake 
730                   Shane Meadows
1011                   Mary Lambert
74                   Maclain Nelson
496   Nanette Burstein|Brett Morgen

                                               keywords  runtime  \
859   prostitute|red-light disctrict|human trafficki...       85   
594   prison|police|rapist|wrongful arrest|serial ra...      119   
393   sport|high school|basketball|high school baske...      105   
731                                                 NaN       75   
858                   bus|junkie|heroin|career|musical      107   
913              bible|homosexuality|lesbian|religion       98   
730                                                 NaN       96   
1011                                    woman director      105   
74                                                  NaN      119   
496   cocaine|arranged marriage|love|hollywood|woman...       93   

                   genres                               production_companies  \
859           Documentary                                                NaN   
594           Documentary                           Florentine Films|WETA   
393    Documentary|Family                              Harvey Mason Media   
731     Documentary|Music                                   Final Frame|C5   
858     Documentary|Music                                                NaN   
913           Documentary                                                NaN   
730           Documentary                                                NaN   
1011             Thriller                            Warner Bros. Pictures   
74    Comedy|Drama|Family                   Escapology|Main Dog Productions   
496           Documentary  Ministry of Propaganda Films|Woodland Pictures...   

     release_date  vote_count  vote_average  release_year  Revenue_Levels  \
859        12/8/04          23           6.4          2004  Low (< $7.8MM)   
594        5/24/12          22           6.4          2012  Low (< $7.8MM)   
393         9/6/08          10           6.4          2008  Low (< $7.8MM)   
731        9/19/13          14           7.4          2013  Low (< $7.8MM)   
858        5/14/04          12           6.8          2004  Low (< $7.8MM)   
913        10/5/07          10           6.1          2007  Low (< $7.8MM)   
730        5/28/13          10           6.0          2013  Low (< $7.8MM)   
1011       7/19/00          12           5.2          2000  Low (< $7.8MM)   
74         8/14/15          10           6.5          2015  Low (< $7.8MM)   
496        1/18/02          10           7.4          2002  Low (< $7.8MM)   

                 Budget_Levels           Runtime_Levels Year_Levels  
```

```
859                Low (< $6.0MM)            Low (< 90min)         2Ks
594                           NaN       High(112 to 900min)         2Ks
393                           NaN  Mod-High(99 to 112 min)         2Ks
731                           NaN            Low (< 90min)         2Ks
858                           NaN  Mod-High(99 to 112 min)         2Ks
913                           NaN      Medium (90 to 99min)        2Ks
730                           NaN      Medium (90 to 99min)        2Ks
1011  Medium ($6.0MM to $18MM)  Mod-High(99 to 112 min)         90s
74                            NaN       High(112 to 900min)         2Ks
496                Low (< $6.0MM)      Medium (90 to 99min)        2Ks
```

The above table shows 10 movies dataset with low revenue and low popularity. We will do more categorical analyses based on this extracted dataset.

**Top 10 movies with high popularity in High revenue movies**

In [365]:
```python
#showing the top 10 movies original title
#best_movies['original_title'].head(10)
best_movies.iloc[:11,np.r_[1:2,4:8,9:11,13:15]]
```

Out[365]:
```
     popularity                           original_title  \
1     32.985763                           Jurassic World
2     28.419936                         Mad Max: Fury Road
64    24.949134                             Interstellar
65    14.311205                  Guardians of the Galaxy
3     13.112507                                Insurgent
66    12.971027       Captain America: The Winter Soldier
133   12.037933                                Star Wars
4     11.173104             Star Wars: The Force Awakens
67    10.739009      The Hunger Games: Mockingjay - Part 1
68    10.174599  The Hobbit: The Battle of the Five Armies
139    9.432768                                   Avatar

                                                  cast  \
1    Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
2    Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
64   Matthew McConaughey|Jessica Chastain|Anne Hath...
65   Chris Pratt|Zoe Saldana|Dave Bautista|Vin Dies...
3    Shailene Woodley|Theo James|Kate Winslet|Ansel...
66   Chris Evans|Scarlett Johansson|Sebastian Stan|...
133  Mark Hamill|Harrison Ford|Carrie Fisher|Peter ...
4    Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
67   Jennifer Lawrence|Josh Hutcherson|Liam Hemswor...
68   Martin Freeman|Ian McKellen|Richard Armitage|K...
139  Sam Worthington|Zoe Saldana|Sigourney Weaver|S...

               director  \
1       Colin Trevorrow
```

```
2             George Miller
64        Christopher Nolan
65               James Gunn
3          Robert Schwentke
66   Joe Russo|Anthony Russo
133            George Lucas
4               J.J. Abrams
67         Francis Lawrence
68            Peter Jackson
139           James Cameron

                                                keywords  \
1    monster|dna|tyrannosaurus rex|velociraptor|island
2     future|chase|post-apocalyptic|dystopia|australia
64   saving the world|artificial intelligence|fathe...
65   marvel comic|spaceship|space|scene during end ...
3    based on novel|revolution|dystopia|sequel|dyst...
66    washington d.c.|future|shield|marvel comic|comic
133       android|galaxy|hermit|death star|lightsaber
4              android|spaceship|jedi|space opera|3d
67     resistance|post-apocalyptic|dystopia|war|sequel
68   corruption|elves|dwarves|orcs|middle-earth (to...
139  culture clash|future|space war|space colony|so...

                                        genres  \
1    Action|Adventure|Science Fiction|Thriller
2    Action|Adventure|Science Fiction|Thriller
64             Adventure|Drama|Science Fiction
65            Action|Science Fiction|Adventure
3           Adventure|Science Fiction|Thriller
66            Action|Adventure|Science Fiction
133           Adventure|Action|Science Fiction
4     Action|Adventure|Science Fiction|Fantasy
67          Science Fiction|Adventure|Thriller
68                           Adventure|Fantasy
139   Action|Adventure|Fantasy|Science Fiction

                                  production_companies  vote_average  \
1    Universal Studios|Amblin Entertainment|Legenda...           6.5
2    Village Roadshow Pictures|Kennedy Miller Produ...           7.1
64   Paramount Pictures|Legendary Pictures|Warner B...           8.0
65   Marvel Studios|Moving Picture Company (MPC)|Bu...           7.9
3    Summit Entertainment|Mandeville Films|Red Wago...           6.3
66                                      Marvel Studios           7.6
133   Lucasfilm|Twentieth Century Fox Film Corporation           7.9
4           Lucasfilm|Truenorth Productions|Bad Robot           7.5
67                                 Lionsgate|Color Force           6.6
68   WingNut Films|New Line Cinema|3Foot7|Metro-Gol...           7.1
```

