Final

December 17, 2017

Massive DataMining and Deep Learning - CS671 Rutgers
Data Preprocessing and Data Cleaning
Lets import all the packages we require for the project

```
In [2]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import plotly.offline as pyo
        from plotly.graph_objs import *
        import plotly.graph_objs as go
        from plotly.offline import init_notebook_mode,iplot
        from sklearn.preprocessing import Imputer
        from sklearn.decomposition import PCA # Principal Component Analysis module
        from sklearn.cluster import KMeans # KMeans clustering
        import nltk
        from nltk.corpus import wordnet
        PS = nltk.stem.PorterStemmer()
        from plotly.offline import init_notebook_mode,iplot
        init_notebook_mode(connected=True)
        import warnings
        warnings.filterwarnings('ignore')

        from subprocess import check_output

        import json
        get_ipython().magic(u'matplotlib inline')
```

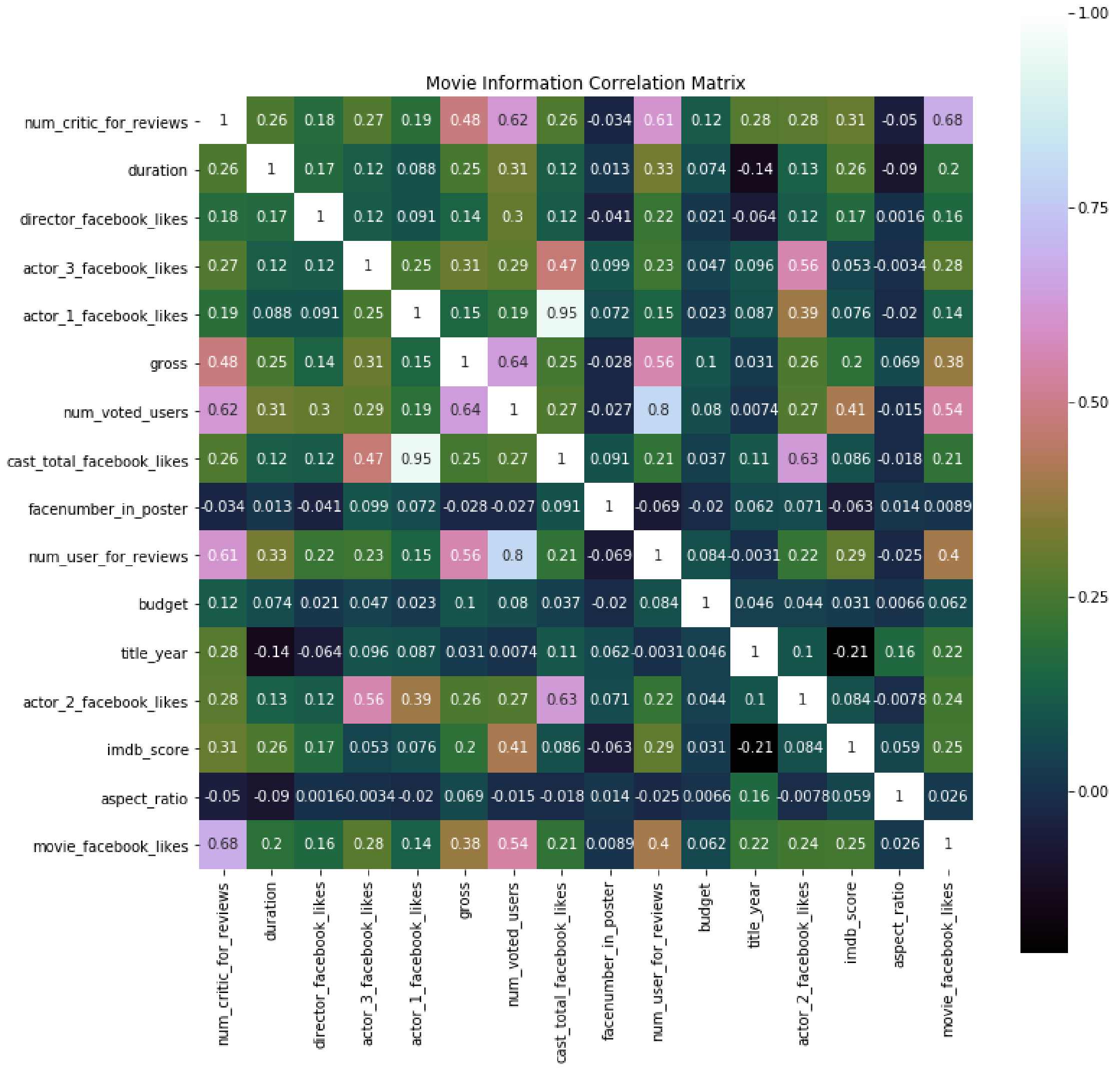
Loading the datasets required

```
In [3]: movies_data = pd.read_csv('tmdb_5000_movies.csv')
        credits_data = pd.read_csv('tmdb_5000_credits.csv')
        movie_data_metadata = pd.read_csv("movie_metadata.csv", sep=",", header=0)
        data_new = pd.read_csv('movie_metadata.csv')
```

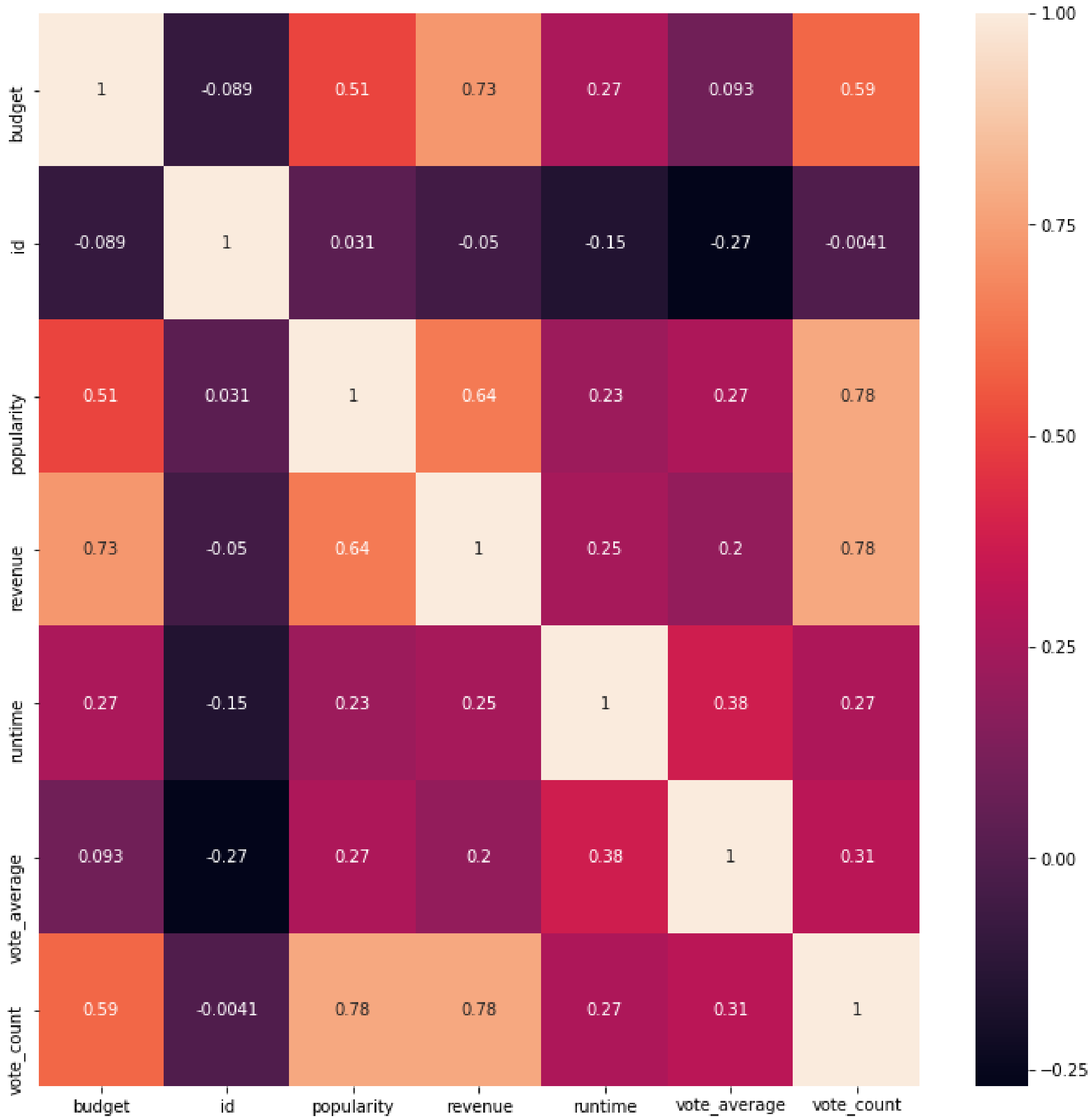
Before we brgin, lets have a look at the correlatioon between the features in the meta_data

```
In [4]: correlation_data = movie_data_metadata.corr()
        plt.figure(figsize = (12,12))
```