```
139  Ingenious Film Partners|Twentieth Century Fox ...           7.1

     release_year
1            2015
2            2015
64           2014
65           2014
3            2015
66           2014
133          1977
4            2015
67           2014
68           2014
139          2009
```

**Top 10 movies with low popularity in low revenue movies**

In [366]:
```
#showing the top 10 movies wih low revenue
worst_movies.iloc[:11,np.r_[1:2,4:8,9:11,13:15]]
```

Out[366]:
```
      popularity                    original_title  \
859     0.001117              Born into Brothels
594     0.001783             The Central Park Five
393     0.005391                  More Than a Game
731     0.006115            Mistaken for Strangers
858     0.006346                              DiG!
913     0.006681         For the Bible Tells Me So
730     0.015722  The Stone Roses: Made of Stone
1011    0.015997                       The In Crowd
74      0.017625              Once I Was a Beehive
496     0.017708          The Kid Stays in the Picture
954     0.018196                           Top Dog

                                                    cast  \
859          Zana Briski|Avijit|Geeta Masi|Kochi|Mamuni
594   Antron McCray|Kevin Richardson|Yusef Salaam|Ra...
393   LeBron James|Romeo Travis|Sian Cotton|Willie M...
731   Matt Berninger|Tom Berninger|Aaron Dessner|Bry...
858   The Dandy Warhols|The Brian Jonestown Massacre...
913   Imogene Robinson|Victor Robinson|Gene Robinson...
730   Ian Brown|Gary 'Mani' Mounfield|John Squire|Al...
1011  Susan Ward|Lori Heuring|Matthew Settle|Nathan ...
74    Paris Warner|Lisa Clark|Hailey Smith|Clare Nie...
496   Robert Evans|Eddie Albert|Francis Ford Coppola...
954   Chuck Norris|Michele Lamar Richards|Carmine Ca...

                        director  \
859     Zana Briski|Ross Kauffman
```

```
594         Sarah Burns|Ken Burns
393             Kristopher Belman
731                 Tom Berninger
858                  Ondi Timoner
913           Daniel G. Karslake 
730                 Shane Meadows
1011                 Mary Lambert
74                 Maclain Nelson
496   Nanette Burstein|Brett Morgen
954                  Aaron Norris

                                               keywords  \
859   prostitute|red-light disctrict|human trafficki...
594   prison|police|rapist|wrongful arrest|serial ra...
393   sport|high school|basketball|high school baske...
731                                                 NaN
858                     bus|junkie|heroin|career|musical
913                 bible|homosexuality|lesbian|religion
730                                                 NaN
1011                                      woman director
74                                                  NaN
496   cocaine|arranged marriage|love|hollywood|woman...
954                                           police dog

                                       genres  \
859                               Documentary
594                               Documentary
393                        Documentary|Family
731                         Documentary|Music
858                         Documentary|Music
913                               Documentary
730                               Documentary
1011                                 Thriller
74                        Comedy|Drama|Family
496                               Documentary
954   Action|Adventure|Comedy|Family|Thriller

                                   production_companies  vote_average  \
859                                                 NaN           6.4
594                              Florentine Films|WETA           6.4
393                                  Harvey Mason Media           6.4
731                                      Final Frame|C5           7.4
858                                                 NaN           6.8
913                                                 NaN           6.1
730                                                 NaN           6.0
1011                             Warner Bros. Pictures           5.2
74                       Escapology|Main Dog Productions           6.5
496   Ministry of Propaganda Films|Woodland Pictures...           7.4
```

```
954                                               NaN          4.7

      release_year
859           2004
594           2012
393           2008
731           2013
858           2004
913           2007
730           2013
1011          2000
74            2015
496           2002
954           1995
```

Above tables show top 10 movies, director, cast, keywords, genres, production companies,vote average and release year with high/low revenue and high/low popularity. As we can see in the dataset, attributes cast,keywords and production companies have special character '|'. It needs to be splitted. We will see how we can do this

**Splitting String data in dataset**

Splitting string data is done for the dataset with high revenue (i.e > 90 million dollar

Splitting string data is done for the dataset with low revenue (i.e < 7.8 million doallar)

In [367]:
```
#function which will take any column as argument from and keep its track
def data(column):
    #will take a column, and separate the string by '|'
    data = profit_movie_data[column].str.cat(sep = '|')

    #giving pandas series and storing the values separately
    data = pd.Series(data.split('|'))

    #arranging in descending order
    count = data.value_counts(ascending = False)

    return count
```

In [368]:
```
#function which will take any column as argument from and keep its track
def data_worst(column):
    #will take a column, and separate the string by '|'
    data_worst = worst_profit_movie_data[column].str.cat(sep = '|')

    #giving pandas series and storing the values separately
    data_worst = pd.Series(data_worst.split('|'))

    #arranging in descending order
    count = data_worst.value_counts(ascending = False)
```

```
        return count
```

**Top Genres in HIgh revenue movies**

```
In [369]: # Top genres in best MOvies
          genr = data('genres')
          genr.sort_values(ascending = False, inplace = True)
          genr.head()

Out[369]: Comedy       487
          Action       485
          Drama        457
          Adventure    407
          Thriller     389
          dtype: int64
```

**Less popular genres in low revenue movies**

```
In [370]: # Less popular genres in best movies
          genr_worst = data_worst('genres')
          genr_worst.sort_values(ascending = False, inplace = True)
          genr_worst.tail()

Out[370]: Animation    36
          History      29
          War          27
          Foreign      19
          Western      19
          dtype: int64
```

**Top directors in HIgh revenue movies**

```
In [371]: # top directors in best movies
          director = data('director')
          director.sort_values(ascending = False, inplace = True)
          director.head()

Out[371]: Steven Spielberg    23
          Robert Zemeckis     12
          Ron Howard          12
          Clint Eastwood      11
          Tim Burton          11
          dtype: int64
```

**Less Popular directors in Low revenue movies**

In [372]:
```
# less popular directors in best movies
director_worst = data_worst('director')
director_worst.sort_values(ascending = False, inplace = True)
director_worst.tail()
```

Out[372]:
```
Rob Zombie                1
Marvin Kren               1
Henry Bean                1
Lancelot Oduwa Imasuen    1
Ãlex de la Iglesia        1
dtype: int64
```

#### Top actors in HIgh revenue movies

In [373]:
```
# top actors in best movies
casts = data('cast')
casts.sort_values(ascending = False, inplace = True)
casts.head()
```

Out[373]:
```
Tom Cruise            26
Brad Pitt             25
Tom Hanks             24
Sylvester Stallone    22
Matt Damon            22
dtype: int64
```

#### Less POpular Directors in low revenue movies

In [374]:
```
# less popular actors in best movies
casts_worst = data_worst('cast')
casts_worst.sort_values(ascending = False, inplace = True)
casts_worst.tail()
```

Out[374]:
```
Blake Ritson            1
Zoe Lister-Jones        1
Monte Markham           1
Toor Pekai Yousafzai    1
Candy Clark             1
dtype: int64
```

#### Top Production Companies in High Revenue movies

In [375]:
```
# top production companies in best movies
prod = data('production_companies')
prod.sort_values(ascending = False, inplace = True)
prod.head()
```

Out[375]:
```
Warner Bros.                                168
Universal Pictures                          161
```

```
Paramount Pictures                        130
Twentieth Century Fox Film Corporation    115
Columbia Pictures                          95
dtype: int64
```

#### Less POpular Production Companies in Low revenue movies

In [376]:
```
# less popular production companies in best movies
prod_worst = data_worst('production_companies')
prod_worst.sort_values(ascending = False, inplace = True)
prod_worst.tail()
```

Out[376]:
```
Renn Productions           1
Sodium Fox                 1
Starburns Industries       1
Independent                1
Bridgit Folman Film Gang   1
dtype: int64
```

#### Top Keywords in High revenue MOvies

In [377]:
```
# top keywords in best movies
key = data('keywords')
key.sort_values(ascending = False, inplace = True)
key.head()
```

Out[377]:
```
based on novel          66
dystopia                45
duringcreditsstinger    44
new york                30
sequel                  30
dtype: int64
```

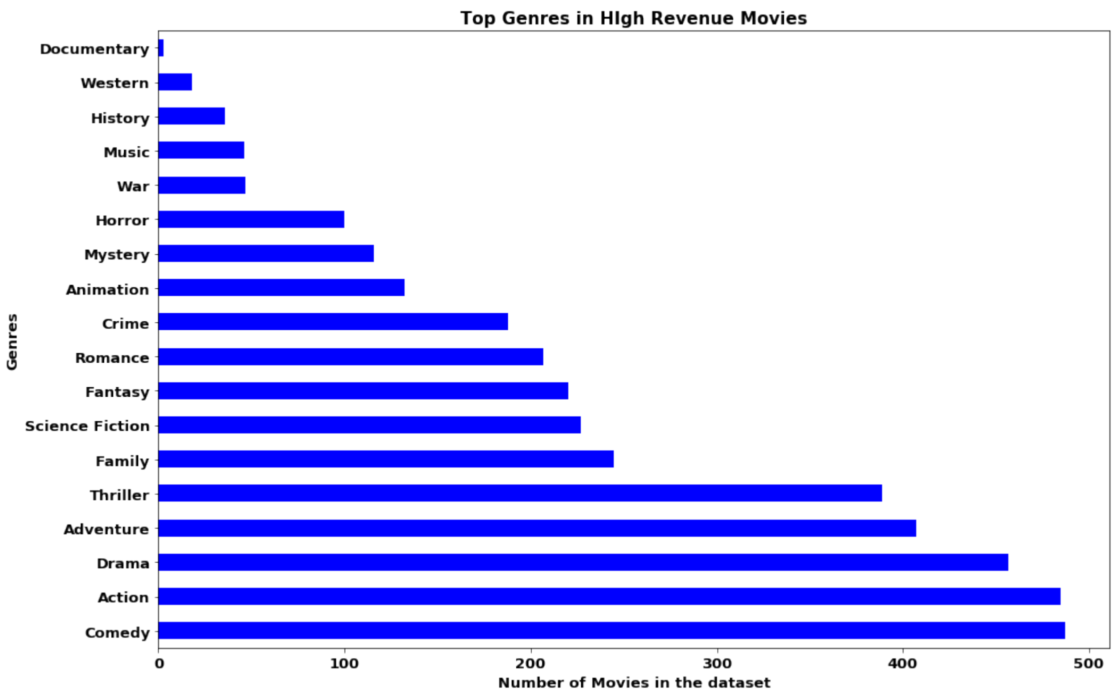
#### Less POpular keywords in Low revenue movies

In [378]:
```
# less popular keywords in best movies
key_worst = data_worst('keywords')
key_worst.sort_values(ascending = False, inplace = True)
key_worst.tail()
```

Out[378]:
```
alcoholic drink    1
mafia boss         1
laser              1
halo               1
female soldier     1
dtype: int64
```

We will see above analyses results visually
### Research Question 2: (What kind of Genres are top in High Revenue movies?)

```
In [379]: #lets plot the points in descending order top to bottom as we have data in same format
          #genr.sort_values(ascending = False, inplace = True)

          #ploting
          genr. plot.barh(color = 'b', fontsize = 13)

          #title
          plt.title('Top Genres in HIgh Revenue Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in the dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Genres', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')