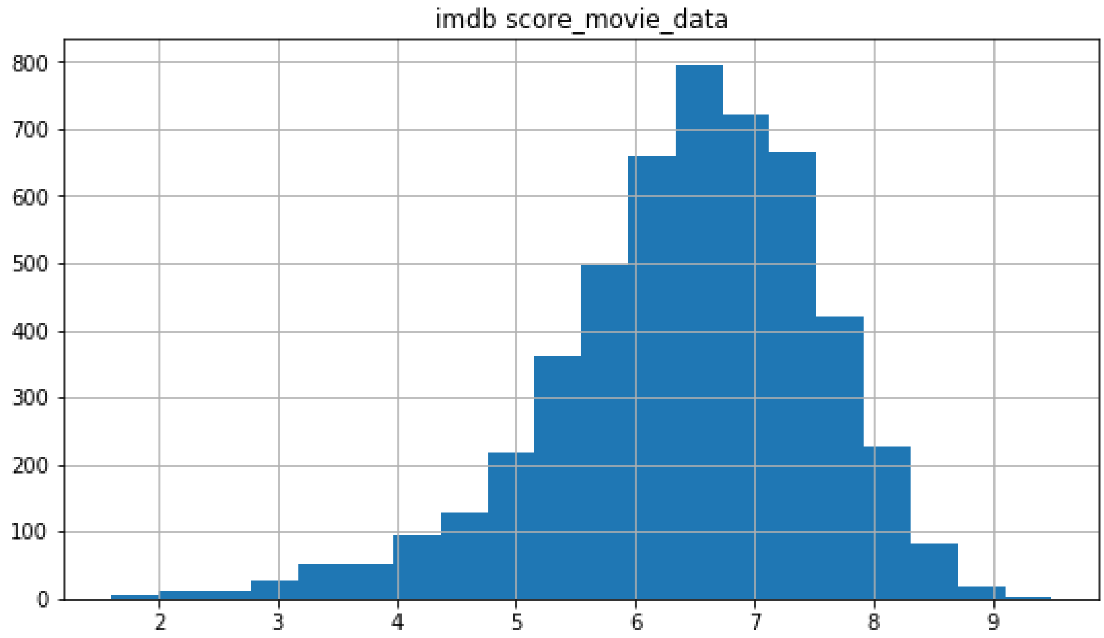
```
sns.heatmap(correlation_data, vmax=1, square=True, annot=True,cmap='cubehelix')

plt.title("Movie Information Correlation Matrix")
plt.show()
```




```
In [5]: fig, ax = plt.subplots(figsize=(12,12))
        sns.heatmap(data=movies_data.corr(),annot=True)
        plt.show()
```

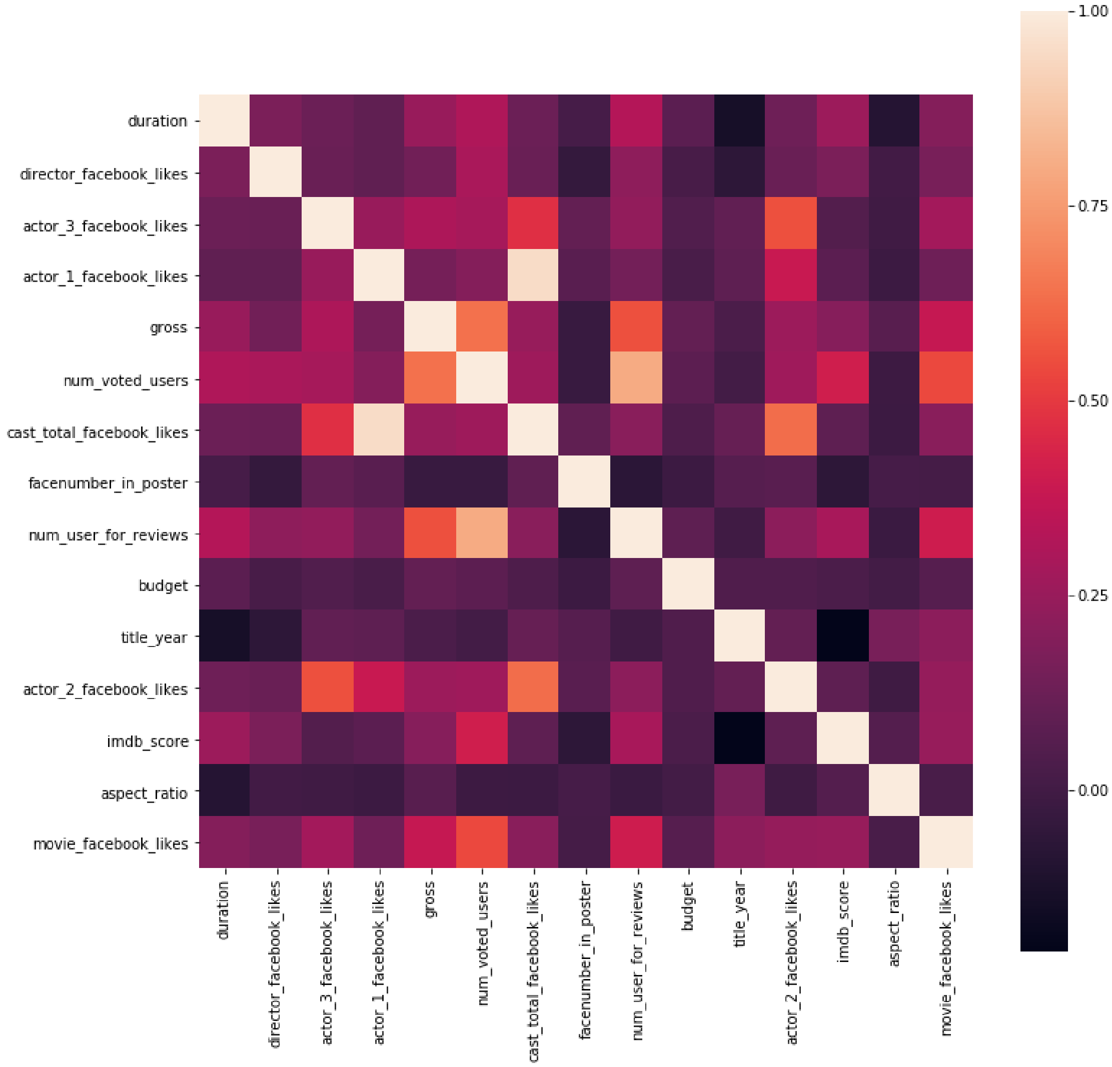


In [6]:
```
plt.rcParams['figure.figsize'] = (9.0, 5.0)
scores_data = pd.DataFrame({"imdb score_movie_data":movie_data_metadata["imdb_score"]}
scores_data.hist(bins=20)
plt.show()
```

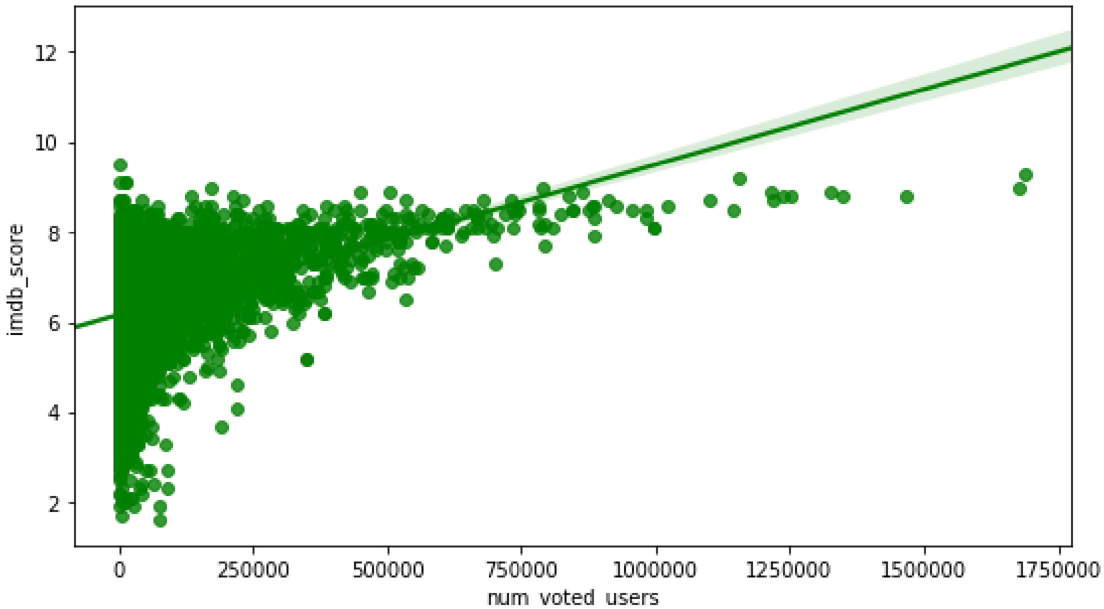


Let's just start with some easy questions to get familiar with the data. So what does the data look like? We'll start with taking a look at the movies data frame.

```
In [7]: corr = movie_data_metadata.select_dtypes(include = ['float64', 'int64']).iloc[:, 1:].co
        plt.figure(figsize=(12, 12))
        sns.heatmap(corr, vmax=1, square=True)
        plt.show()
```




```
In [8]: sns.regplot(x = 'num_voted_users', y = 'imdb_score', data = movie_data_metadata, color
        plt.show()
```




```
In [9]: movies_data.head()
```

```
Out[9]:       budget                                             genres  \
        0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
        1  300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "...
        2  245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
        3  250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
        4  260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...

                                                  homepage      id  \
        0                      http://www.avatarmovie.com/   19995
        1  http://disney.go.com/disneypictures/pirates/       285
        2   http://www.sonypictures.com/movies/spectre/  206647
        3             http://www.thedarkknightrises.com/   49026
        4           http://movies.disney.com/john-carter   49529

                                                    keywords original_language  \
        0  [{"id": 1463, "name": "culture clash"}, {"id":...                en
        1  [{"id": 270, "name": "ocean"}, {"id": 726, "na...                en
        2  [{"id": 470, "name": "spy"}, {"id": 818, "name...                en
        3  [{"id": 849, "name": "dc comics"}, {"id": 853,...                en
        4  [{"id": 818, "name": "based on novel"}, {"id":...                en

                                    original_title  \
        0                                   Avatar
        1  Pirates of the Caribbean: At World's End
        2                                  Spectre
```

```
3                     The Dark Knight Rises
4                               John Carter

                                            overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di...  150.437577
1  Captain Barbossa, long believed to be dead, ha...  139.082615
2  A cryptic message from Bonds past sends him o...  107.376788
3  Following the death of District Attorney Harve...  112.312950
4  John Carter is a war-weary, former military ca...   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289...
1  [{"name": "Walt Disney Pictures", "id": 2}, {"...
2  [{"name": "Columbia Pictures", "id": 5}, {"nam...
3  [{"name": "Legendary Pictures", "id": 923}, {"...
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries release_date     revenue  \
0  [{"iso_3166_1": "US", "name": "United States o...   2009-12-10  2787965087
1  [{"iso_3166_1": "US", "name": "United States o...   2007-05-19   961000000
2  [{"iso_3166_1": "GB", "name": "United Kingdom"...   2015-10-26   880674609
3  [{"iso_3166_1": "US", "name": "United States o...   2012-07-16  1084939099
4  [{"iso_3166_1": "US", "name": "United States o...   2012-03-07   284139100

   runtime                                   spoken_languages    status  \
0    162.0  [{"iso_639_1": "en", "name": "English"}, {"iso...  Released
1    169.0           [{"iso_639_1": "en", "name": "English"}]  Released
2    148.0  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...  Released
3    165.0           [{"iso_639_1": "en", "name": "English"}]  Released
4    132.0           [{"iso_639_1": "en", "name": "English"}]  Released

                                      tagline  \
0                   Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                         A Plan No One Escapes
3                               The Legend Ends
4            Lost in our world, found in another.

                                      title  vote_average  vote_count
0                                    Avatar           7.2       11800
1  Pirates of the Caribbean: At World's End           6.9        4500
2                                   Spectre           6.3        4466
3                     The Dark Knight Rises           7.6        9106
4                               John Carter           6.1        2124
```

In [10]:
```
list(movies_data.columns.values)
```

Out[10]:
```
['budget',
 'genres',
```

```
 'homepage',
 'id',
 'keywords',
 'original_language',
 'original_title',
 'overview',
 'popularity',
 'production_companies',
 'production_countries',
 'release_date',
 'revenue',
 'runtime',
 'spoken_languages',
 'status',
 'tagline',
 'title',
 'vote_average',
 'vote_count']
```

In [11]:
```
list(credits_data.columns.values)
```

Out[11]:
```
['movie_id', 'title', 'cast', 'crew']
```

In [12]:
```
movie_data_metadata.dtypes
```

Out[12]:
```
color                         object
director_name                 object
num_critic_for_reviews       float64
duration                     float64
director_facebook_likes      float64
actor_3_facebook_likes       float64
actor_2_name                  object
actor_1_facebook_likes       float64
gross                        float64
genres                        object
actor_1_name                  object
movie_title                   object
num_voted_users                int64
cast_total_facebook_likes      int64
actor_3_name                  object
facenumber_in_poster         float64
plot_keywords                 object
movie_imdb_link               object
num_user_for_reviews         float64
language                      object
country                       object
content_rating                object
budget                       float64
title_year                   float64
```

```
actor_2_facebook_likes       float64
imdb_score                   float64
aspect_ratio                 float64
movie_facebook_likes           int64
dtype: object
```

The columns are a bit in an awkward order to take a fine look at the data. A preferable first column of this data frame, would, for example, be the title of the movie and not the movie's budget.

```
In [13]: credits_data.dtypes
```

```
Out[13]: movie_id     int64
         title       object
         cast        object
         crew        object
         dtype: object
```

```
In [14]: credits_data.head()
```

```
Out[14]:    movie_id                                     title  \
         0     19995                                    Avatar
         1       285  Pirates of the Caribbean: At World's End
         2    206647                                   Spectre
         3     49026                     The Dark Knight Rises
         4     49529                               John Carter

                                                         cast  \
         0  [{"cast_id": 242, "character": "Jake Sully", "...
         1  [{"cast_id": 4, "character": "Captain Jack Spa...
         2  [{"cast_id": 1, "character": "James Bond", "cr...
         3  [{"cast_id": 2, "character": "Bruce Wayne / Ba...
         4  [{"cast_id": 5, "character": "John Carter", "c...

                                                         crew
         0  [{"credit_id": "52fe48009251416c750aca23", "de...
         1  [{"credit_id": "52fe4232c3a36847f800b579", "de...
         2  [{"credit_id": "54805967c3a36829b5002c41", "de...
         3  [{"credit_id": "52fe4781c3a36847f81398c3", "de...
         4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de...
```

So this data frame has way fewer columns. The cast and crew might be interesting later on. Since this data frame contains only two extra columns, we'll try to merge it with the movies data frame. If they are in the same order, we can just concatenate the data frames, so let's see if in both data frames every row is about the same movie:

```
In [15]: (credits_data['title']==movies_data['title']).describe()
```

Out[15]:
```
count      4803
unique        1
top        True
freq       4803
Name: title, dtype: object
```

This tells us that every row in the credits data base has the same movie title as the same row in the movies data base. To prevent getting duplicate columns, we'll remove the movie_id and title column from the credits data frame and concatenate them.

In [16]:
```
del credits_data['title']
del credits_data['movie_id']
movie_DataFrame = pd.concat([movies_data, credits_data], axis=1)
```

In [17]:
```
movie_DataFrame.head()
```

Out[17]:
```
      budget                                             genres  \
0  237000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
1  300000000  [{"id": 12, "name": "Adventure"}, {"id": 14, "...
2  245000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
3  250000000  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4  260000000  [{"id": 28, "name": "Action"}, {"id": 12, "nam...

                                      homepage      id  \
0                  http://www.avatarmovie.com/   19995
1  http://disney.go.com/disneypictures/pirates/     285
2   http://www.sonypictures.com/movies/spectre/  206647
3            http://www.thedarkknightrises.com/   49026
4          http://movies.disney.com/john-carter   49529

                                            keywords original_language  \
0  [{"id": 1463, "name": "culture clash"}, {"id":...                en
1  [{"id": 270, "name": "ocean"}, {"id": 726, "na...                en
2  [{"id": 470, "name": "spy"}, {"id": 818, "name...                en
3  [{"id": 849, "name": "dc comics"}, {"id": 853,...                en
4  [{"id": 818, "name": "based on novel"}, {"id":...                en

                             original_title  \
0                                    Avatar
1  Pirates of the Caribbean: At World's End
2                                   Spectre
3                     The Dark Knight Rises
4                               John Carter

                                            overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di...  150.437577
1  Captain Barbossa, long believed to be dead, ha...  139.082615
2  A cryptic message from Bonds past sends him o...  107.376788
3  Following the death of District Attorney Harve...  112.312950
```

```
4  John Carter is a war-weary, former military ca...   43.926995

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289...
1  [{"name": "Walt Disney Pictures", "id": 2}, {"...
2  [{"name": "Columbia Pictures", "id": 5}, {"nam...
3  [{"name": "Legendary Pictures", "id": 923}, {"...
4        [{"name": "Walt Disney Pictures", "id": 2}]

                        ...                            revenue runtime  \
0                       ...                         2787965087   162.0
1                       ...                          961000000   169.0
2                       ...                          880674609   148.0
3                       ...                         1084939099   165.0
4                       ...                          284139100   132.0

                                    spoken_languages    status  \
0  [{"iso_639_1": "en", "name": "English"}, {"iso...  Released
1           [{"iso_639_1": "en", "name": "English"}]  Released
2  [{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...  Released
3           [{"iso_639_1": "en", "name": "English"}]  Released
4           [{"iso_639_1": "en", "name": "English"}]  Released

                                          tagline  \
0                     Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                            A Plan No One Escapes
3                                  The Legend Ends
4            Lost in our world, found in another.

                                      title vote_average vote_count  \
0                                    Avatar          7.2      11800
1  Pirates of the Caribbean: At World's End          6.9       4500
2                                   Spectre          6.3       4466
3                     The Dark Knight Rises          7.6       9106
4                               John Carter          6.1       2124

                                                cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "...
1  [{"cast_id": 4, "character": "Captain Jack Spa...
2  [{"cast_id": 1, "character": "James Bond", "cr...
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba...
4  [{"cast_id": 5, "character": "John Carter", "c...

                                                crew
0  [{"credit_id": "52fe48009251416c750aca23", "de...
1  [{"credit_id": "52fe4232c3a36847f800b579", "de...
2  [{"credit_id": "54805967c3a36829b5002c41", "de...
```

```
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de...
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de...

[5 rows x 22 columns]
```

create a new dataframe with all the columns we would be using

In [18]:
```python
new_columns_data = ['id','title','release_date','popularity','vote_average','vote_cou
           'budget','revenue','genres','keywords','cast','crew','tagline', 'runtime',
           'production_countries', 'status']

movie_DataFrame2 = movie_DataFrame[new_columns_data]
movie_DataFrame2.head()
```

Out[18]:
```
       id                                     title release_date  popularity  \
0   19995                                    Avatar   2009-12-10  150.437577
1     285  Pirates of the Caribbean: At World's End   2007-05-19  139.082615
2  206647                                   Spectre   2015-10-26  107.376788
3   49026                     The Dark Knight Rises   2012-07-16  112.312950
4   49529                               John Carter   2012-03-07   43.926995

   vote_average  vote_count     budget     revenue  \
0           7.2       11800  237000000  2787965087
1           6.9        4500  300000000   961000000
2           6.3        4466  245000000   880674609
3           7.6        9106  250000000  1084939099
4           6.1        2124  260000000   284139100

                                              genres  \
0  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
1  [{"id": 12, "name": "Adventure"}, {"id": 14, "...
2  [{"id": 28, "name": "Action"}, {"id": 12, "nam...
3  [{"id": 28, "name": "Action"}, {"id": 80, "nam...
4  [{"id": 28, "name": "Action"}, {"id": 12, "nam...

                                            keywords  \
0  [{"id": 1463, "name": "culture clash"}, {"id":...
1  [{"id": 270, "name": "ocean"}, {"id": 726, "na...
2  [{"id": 470, "name": "spy"}, {"id": 818, "name...
3  [{"id": 849, "name": "dc comics"}, {"id": 853,...
4  [{"id": 818, "name": "based on novel"}, {"id":...

                                                cast  \
0  [{"cast_id": 242, "character": "Jake Sully", "...
1  [{"cast_id": 4, "character": "Captain Jack Spa...
2  [{"cast_id": 1, "character": "James Bond", "cr...
3  [{"cast_id": 2, "character": "Bruce Wayne / Ba...
4  [{"cast_id": 5, "character": "John Carter", "c...
```

```
                                                crew  \
0  [{"credit_id": "52fe48009251416c750aca23", "de...
1  [{"credit_id": "52fe4232c3a36847f800b579", "de...
2  [{"credit_id": "54805967c3a36829b5002c41", "de...
3  [{"credit_id": "52fe4781c3a36847f81398c3", "de...
4  [{"credit_id": "52fe479ac3a36847f813eaa3", "de...

                                          tagline  runtime  \
0                     Enter the World of Pandora.    162.0
1  At the end of the world, the adventure begins.    169.0
2                         A Plan No One Escapes    148.0
3                               The Legend Ends    165.0
4           Lost in our world, found in another.    132.0

                                production_companies  \
0  [{"name": "Ingenious Film Partners", "id": 289...
1  [{"name": "Walt Disney Pictures", "id": 2}, {"...
2  [{"name": "Columbia Pictures", "id": 5}, {"nam...
3  [{"name": "Legendary Pictures", "id": 923}, {"...
4        [{"name": "Walt Disney Pictures", "id": 2}]

                                production_countries    status
0  [{"iso_3166_1": "US", "name": "United States o...  Released
1  [{"iso_3166_1": "US", "name": "United States o...  Released
2  [{"iso_3166_1": "GB", "name": "United Kingdom"...  Released
3  [{"iso_3166_1": "US", "name": "United States o...  Released
4  [{"iso_3166_1": "US", "name": "United States o...  Released
```