          #ploting the graph
          plt.show()
          genr.head()
```

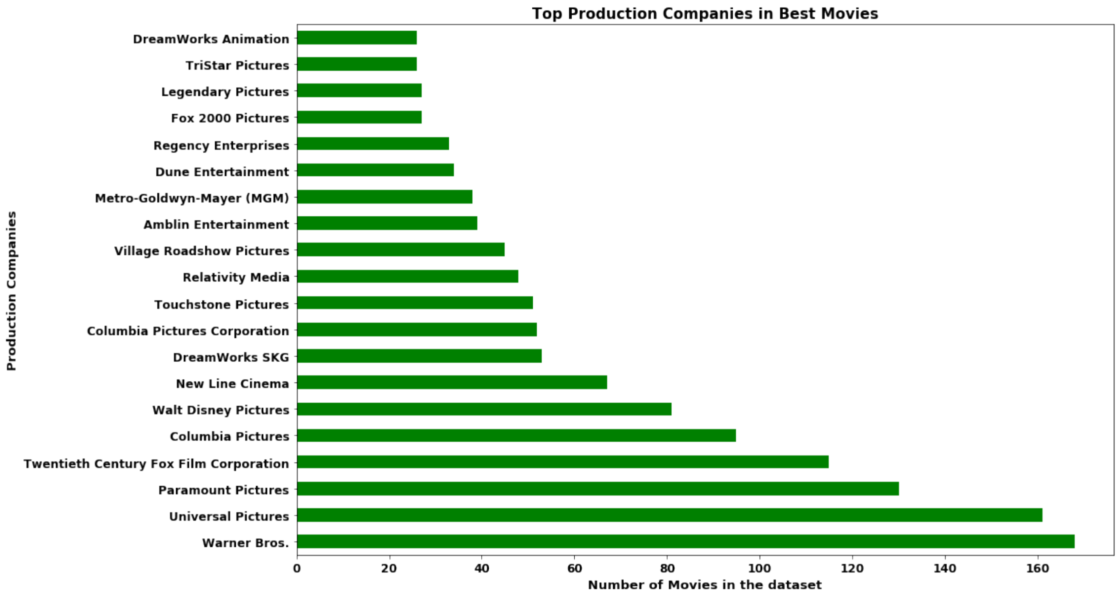



```
Out[379]: Comedy       487
          Action       485
          Drama        457
          Adventure    407
          Thriller     389
          dtype: int64
```

The above chart indicates Comedy genres play vital role in about 487 movies for the popularity. It is followed by Action and Drama. Adventure and Thriller genres also play vital rolse in popularity of the movie

### Research Question 3: (Which Production Companies are top in Best Revenue movies?)

In [380]:
```
#lets plot the points in descending order top to bottom as we have data in same format

#prod.sort_values(ascending = False,inplace=True)

#ploting
prod.head(20).plot.barh(color = 'g', fontsize = 12)

#title
plt.title('Top Production Companies in Best Movies',fontsize = 15,weight='bold')

# on x axis
plt.xlabel('Number of Movies in the dataset', color = 'black', fontsize = 13, weight =
plt.ylabel('Production Companies', color = 'black', fontsize = 13, weight='bold')
plt.xticks(weight='bold')
plt.yticks(weight='bold')

#ploting the graph
plt.show()
prod.head()
```



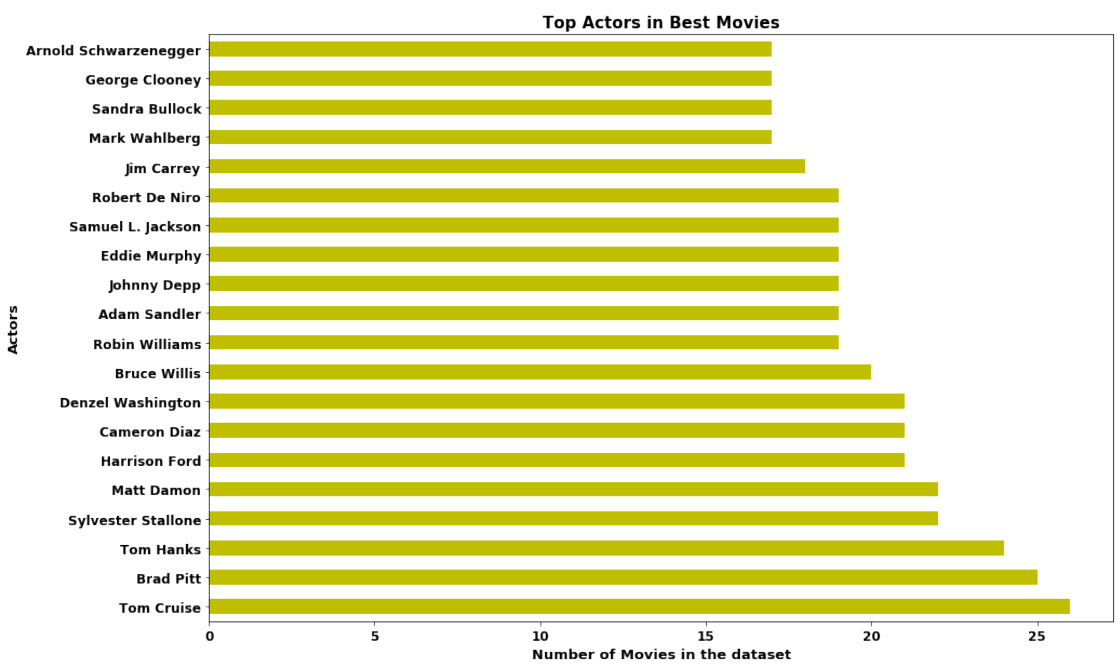

Out[380]:
```
Warner Bros.                              168
Universal Pictures                        161
```

```
Paramount Pictures                          130
Twentieth Century Fox Film Corporation     115
Columbia Pictures                            95
dtype: int64
```

From above chart, it is clear that WarnerBrothers tops the list with high number of movies. it is followed by UNiversal Pictures and paramount pictures

### Research Question 4: (Which Actors are top in Best Revenue movies?)

```
In [381]: #lets plot the points in descending order top to bottom as we have data in same format
          #director.sort_values(ascending = False, inplace = True)

          #ploting
          casts.head(20).plot.barh(color = 'y', fontsize = 12)

          #title
          plt.title('Top Actors in Best Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in the dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Actors', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')

          #ploting the graph
          plt.show()
          casts.head()
```

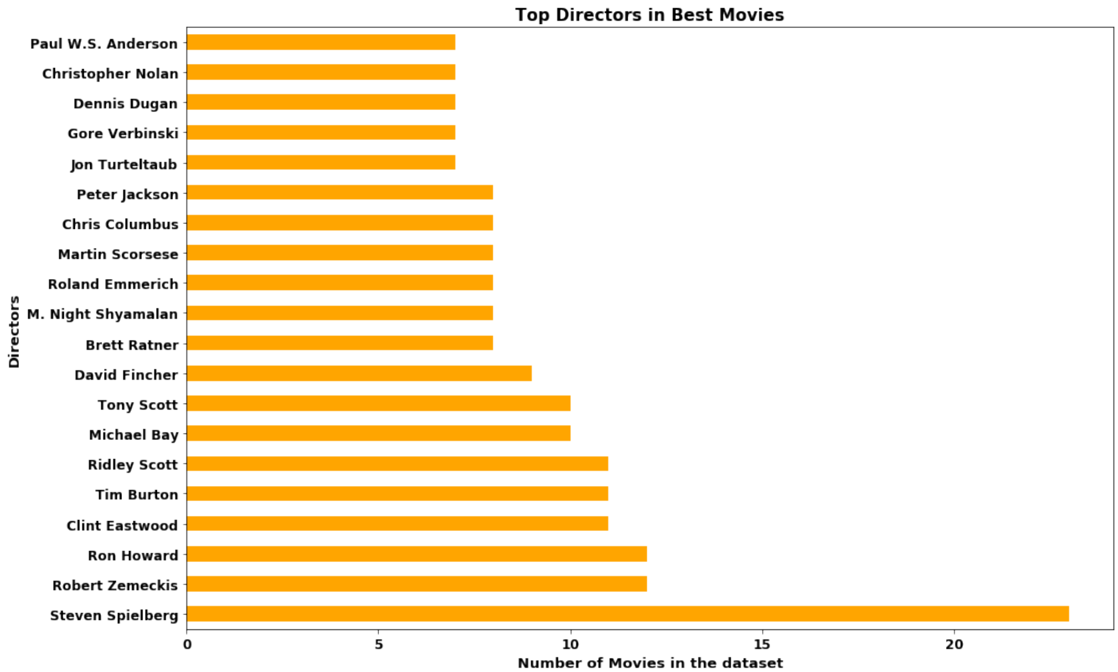


```
Out[381]: Tom Cruise            26
          Brad Pitt             25
          Tom Hanks             24
          Sylvester Stallone    22
          Matt Damon            22
          dtype: int64
```

Abvoe chart shows top actor Tom Cruise played 26 movies in high revenue movies. he is followed by Brad Pitt and Tom Hanks.

### Research Question 5: (Which directors are top in Best Revenue movies?)

```
In [382]: #lets plot the points in descending order top to bottom as we have data in same format
          #director.sort_values(ascending = False, inplace = True)

          #ploting
          director.head(20).plot.barh(color = 'orange', fontsize = 12)

          #title
          plt.title('Top Directors in Best Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in the dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Directors', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')

          #ploting the graph
          plt.show()
          director.head()
```



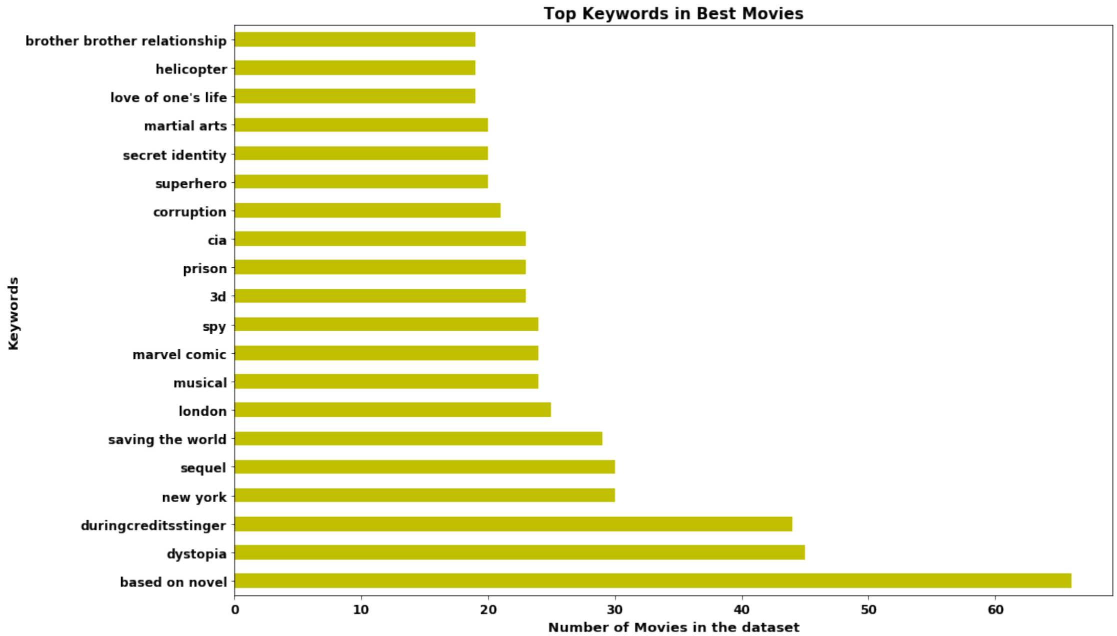

```
Out[382]: Steven Spielberg    23
          Robert Zemeckis     12
          Ron Howard          12
          Clint Eastwood      11
          Tim Burton          11
          dtype: int64
```

It is clear from the above chart that director Steven Spielberg tops the list with 23 movies in high revenue movies. He is followed by Ron Howard and Robert Zemeckis

### Research Question 6: (Which keywords are top in Best Revenue movies?)

```
In [383]: #lets plot the points in descending order top to bottom as we have data in same format
          #director.sort_values(ascending = False, inplace = True)

          #ploting
          key.head(20).plot.barh(color = 'y', fontsize = 12)

          #title
          plt.title('Top Keywords in Best Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in the dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Keywords', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')
```