We also notice that the columns 'genres', 'keywords', 'production_companies', 'production_countries' and 'spoken_languages' are of the dictionary type, so right now they are quite hard to read, but later on we will find a way to work with them.

```
In [19]: movie_DataFrame2.describe().round()
```

```
Out[19]:              id  popularity  vote_average  vote_count       budget  \
         count    4803.0      4803.0        4803.0      4803.0       4803.0
         mean    57165.0        21.0           6.0       690.0   29045040.0
         std     88695.0        32.0           1.0      1235.0   40722391.0
         min         5.0         0.0           0.0         0.0          0.0
         25%      9014.0         5.0           6.0        54.0     790000.0
         50%     14629.0        13.0           6.0       235.0   15000000.0
         75%     58610.0        28.0           7.0       737.0   40000000.0
         max    459488.0       876.0          10.0     13752.0  380000000.0

                      revenue  runtime
         count   4.803000e+03   4801.0
         mean    8.226064e+07    107.0
```

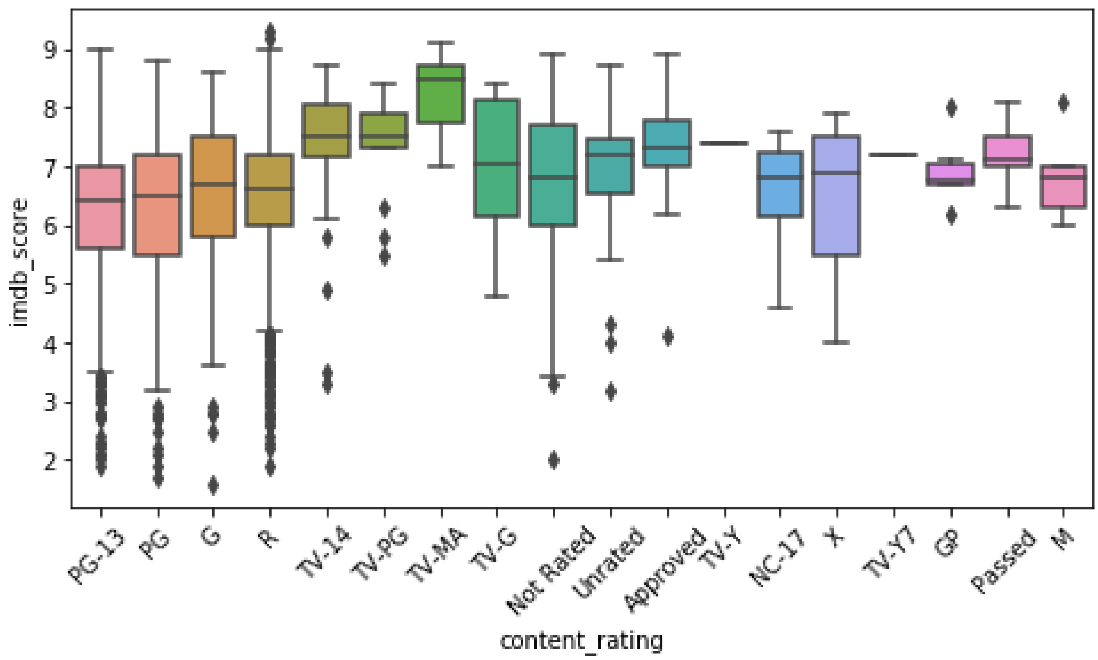
```
std    1.628571e+08     23.0
min    0.000000e+00      0.0
25%    0.000000e+00     94.0
50%    1.917000e+07    103.0
75%    9.291719e+07    118.0
max    2.787965e+09    338.0
```

In [20]:
```
my_imputer = Imputer()
temp=movie_DataFrame2
X2 = my_imputer.fit_transform(movie_DataFrame2[['runtime']])
movie_DataFrame2['runtime'] = X2
movie_DataFrame2.describe().round()
```

Out[20]:
```
             id  popularity  vote_average  vote_count       budget  \
count    4803.0      4803.0        4803.0      4803.0       4803.0
mean    57165.0        21.0           6.0       690.0   29045040.0
std     88695.0        32.0           1.0      1235.0   40722391.0
min         5.0         0.0           0.0         0.0          0.0
25%      9014.0         5.0           6.0        54.0     790000.0
50%     14629.0        13.0           6.0       235.0   15000000.0
75%     58610.0        28.0           7.0       737.0   40000000.0
max    459488.0       876.0          10.0     13752.0  380000000.0

            revenue  runtime
count  4.803000e+03   4803.0
mean   8.226064e+07    107.0
std    1.628571e+08     23.0
min    0.000000e+00      0.0
25%    0.000000e+00     94.0
50%    1.917000e+07    103.0
75%    9.291719e+07    118.0
max    2.787965e+09    338.0
```

So now at least all the numerical columns are complete. Let's take a quick look at how all the variables are distributed.

In [21]:
```
plt.figure(figsize = (8, 4))
sns.boxplot(x = 'content_rating', y = 'imdb_score',  data = movie_data_metadata)
xt = plt.xticks(rotation=45)
```




```
In [22]: plt.show()
```

```
In [23]: del movie_DataFrame2['id']
```

```
In [24]: movie_DataFrame2['vote_classes'] = pd.cut(movie_DataFrame2['vote_average'],4, labels=
```

since big values are tough to plot, lets take the log values of them and then plot them

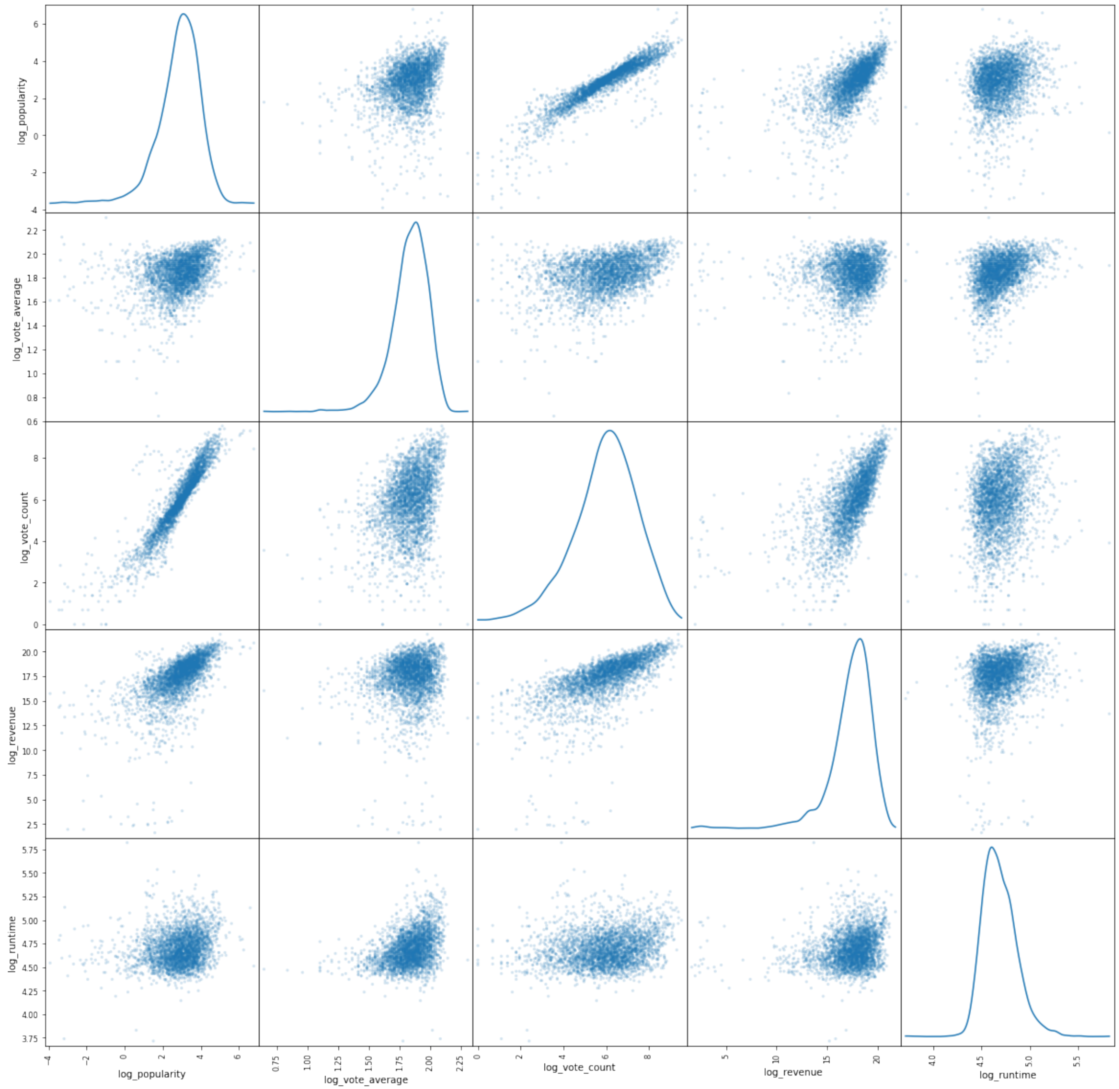
```
In [25]: movie_DataFrame2['log_budget'] = np.log(movie_DataFrame2['budget'])
         movie_DataFrame2['log_popularity'] = np.log(movie_DataFrame2['popularity'])
         movie_DataFrame2['log_vote_average'] = np.log(movie_DataFrame2['vote_average'])
         movie_DataFrame2['log_vote_count'] = np.log(movie_DataFrame2['vote_count'])
         movie_DataFrame2['log_revenue']= np.log(movie_DataFrame2['revenue'])
         movie_DataFrame2['log_runtime']= np.log(movie_DataFrame2['runtime'])
         movie_DataFrame3=movie_DataFrame2[movie_DataFrame2.columns[-5:]]
```

```
In [26]: movie_DataFrame3=movie_DataFrame3[movie_DataFrame3.replace([np.inf, -np.inf], np.nan)
         movie_DataFrame3=movie_DataFrame3.dropna(axis=1)
```

```
In [27]: from pandas.plotting import scatter_matrix
         scatter_matrix(movie_DataFrame3,alpha=0.2, figsize=(20, 20), diagonal='kde')
```

```
Out[27]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1a20825f10>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x1a20911f50>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x1a20d56350>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x1a17444090>,
```

```
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a17457b90>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1a21087850>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a210d5290>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a210f30d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a211655d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a21124990>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1a211ed1d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a21230ad0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a2127d390>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a2129ca10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a212fae50>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1a21347890>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a21368e90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a213d9bd0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a2135e510>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a2145f650>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x1a214ad590>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a214fa550>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a2152d250>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a21579490>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x1a215c8250>]], dtype=objec
```