```
#ploting the graph
plt.show()
key.head()
```



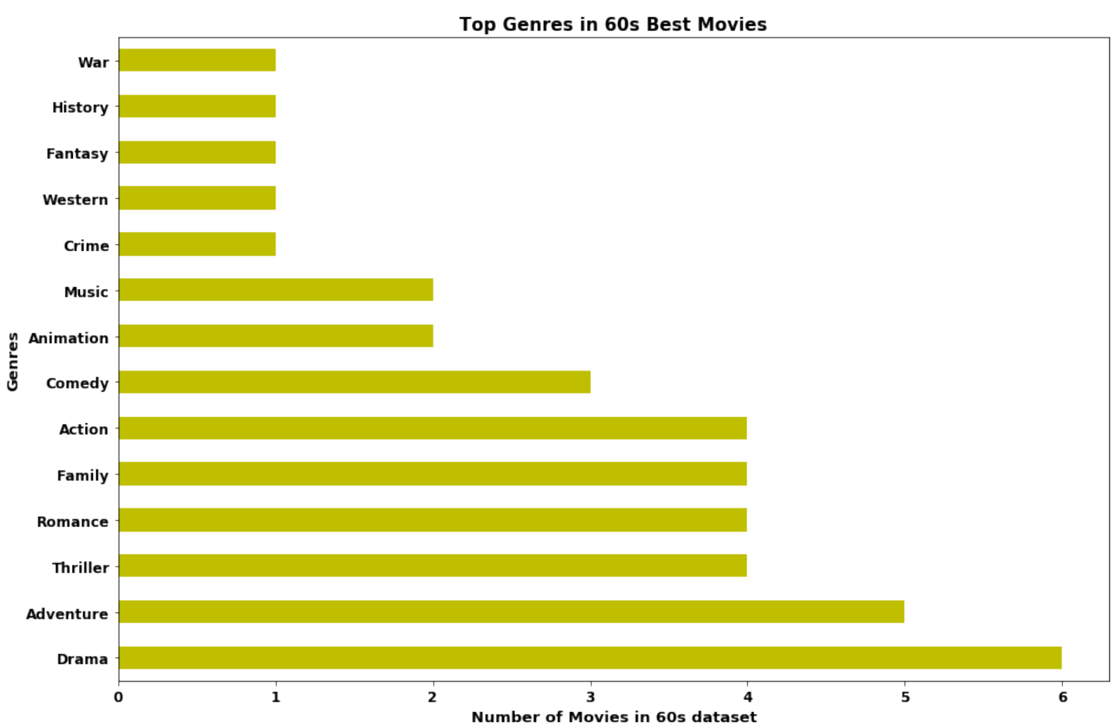

```
Out[383]: based on novel            66
          dystopia                  45
          duringcreditsstinger      44
          new york                  30
          sequel                    30
          dtype: int64
```

Above chart indicates that novel keyword plays important role in popular movies.
### Research Question 7: (Which Genres are top during 60s and 2Ks Best Revenue movies?)

IN order to find top generes during 60s and 2Ks , i selected high revenue movies from dataset for 60s and 2KS.

```
In [384]: #  finding number of genres in 1960s

          best_movies_60s_data = best_movies[best_movies['Year_Levels']=='60s']

          best_movies_60s_genre= best_movies_60s_data['genres'].str.cat(sep = '|')


          best_movie_60s_genre_words = pd.Series(best_movies_60s_genre.split('|'))
```

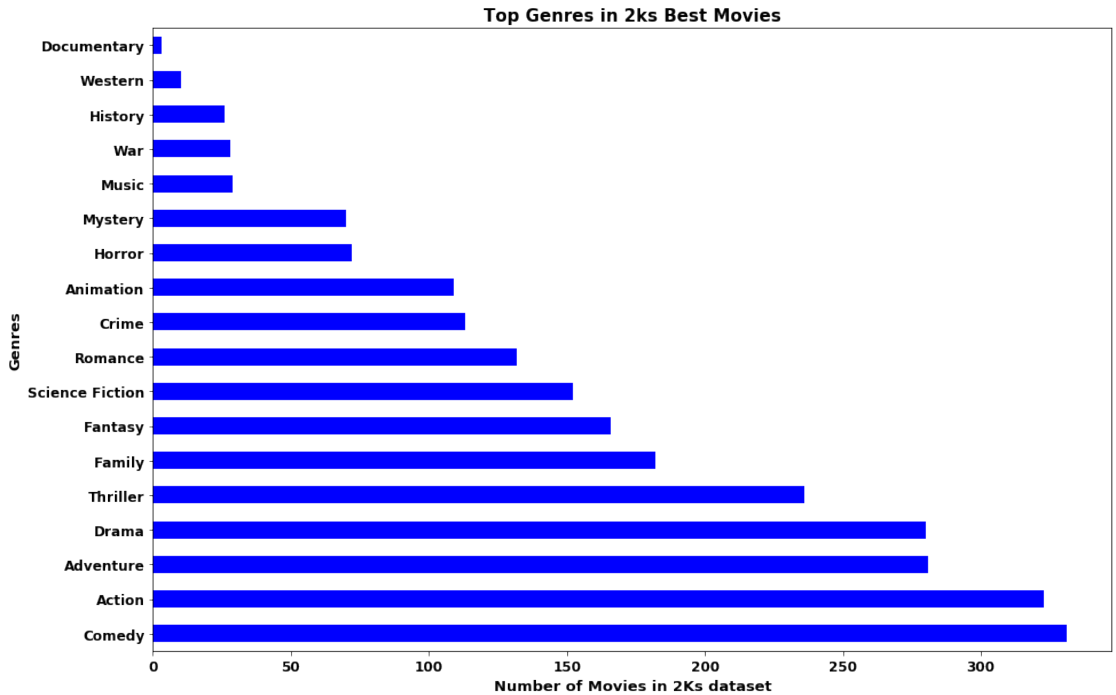
```
genre_60s= best_movie_60s_genre_words.value_counts()

#plotting
genre_60s.plot.barh(color = 'y', fontsize = 12)

#title
plt.title('Top Genres in 60s Best Movies',fontsize = 15,weight='bold')

# on x axis
plt.xlabel('Number of Movies in 60s dataset', color = 'black', fontsize = 13, weight =
plt.ylabel('Genres', color = 'black', fontsize = 13, weight='bold')
plt.xticks(weight='bold')
plt.yticks(weight='bold')

#ploting the graph
plt.show()
print(genre_60s)
```




```
Drama         6
Adventure     5
Thriller      4
Romance       4
Family        4
```

```
Action       4
Comedy       3
Animation    2
Music        2
Crime        1
Western      1
Fantasy      1
History      1
War          1
dtype: int64
```

In [385]:
```
#  finding number of genres in 2Ks

best_movies_2Ks_data = best_movies[best_movies['Year_Levels']=='2Ks']

best_movies_2ks_genre= best_movies_2Ks_data['genres'].str.cat(sep = '|')

best_movie_2ks_genre_words = pd.Series(best_movies_2ks_genre.split('|'))

genre_2ks= best_movie_2ks_genre_words.value_counts()

#plotting
genre_2ks.plot.barh(color = 'b', fontsize = 12)

#title
plt.title('Top Genres in 2ks Best Movies',fontsize = 15,weight='bold')

# on x axis
plt.xlabel('Number of Movies in 2Ks dataset', color = 'black', fontsize = 13, weight =
plt.ylabel('Genres', color = 'black', fontsize = 13, weight='bold')
plt.xticks(weight='bold')
plt.yticks(weight='bold')

#ploting the graph
plt.show()
print(genre_2ks)
```

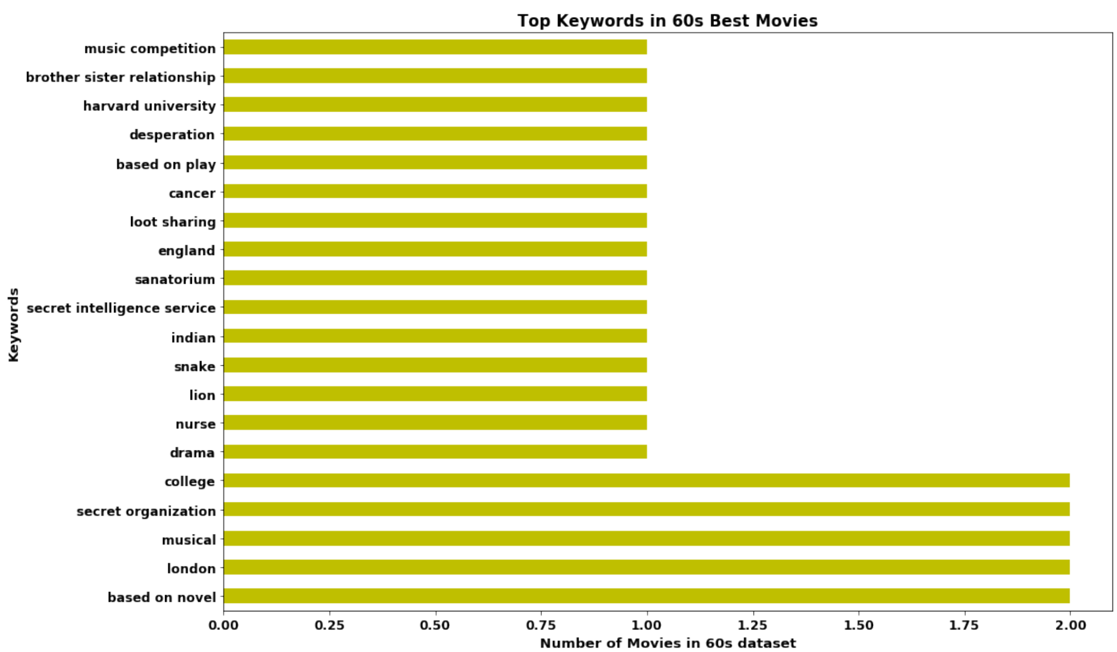



```
Comedy             331
Action             323
Adventure          281
Drama              280
Thriller           236
Family             182
Fantasy            166
Science Fiction    152
Romance            132
Crime              113
Animation          109
Horror              72
Mystery             70
Music               29
War                 28
History             26
Western             10
Documentary          3
dtype: int64
```

Above plot shows the 60s and 2Ks, top genres in best movies. It shows during 60s drama was popular. During 2Ks Comedy was popular. 60s dataset is less compared to 2Ks.

### Research Question 8: (Which Keywords are top during 60s and 2Ks Best Revenue movies?)

```
In [386]: #  finding number of keywords in 1960s

          best_movies_60s_data = best_movies[best_movies['Year_Levels']=='60s']

          best_movies_60s_keywords = best_movies_60s_data['keywords'].str.cat(sep = '|')

          best_movie_60s_keywords_words = pd.Series(best_movies_60s_keywords.split('|'))

          keywords_60s= best_movie_60s_keywords_words.value_counts()

          #plotting
          keywords_60s.head(20).plot.barh(color = 'y', fontsize = 12)

          #title
          plt.title('Top Keywords in 60s Best Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in 60s dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Keywords', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')

          #ploting the graph
          plt.show()
          print(keywords_60s)
```

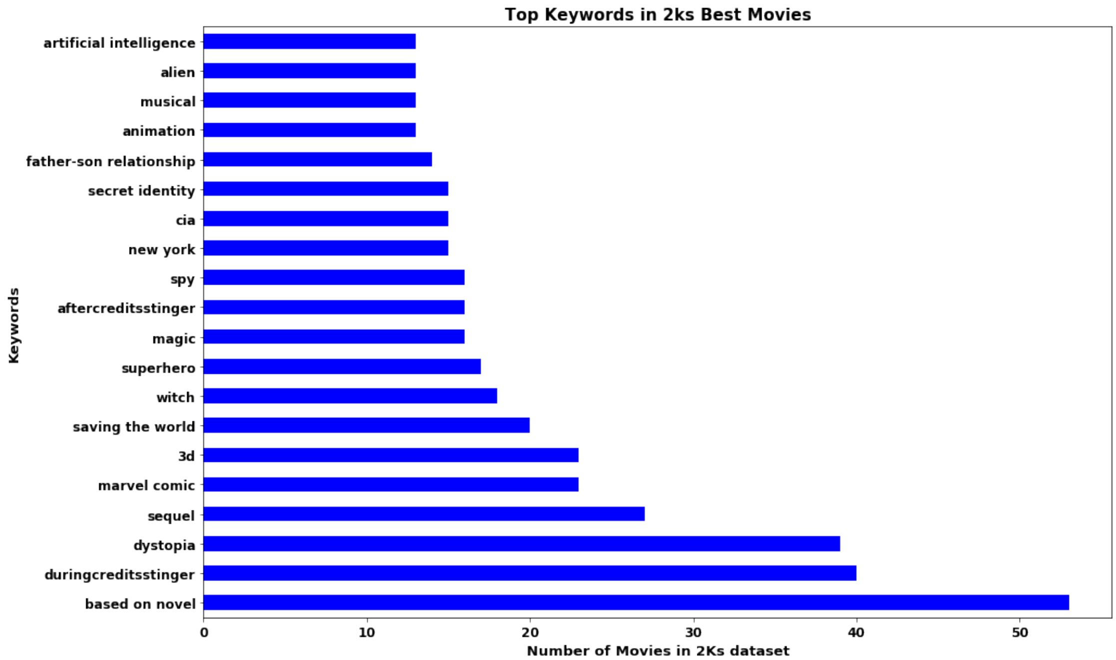