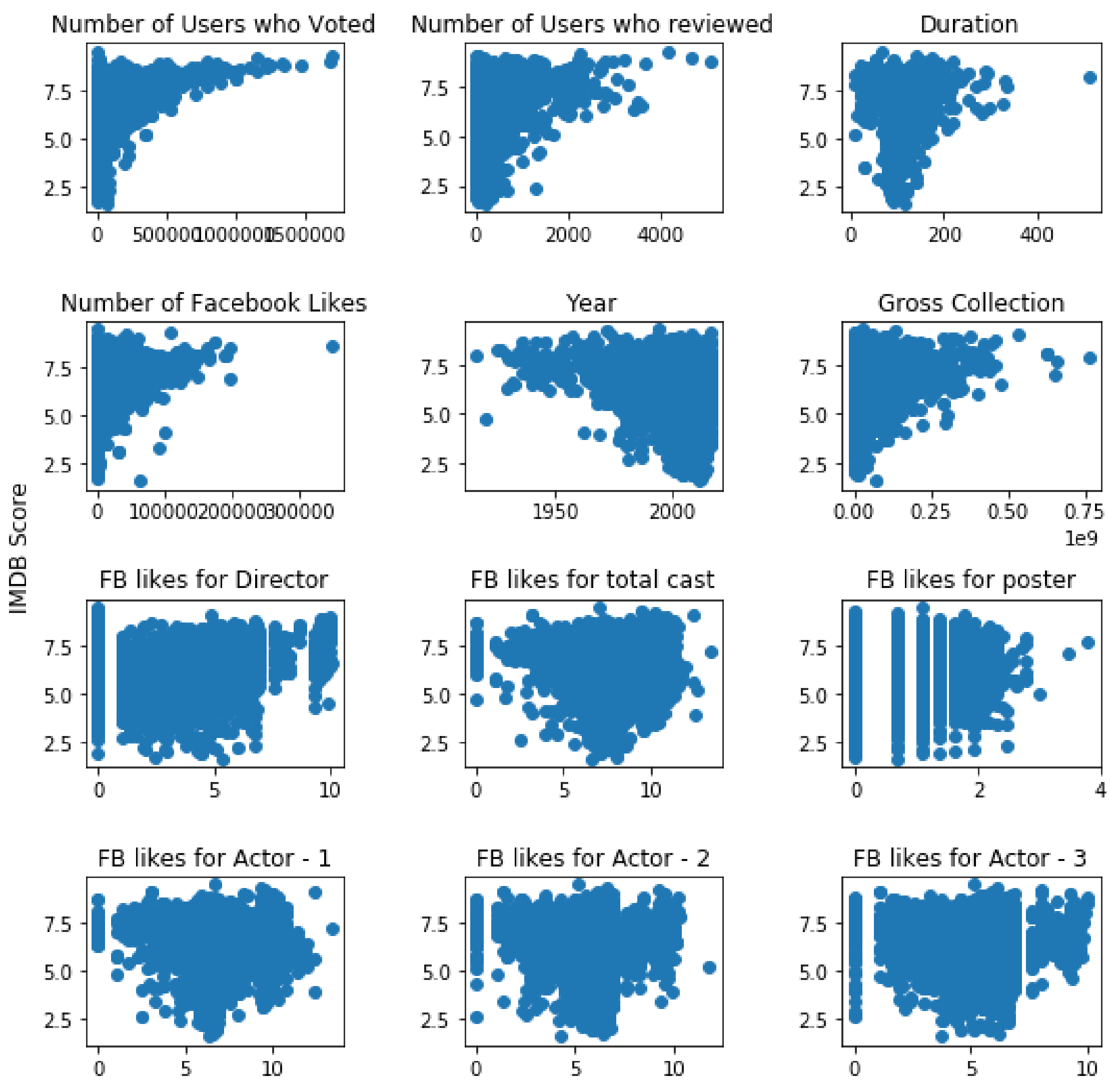



```
In [28]: plt.show()
```

```
In [29]: plt.figure(1)

         f, axarr = plt.subplots(4, 3, figsize=(8, 8))
         score_movie_data = movie_data_metadata.imdb_score.values

         axarr[0, 0].scatter(movie_data_metadata.num_voted_users.values, score_movie_data)
         axarr[0, 0].set_title('Number of Users who Voted')
         axarr[0, 1].scatter(movie_data_metadata.num_user_for_reviews.values, score_movie_data
         axarr[0, 1].set_title('Number of Users who reviewed')
         axarr[0, 2].scatter(movie_data_metadata.duration.values, score_movie_data)
         axarr[0, 2].set_title('Duration')
         axarr[1, 0].scatter(movie_data_metadata.movie_facebook_likes.values, score_movie_data
```

```
axarr[1, 0].set_title('Number of Facebook Likes')
axarr[1, 1].scatter(movie_data_metadata.title_year.values, score_movie_data)
axarr[1, 1].set_title('Year')
axarr[1, 2].scatter(movie_data_metadata.gross.values, score_movie_data)
axarr[1, 2].set_title('Gross Collection')

axarr[2, 0].scatter(np.log1p(movie_data_metadata.director_facebook_likes.values), sco
axarr[2, 0].set_title('FB likes for Director')
axarr[2, 1].scatter(np.log1p(movie_data_metadata.cast_total_facebook_likes.values), s
axarr[2, 1].set_title('FB likes for total cast')
axarr[2, 2].scatter(np.log1p(movie_data_metadata.facenumber_in_poster.values), score_
axarr[2, 2].set_title('FB likes for poster')


axarr[3, 0].scatter(np.log1p(movie_data_metadata.actor_1_facebook_likes.values), score
axarr[3, 0].set_title('FB likes for Actor - 1')
axarr[3, 1].scatter(np.log1p(movie_data_metadata.actor_2_facebook_likes.values), score
axarr[3, 1].set_title('FB likes for Actor - 2')
axarr[3, 2].scatter(np.log1p(movie_data_metadata.actor_3_facebook_likes.values), score
axarr[3, 2].set_title('FB likes for Actor - 3')


f.text(-0.01, 0.5, 'IMDB Score', va='center', rotation='vertical', fontsize = 12)
plt.tight_layout()
```

```
<matplotlib.figure.Figure at 0x1a217eb350>
```




```
In [30]: plt.show()
```

```
In [31]: Early_movie_DataFrame = movie_DataFrame2[movie_DataFrame2.columns[0:16]]
```

Let's take a closer look at our non-numerical variables. We choose to start with looking at the genres, since this variable has got the least variability, should be the most easy target for analysis.

The genres column contains variables of the string type, while they are in dictionaries. Moreover, the colomn is a json column. To analyse and understand the data it is necessary to change the type of the variable and filter the columns. Despite the fact that we already loaded our data for the exploration, we'll reload it here and make sure to load the json columns correctly. To do this, we made use of a few tricks found in another Kernel*

```
In [32]: def load_TMDB_movie_json_data(path):
             df = pd.read_csv(path)
```

```
    df['release_date'] = pd.to_datetime(df['release_date']).apply(lambda x: x.date())
    json_columns = ['genres', 'keywords', 'production_countries', 'production_compani
    for column in json_columns:
        df[column] = df[column].apply(json.loads)
    return df

def load_TMDB_credits_json_data(path):
    df = pd.read_csv(path)
    json_columns = ['cast', 'crew']
    for column in json_columns:
        df[column] = df[column].apply(json.loads)
    return df

def pipeline_to_flatten_names(keywords):
    return '|'.join([x['name'] for x in keywords])

credits_data = load_TMDB_credits_json_data("tmdb_5000_credits.csv")
movies_data = load_TMDB_movie_json_data("tmdb_5000_movies.csv")

del credits_data['title']
df = pd.concat([movies_data, credits_data], axis=1)

df['genres'] = df['genres'].apply(pipeline_to_flatten_names)

genres_data = set()
for s in df['genres'].str.split('|'):
    genres_data = set().union(s, genres_data)
genres_data = list(genres_data)
genres_data.remove('')
```

In [33]:
```
DafaFrame_cleaned = df[['title','vote_average','release_date','runtime','budget','reve

for genre in genres_data:
    DafaFrame_cleaned[genre] = df['genres'].str.contains(genre).apply(lambda x:1 if x
DafaFrame_cleaned[:5]

DafaFrame_cleaned.head()
```