```
based on novel                          2
```

| | |
|---|---|
| london | 2 |
| musical | 2 |
| secret organization | 2 |
| college | 2 |
| drama | 1 |
| nurse | 1 |
| lion | 1 |
| snake | 1 |
| indian | 1 |
| secret intelligence service | 1 |
| sanatorium | 1 |
| england | 1 |
| loot sharing | 1 |
| cancer | 1 |
| based on play | 1 |
| desperation | 1 |
| harvard university | 1 |
| brother sister relationship | 1 |
| music competition | 1 |
| animation | 1 |
| florida | 1 |
| dog | 1 |
| snow storm | 1 |
| world war i | 1 |
| wedding | 1 |
| wyoming | 1 |
| feral child | 1 |
| fighter pilot | 1 |
| nuclear radiation | 1 |
| japan | 1 |
| puppy | 1 |
| suicide attempt | 1 |
| dalmatian | 1 |
| older woman younger man relationship | 1 |
| bank | 1 |
| world war ii | 1 |
| historical figure | 1 |
| parents kids relationship | 1 |
| dancing | 1 |
| airport | 1 |
| bomb | 1 |
| aston martin | 1 |
| fort knox | 1 |
| loss of family | 1 |
| austria | 1 |
| assassination | 1 |
| love triangle | 1 |
| helicopter | 1 |

```
paris                                       1
romance                                     1
seduction                                   1
dtype: int64
```

```
In [387]: #  finding number of keywords in 2Ks

          best_movies_2Ks_data = best_movies[best_movies['Year_Levels']=='2Ks']

          best_movies_2ks_keywords= best_movies_2Ks_data['keywords'].str.cat(sep = '|')

          best_movie_2ks_keywords_words = pd.Series(best_movies_2ks_keywords.split('|'))

          keywords_2ks= best_movie_2ks_keywords_words.value_counts()

          #plotting
          keywords_2ks.head(20).plot.barh(color = 'b', fontsize = 12)

          #title
          plt.title('Top Keywords in 2ks Best Movies',fontsize = 15,weight='bold')

          # on x axis
          plt.xlabel('Number of Movies in 2Ks dataset', color = 'black', fontsize = 13, weight =
          plt.ylabel('Keywords', color = 'black', fontsize = 13, weight='bold')
          plt.xticks(weight='bold')
          plt.yticks(weight='bold')

          #ploting the graph
          plt.show()
          print(keywords_2ks)
```




| | |
|---|---|
| based on novel | 53 |
| duringcreditsstinger | 40 |
| dystopia | 39 |
| sequel | 27 |
| marvel comic | 23 |
| 3d | 23 |
| saving the world | 20 |
| witch | 18 |
| superhero | 17 |
| magic | 16 |
| aftercreditsstinger | 16 |
| spy | 16 |
| new york | 15 |
| cia | 15 |
| secret identity | 15 |
| father-son relationship | 14 |
| animation | 13 |
| musical | 13 |
| alien | 13 |
| artificial intelligence | 13 |
| future | 13 |
| monster | 12 |
| love of one's life | 12 |
| assassin | 12 |
| undercover | 12 |
| paris | 12 |

```
prison                        11
corruption                    11
biography                     11
secret                        11
                              ..
southeast asia                 1
descendant                     1
flashback                      1
poem                           1
safe                           1
based on comic strip           1
suffocation                    1
children's book                1
arbitrary law                  1
imprisonment                   1
priest                         1
mine                           1
syringe                        1
creek                          1
temple                         1
court case                     1
suicide attempt                1
liberation of prisoners        1
depression                     1
south africa                   1
labor pain                     1
fireworks                      1
supernatural horror            1
group of friends               1
recording studio               1
earthquake                     1
police sniper                  1
motel                          1
socially deprived family       1
hatred                         1
Length: 1985, dtype: int64
```

Above plot shows the 60s and 2Ks, top keywords in best movies. It shows during 60s keyword "london" was popular. During 2Ks keyword "based on novel" was popular. 60s dataset is less compared to 2Ks.

## Conclusions

### 1.2.3 General Explore

Here, I explored some general questions. overall, budget increased over the period of time. Particularly from 1995 onwards, budget of the movie were increased double.

Similarly revenue also increased over the period of time. Overall the mean popularity increases slowly with time. It is due to number of people watching movies and voting from various sources increased over the period of time. Surprisingly the average vote trend is decreasing slowly over the period of time. The Reason for the decreasing trend may be due to applying strict filter to the vote average over the period of time inorder to get accurate average vote. The drastic increase in number of movies released over the period of time. During economic downtime, the number of movies released were less. After 2005, the number of movies released were so high compared to 60s to 90s.This may be due to growth in economy and increase in number of people watching movies through different platforms all over the world. Maximum number of movies are produced with mean runtime of 103 min.

### 1.2.4 Properties Associated with Successful Movies

At this part, I found out the properties that are associated with high popularity movies. HIgh budget movies are in high popularity level compared to low budget movies. Similarly, HIgh revenue movies are in high popularity level compared to low revenue movies. HIgh runtime movies are in high popularity level compared to low runtime movies. popular movies are largely associated with high BUdget movies and the high runtime movies. HIgh runtime has high voting average compared to low runtime movies.

Comedy genres play vital role in about maximum number of movies for the popularity. It is followed by Action and Drama. Adventure and Thriller genres also play vital rolse in popularity of the movie. Production company “Warner Brothers” tops the list with high number of movies. It is followed by UNiversal Pictures and paramount pictures. Actor “Tom Cruise” played maximum number of movies in high revenue popularity movies. He is followed by Brad Pitt and Tom Hanks. Director “Steven Spielberg” tops the list with maximum number of movies in high revenue popularity movies. He is followed by Ron Howard and Robert Zemeckis. Novel keyword plays important role in popular movies

During 60s, genre Drama was popular, but during 2Ks Comedy genre was popular. Similarly, during 60s, keyword “london” was popular, but during 2Ks keyword “based on novel” was popular.

## Limitations

1. Data quality: Some Values in BUdget and revenue columns are very small number with value less than 100. Some revenue and budget columns are having zero values and missing. 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.

2. As per TMDb, the popularity doesn’t have the upperbound , but it actually have the high probability of having outliers.

3. Units of revenue and budget column: It is not sure whether the budget and revenue columns are in US dollar or not.

4. The inflation effect: I used the revenue and budget data to explore and I didn't use the adjusted data due to inflation.

5. I dicussed the properties are associated with successful movies. The successful I defined here are high revenue. But I didn't find the properties of high popularity and voting score. I just assume the high revenue level are with higher popularity, which I found in general exploration part.

6. 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.

In [388]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[388]: 0