Out[33]:
```
                                      title  vote_average release_date  \
0                                    Avatar           7.2   2009-12-10
1  Pirates of the Caribbean: At World's End           6.9   2007-05-19
2                                   Spectre           6.3   2015-10-26
3                     The Dark Knight Rises           7.6   2012-07-16
4                               John Carter           6.1   2012-03-07

   runtime     budget     revenue  Mystery  Crime  Drama  Animation  \
0    162.0  237000000  2787965087        0      0      0          0
1    169.0  300000000   961000000        0      0      0          0
```

```
2    148.0  245000000   880674609        0      1      0            0
3    165.0  250000000  1084939099        0      1      1            0
4    132.0  260000000   284139100        0      0      0            0

     ...       Romance  Comedy  Family  Fantasy  Horror  Thriller  \
0    ...             0       0       0        1       0         0
1    ...             0       0       0        1       0         0
2    ...             0       0       0        0       0         0
3    ...             0       0       0        0       0         1
4    ...             0       0       0        0       0         0

   Science Fiction  Western  TV Movie  Adventure
0                1        0         0          1
1                0        0         0          1
2                0        0         0          1
3                0        0         0          0
4                1        0         0          1

[5 rows x 26 columns]
```

Successfully converted JSON type to proper formatted data ready for preprocessing and learning algorithms

In [34]:
```
df['genres']
```

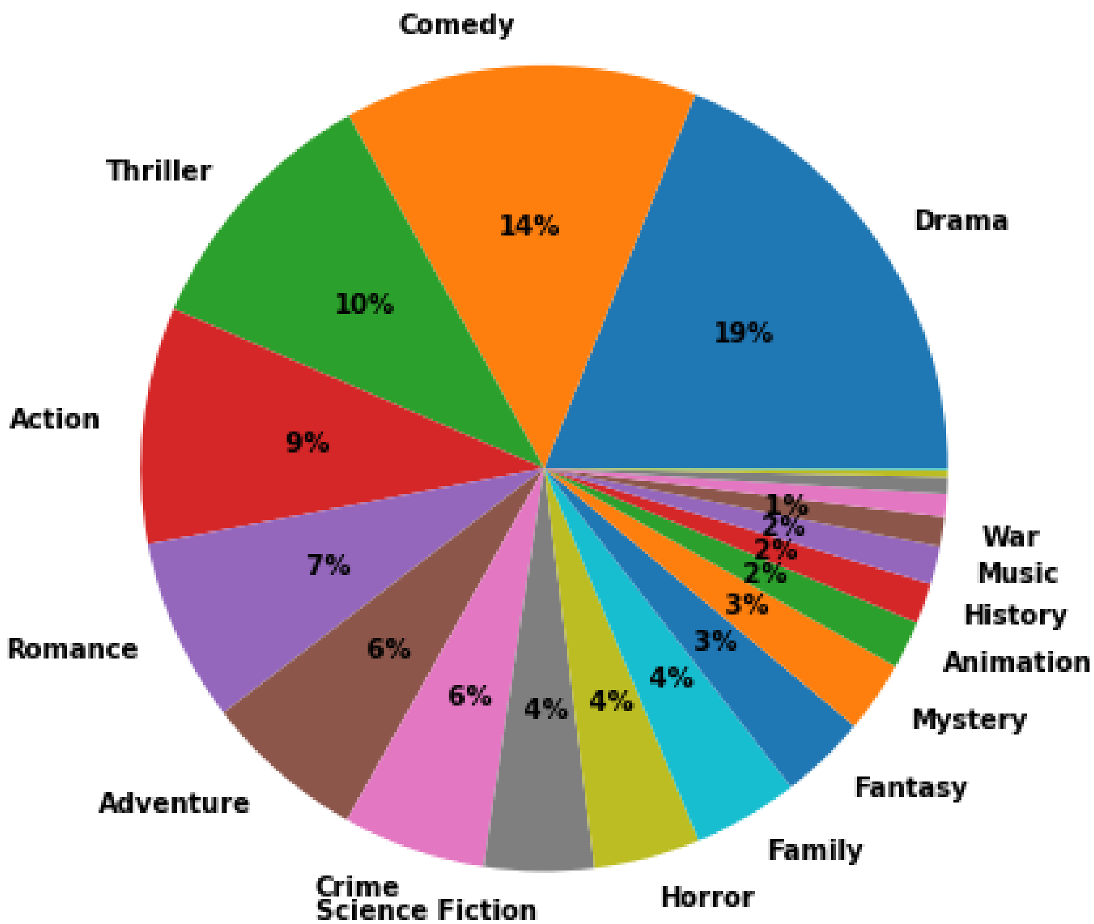
Out[34]:
```
0        Action|Adventure|Fantasy|Science Fiction
1                        Adventure|Fantasy|Action
2                          Action|Adventure|Crime
3                     Action|Crime|Drama|Thriller
4                Action|Adventure|Science Fiction
5                        Fantasy|Action|Adventure
6                                Animation|Family
7                Action|Adventure|Science Fiction
8                        Adventure|Fantasy|Family
9                        Action|Adventure|Fantasy
10       Adventure|Fantasy|Action|Science Fiction
11                 Adventure|Action|Thriller|Crime
12                       Adventure|Fantasy|Action
13                       Action|Adventure|Western
14       Action|Adventure|Fantasy|Science Fiction
15                       Adventure|Family|Fantasy
16               Science Fiction|Action|Adventure
17                       Adventure|Action|Fantasy
18                  Action|Comedy|Science Fiction
19                       Action|Adventure|Fantasy
20                       Action|Adventure|Fantasy
21                               Action|Adventure
22                              Adventure|Fantasy
```

```
23                             Adventure|Fantasy
24                        Adventure|Drama|Action
25                        Drama|Romance|Thriller
26              Adventure|Action|Science Fiction
27     Thriller|Action|Adventure|Science Fiction
28     Action|Adventure|Science Fiction|Thriller
29                     Action|Adventure|Thriller
                           ...
4773                                      Comedy
4774                               Drama|Romance
4775                                Drama|Comedy
4776                                Comedy|Drama
4777                                       Drama
4778                 Action|Drama|Crime|Thriller
4779                                      Comedy
4780                        Thriller|Crime|Drama
4781                              Comedy|Romance
4782                                Drama|Family
4783                             Thriller|Horror
4784                        Drama|Comedy|Romance
4785                                       Drama
4786                              Comedy|Romance
4787                    Science Fiction|Thriller
4788                         Horror|Comedy|Crime
4789                                       Drama
4790                               Drama|Foreign
4791                                      Horror
4792               Crime|Horror|Mystery|Thriller
4793                                       Drama
4794                      Thriller|Horror|Comedy
4795                                       Drama
4796              Science Fiction|Drama|Thriller
4797                            Foreign|Thriller
4798                       Action|Crime|Thriller
4799                              Comedy|Romance
4800               Comedy|Drama|Romance|TV Movie
4801
4802                                 Documentary
Name: genres, Length: 4803, dtype: object
```

Let's see which genre's contribute more to the industry

In [35]:
```
plt.rc('font', weight='bold')
f, ax = plt.subplots(figsize=(5,5))
genre_data_count = []
for genre in genres_data:
    genre_data_count.append([genre, DafaFrame_cleaned[genre].values.sum()])
genre_data_count.sort(key = lambda x:x[1], reverse = True)
```

```
labels_ForGenre, sizes_ForGenre = zip(*genre_data_count)
labels_selected = [n if v > sum(sizes_ForGenre) * 0.01 else '' for n, v in genre_data_
ax.pie(sizes_ForGenre, labels=labels_selected,
      autopct = lambda x:'{:2.0f}%'.format(x) if x>1 else '',
      shadow = False, startangle=0)
ax.axis('equal')
plt.tight_layout()
```



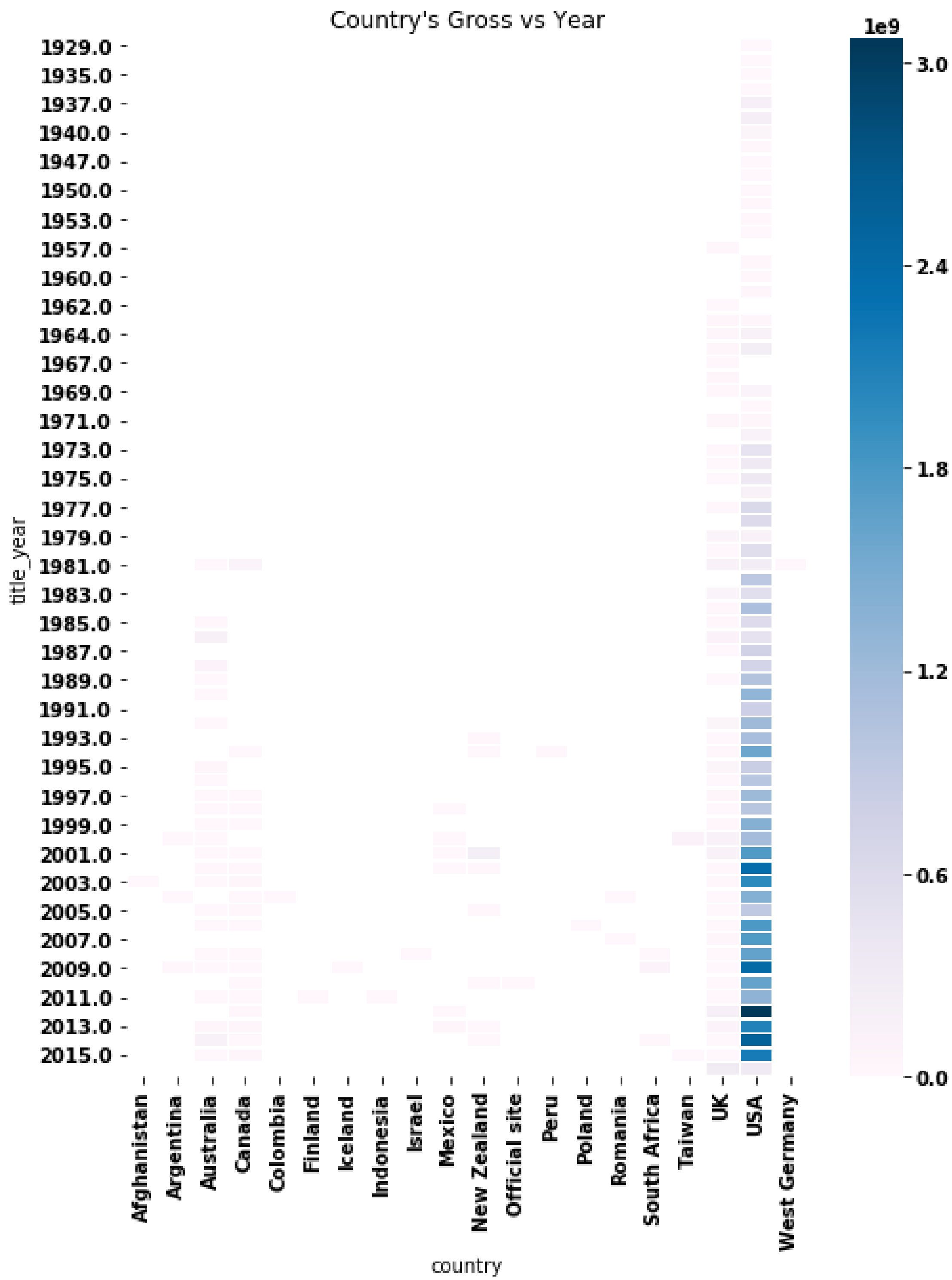
This pie chart shows which genres are most common in the movies dataset. We find that drama movies are most common, followed by comedy. Afterwards, thriller and action movies are the most popular. Interestingly, half of the movies is from the top 5 genres. (51%). This suggest that the main genre of the most movies are drama, comedy, thriller, action. However, the top 5 most common genres could be seen as more general descriptions.

Now let's try to get a more in depth view of the genres. In this cell we calculate the average votes, budget, and revenue for the different genres. we create a new data frame consisiting of every genre and the calculated averages.

```
In [36]: plt.show()
```

In [37]:
```
movie_data_metadata['diff_gross'] = movie_data_metadata['gross'] - movie_data_metadat
movie_data_metadata_copy_DropNA = movie_data_metadata.copy().dropna()
```

In [38]:
```
gross_DataBy_country = movie_data_metadata_copy_DropNA.groupby(movie_data_metadata['c
gross_DataBy_country_index = gross_DataBy_country[:20].index

gross_DataBy_country_pivot = pd.pivot_table(data = movie_data_metadata_copy_DropNA[mo
                              index=['title_year'],
                              columns=['country'],
                              values=['diff_gross'],
                              aggfunc='sum')
fig,ax = plt.subplots(figsize=(8,10))
sns.heatmap(gross_DataBy_country_pivot['diff_gross'],vmin=0,linewidth=.5,annot=False,
plt.title('Country\'s Gross vs Year')
ticks = plt.setp(ax.get_xticklabels(),rotation=90)
del fig,ax,ticks
```




```
In [39]: plt.show()

In [40]: data_mean_per_genre = pd.DataFrame(genres_data)
```

By votes, budget, revenue

In [41]:
```
#Mean votes average
new_array_genre_data = []*len(genres_data)
for genre in genres_data:
    new_array_genre_data.append(DafaFrame_cleaned.groupby(genre, as_index=True)['vote_
new_array_genre_data2 = []*len(genres_data)
for i in range(len(genres_data)):
    new_array_genre_data2.append(new_array_genre_data[i][1])

data_mean_per_genre['mean_votes_average']=new_array_genre_data2

#Mean budget
new_array_genre_data = []*len(genres_data)
for genre in genres_data:
    new_array_genre_data.append(DafaFrame_cleaned.groupby(genre, as_index=True)['budge
new_array_genre_data2 = []*len(genres_data)
for i in range(len(genres_data)):
    new_array_genre_data2.append(new_array_genre_data[i][1])

data_mean_per_genre['mean_budget']=new_array_genre_data2

#Mean revenue
new_array_genre_data = []*len(genres_data)
for genre in genres_data:
    new_array_genre_data.append(DafaFrame_cleaned.groupby(genre, as_index=True)['reven
new_array_genre_data2 = []*len(genres_data)
for i in range(len(genres_data)):
    new_array_genre_data2.append(new_array_genre_data[i][1])

data_mean_per_genre['mean_revenue']=new_array_genre_data2

data_mean_per_genre['profit'] = data_mean_per_genre['mean_revenue']-data_mean_per_genr

data_mean_per_genre
```

Out[41]:

	0	mean_votes_average	mean_budget	mean_revenue \
0	Mystery	6.183908	3.074449e+07	7.830093e+07
1	Crime	6.274138	2.784981e+07	6.615066e+07
2	Drama	6.388594	2.067832e+07	5.211623e+07
3	Animation	6.341453	6.646590e+07	2.256930e+08
4	Music	6.355676	1.590795e+07	4.845595e+07
5	Action	5.989515	5.151075e+07	1.412131e+08
6	Foreign	6.352941	6.580884e+05	3.646515e+05
7	Documentary	6.238182	2.653288e+06	9.838888e+06
8	War	6.713889	3.528246e+07	8.415587e+07
9	History	6.719797	2.990347e+07	5.752356e+07
10	Romance	6.207718	2.031136e+07	6.000239e+07

```
11           Comedy             5.945587  2.531342e+07  7.128950e+07
12           Family             6.029630  5.071951e+07  1.623455e+08
13          Fantasy             6.096698  6.356061e+07  1.933542e+08
14           Horror             5.626590  1.457403e+07  4.354508e+07
15         Thriller             6.010989  3.196821e+07  8.104429e+07
16  Science Fiction             6.005607  5.186555e+07  1.524565e+08
17          Western             6.178049  2.707870e+07  4.624596e+07
18         TV Movie             5.662500  1.150000e+06  0.000000e+00
19        Adventure             6.156962  6.632686e+07  2.086602e+08

          profit
0   4.755644e+07
1   3.830085e+07
2   3.143791e+07
3   1.592271e+08
4   3.254800e+07
5   8.970235e+07
6  -2.934369e+05
7   7.185600e+06
8   4.887342e+07
9   2.762010e+07
10  3.969103e+07
11  4.597608e+07
12  1.116260e+08
13  1.297936e+08
14  2.897105e+07
15  4.907608e+07
16  1.005910e+08
17  1.916726e+07
18 -1.150000e+06
19  1.423333e+08
```

In [42]:
```
data_mean_per_genre.sort_values('mean_votes_average', ascending=False).head()
```

Out[42]:
```
         0  mean_votes_average   mean_budget  mean_revenue        profit
9  History            6.719797  2.990347e+07  5.752356e+07  2.762010e+07
8      War            6.713889  3.528246e+07  8.415587e+07  4.887342e+07
2    Drama            6.388594  2.067832e+07  5.211623e+07  3.143791e+07
4    Music            6.355676  1.590795e+07  4.845595e+07  3.254800e+07
6  Foreign            6.352941  6.580884e+05  3.646515e+05 -2.934369e+05
```

In [43]:
```
data_mean_per_genre.sort_values('mean_budget', ascending=False).head()
```

Out[43]:
```
                  0  mean_votes_average   mean_budget  mean_revenue  \
3         Animation            6.341453  6.646590e+07  2.256930e+08
19        Adventure            6.156962  6.632686e+07  2.086602e+08
13          Fantasy            6.096698  6.356061e+07  1.933542e+08
16  Science Fiction            6.005607  5.186555e+07  1.524565e+08
5            Action            5.989515  5.151075e+07  1.412131e+08
```

```
         profit
3   1.592271e+08
19  1.423333e+08
13  1.297936e+08
16  1.005910e+08
5   8.970235e+07
```

It's very interesting to see that the top 5 highest vote average consists of *History, War, Drama, Music* and *Foreign*, while none of these genres are in either one of the other three categories, which all have the same top 3: *Animation, Adventure, Fantasy*. On the one hand, this is easily explained, since budget and revenue should be closely elated and profit is directly derived from budget and revenue. However, we would have expected a higher correlation between the budget and the quality of a movie.

To go even more in depth, we want to analyse the averages per genre per year.
Therefore, we first extend the dataframe with the year of release per movie.
Afterwards, we create a new dataframe which contains the average votes, average runtime, and average budget per release year and per genre.

In the last step in the cell below, only the rows that contain a 1 for genre are kept, so we create a data frame with only the specific genres.

```
In [44]: from datetime import datetime

         t = DafaFrame_cleaned['release_date']
         t = pd.to_datetime(t)
         t = t.dt.year
         DafaFrame_cleaned['release_year'] = t

         df_list = []*len(genres_data)
         for genre in genres_data:
             df_list.append(DafaFrame_cleaned.groupby([genre,'release_year']).mean().reset_inde

         df_per_genre = []*len(genres_data)
         for i in range(len(df_list)):
             df_per_genre.append(df_list[i][df_list[i].ix[:,0] == 1])
```

create a new table with the cloumns 1988 till 2017

```
In [45]: # Budget
         columns = range(1988,2018)
         data_budget_genre = pd.DataFrame( columns = columns)

         for genre in genres_data:
             temp=(df_per_genre[genres_data.index(genre)].pivot_table(index = genre, columns =
             temp = temp[temp.columns[-30:]].loc[1]
             data_budget_genre.loc[genres_data.index(genre)]=temp
         data_budget_genre['genre']=genres_data

         # Revenue
```

```
columns = range(1988,2018)
data_revenue_genre = pd.DataFrame( columns = columns)

for genre in genres_data:
    temp=(df_per_genre[genres_data.index(genre)].pivot_table(index = genre, columns =
    temp = temp[temp.columns[-30:]].loc[1]
    data_revenue_genre.loc[genres_data.index(genre)]=temp
data_revenue_genre['genre']=genres_data

# Vote average
columns = range(1988,2018)
vote_avg_genre = pd.DataFrame( columns = columns)

for genre in genres_data:
    temp=(df_per_genre[genres_data.index(genre)].pivot_table(index = genre, columns =
    temp = temp[temp.columns[-30:]].loc[1]
    vote_avg_genre.loc[genres_data.index(genre)]=temp
vote_avg_genre['genre']=genres_data
```

0.0.1 Budget per genre per year:

In [46]:
```
data_budget_genre.index = data_budget_genre['genre']
data_budget_genre
```

Out[46]:

genre	1988	1989	1990	1991 \
Mystery	NaN	1.900000e+07	3.550000e+07	NaN
Crime	1.282500e+07	2.300000e+07	4.375000e+07	1.641667e+07
Drama	7.441667e+06	1.237273e+07	1.922250e+07	1.934615e+07
Animation	1.015000e+07	NaN	NaN	NaN
Music	NaN	NaN	NaN	3.800000e+07
Action	1.707143e+07	2.945455e+07	3.837500e+07	2.890909e+07
Foreign	NaN	NaN	NaN	NaN
Documentary	NaN	1.600000e+05	NaN	NaN
War	6.300000e+07	1.366667e+07	NaN	NaN
History	NaN	4.580000e+06	NaN	4.000000e+07
Romance	1.066667e+07	1.333333e+07	1.320000e+07	1.100000e+07
Comedy	1.050000e+07	1.554167e+07	2.429318e+07	2.409091e+07
Family	1.515000e+07	2.000000e+07	1.525000e+07	2.510000e+07
Fantasy	1.100000e+07	2.100000e+07	3.066667e+07	2.650000e+07
Horror	4.733333e+06	6.083333e+06	2.000000e+07	2.050000e+07
Thriller	1.214545e+07	2.437500e+07	3.800000e+07	2.845455e+07
Science Fiction	8.750000e+06	3.000000e+07	3.380000e+07	3.160000e+07
Western	1.300000e+07	NaN	1.100000e+07	NaN
TV Movie	NaN	NaN	NaN	NaN
Adventure	2.088333e+07	2.920000e+07	3.300000e+07	3.010000e+07

```
                        1992          1993          1994          1995  \
genre
Mystery         1.250000e+07  4.366667e+07  2.580000e+07  3.875000e+07
Crime           1.523869e+07  2.187500e+07  2.776923e+07  2.631250e+07
Drama           2.024658e+07  1.556923e+07  2.572500e+07  2.478649e+07
Animation       2.800000e+07  2.800000e+07  4.500000e+07  4.250000e+07
Music           2.250000e+07  9.500000e+06           NaN  0.000000e+00
Action          3.146889e+07  2.241765e+07  3.266667e+07  5.106000e+07
Foreign                  NaN           NaN           NaN           NaN
Documentary              NaN           NaN  7.000000e+05           NaN
War             4.000000e+07  1.100000e+07  3.500000e+07  3.566667e+07
History         3.633333e+07  1.566667e+07  1.800000e+07  5.533333e+07
Romance         2.524365e+07  1.249091e+07  3.022222e+07  2.091765e+07
Comedy          2.566667e+07  1.822143e+07  1.955873e+07  1.801087e+07
Family          1.400000e+07  3.256250e+07  3.383333e+07  3.500000e+07
Fantasy         3.566667e+07  2.466000e+07  1.955556e+07  3.600000e+07
Horror          2.050000e+07  1.666667e+06  2.900000e+07  1.000000e+07
Thriller        1.401255e+07  2.654167e+07  3.288889e+07  2.944792e+07
Science Fiction 2.160000e+07  1.942857e+07  2.900000e+07  3.800000e+07
Western         1.400000e+07  2.500000e+07  6.300000e+07  3.200000e+07
TV Movie                 NaN           NaN           NaN           NaN
Adventure       3.220000e+07  3.439231e+07  3.033333e+07  6.172727e+07

                        1996          1997      ...               2009  \
genre                                           ...
Mystery         4.750000e+07  3.801500e+07      ...       2.591924e+07
Crime           2.217647e+07  3.463487e+07      ...       2.304330e+07
Drama           2.769933e+07  2.724868e+07      ...       1.760139e+07
Animation       4.800000e+07  3.716667e+07      ...       7.900000e+07
Music           2.325000e+07  2.850000e+07      ...       3.472727e+07
Action          5.168182e+07  5.453289e+07      ...       5.524081e+07
Foreign                  NaN  2.250000e+06      ...       8.125018e+05
Documentary              NaN  0.000000e+00      ...       1.600000e+07
War             3.650000e+07           NaN      ...       3.300000e+07
History         1.524051e+07  3.683333e+07      ...       3.581250e+07
Romance         2.131905e+07  2.458333e+07      ...       1.874380e+07
Comedy          2.042432e+07  1.708281e+07      ...       2.536214e+07
Family          3.869125e+07  3.113111e+07      ...       6.843750e+07
Fantasy         4.250000e+07  4.195000e+07      ...       6.671591e+07
Horror          2.250000e+07  3.990200e+07      ...       1.178334e+07
Thriller        3.865278e+07  5.534805e+07      ...       3.357797e+07
Science Fiction 5.133333e+07  5.447368e+07      ...       7.679688e+07
Western                  NaN           NaN      ...                NaN
TV Movie                 NaN           NaN      ...                NaN
Adventure       5.668071e+07  5.863043e+07      ...       8.527778e+07

                        2010          2011          2012          2013  \
genre
```

```
Mystery          3.507574e+07  4.256688e+07  2.800000e+07  4.270000e+07
Crime            2.426559e+07  3.657083e+07  3.061967e+07  3.291946e+07
Drama            2.050320e+07  2.064913e+07  2.686389e+07  2.176040e+07
Animation        9.184615e+07  8.717647e+07  8.334743e+07  7.844118e+07
Music            5.000000e+06  3.040000e+07  3.028571e+07  1.295835e+07
Action           6.367449e+07  5.885432e+07  8.099373e+07  7.233679e+07
Foreign          0.000000e+00  0.000000e+00  2.250000e+05           NaN
Documentary      4.285714e+06  3.850857e+06  1.858333e+06  1.260000e+06
War              2.505785e+07  3.985000e+07  3.500000e+07  1.666667e+07
History          1.121839e+07  2.839175e+07  4.375000e+07  1.585750e+07
Romance          2.892811e+07  2.374046e+07  1.844744e+07  1.796889e+07
Comedy           3.265785e+07  3.292033e+07  2.931458e+07  2.476088e+07
Family           7.154310e+07  6.648036e+07  6.961863e+07  8.284062e+07
Fantasy          8.652857e+07  8.766667e+07  8.830526e+07  1.055953e+08
Horror           1.639074e+07  1.572576e+07  1.151394e+07  1.675803e+07
Thriller         3.280960e+07  3.089882e+07  3.168897e+07  3.583434e+07
Science Fiction  5.022895e+07  5.538656e+07  7.196136e+07  8.151852e+07
Western          2.740000e+07  4.500000e+07  5.000000e+07  2.550000e+08
TV Movie                  NaN  0.000000e+00  2.000000e+06  5.000000e+05
Adventure        9.661667e+07  9.631250e+07  1.237400e+08  9.897204e+07

                         2014          2015          2016  2017  \
genre
Mystery          2.789267e+07  2.315000e+07  2.425000e+07   NaN
Crime            2.157185e+07  3.630000e+07  4.017500e+07   NaN
Drama            2.139409e+07  2.271263e+07  2.543919e+07   0.0
Animation        6.464286e+07  7.092308e+07  7.800000e+07   NaN
Music            1.188890e+07  1.146530e+07  0.000000e+00   NaN
Action           7.582593e+07  6.637717e+07  7.152538e+07   NaN
Foreign                   NaN           NaN           NaN   NaN
Documentary      1.304429e+05  6.746231e+05           NaN   NaN
War              4.860000e+07  3.000000e+07  3.333333e+07   NaN
History          3.342857e+07  2.955556e+07  3.458333e+07   NaN
Romance          2.831250e+07  1.733043e+07  1.377778e+07   NaN
Comedy           2.936936e+07  3.171538e+07  3.951923e+07   0.0
Family           6.386957e+07  7.196176e+07  7.677778e+07   0.0
Fantasy          1.117500e+08  7.800000e+07  1.266531e+08   NaN
Horror           1.102143e+07  4.919697e+06  9.720000e+06   NaN
Thriller         2.289455e+07  2.580746e+07  2.504259e+07   NaN
Science Fiction  7.793462e+07  7.628304e+07  1.045455e+08   NaN
Western          5.666667e+06  3.571429e+07  2.500000e+07   NaN
TV Movie                  NaN           NaN           NaN   NaN
Adventure        1.011081e+08  9.874286e+07  1.120213e+08   NaN

                           genre
genre
Mystery                  Mystery
Crime                      Crime
```

```
Drama                          Drama
Animation                  Animation
Music                          Music
Action                        Action
Foreign                      Foreign
Documentary              Documentary
War                              War
History                      History
Romance                      Romance
Comedy                        Comedy
Family                        Family
Fantasy                      Fantasy
Horror                        Horror
Thriller                    Thriller
Science Fiction  Science Fiction
Western                      Western
TV Movie                    TV Movie
Adventure                  Adventure

[20 rows x 31 columns]
```

0.0.2 Budget per genre per year:

In [47]:
```
data_revenue_genre.index = data_revenue_genre['genre']
data_revenue_genre
```

Out[47]:
```
                         1988          1989          1990          1991  \
genre
Mystery                   NaN  1.108795e+08  2.627117e+08           NaN
Crime            2.593798e+07  5.225724e+07  7.694114e+07  1.049300e+08
Drama            6.138733e+07  7.646573e+07  1.279218e+08  5.803509e+07
Animation        4.250701e+07           NaN           NaN           NaN
Music                     NaN           NaN           NaN  3.441689e+07
Action           6.098073e+07  1.220110e+08  1.163004e+08  7.159942e+07
Foreign                   NaN           NaN           NaN           NaN
Documentary               NaN  6.706368e+06           NaN           NaN
War              1.890156e+08  6.261002e+07           NaN           NaN
History                   NaN  3.353184e+06           NaN  2.054055e+08
Romance          6.211316e+07  3.094118e+07  2.074307e+08  1.939886e+07
Comedy           8.140686e+07  6.035897e+07  1.473084e+08  6.829757e+07
Family           1.180648e+08  1.660000e+08  1.841455e+08  8.272960e+07
Fantasy          9.510781e+07  2.056745e+08  1.998274e+08  1.233066e+08
Horror           2.093621e+07  1.754668e+07  3.435932e+07  1.131872e+08
Thriller         4.710995e+07  5.501500e+07  1.470854e+08  1.229121e+08
Science Fiction  8.674738e+06  1.067135e+08  1.279649e+08  1.391539e+08
Western          4.472664e+07           NaN  2.121044e+08           NaN
TV Movie                  NaN           NaN           NaN           NaN
Adventure        1.027466e+08  1.227315e+08  1.738642e+08  9.219372e+07
```

```
                        1992          1993          1994          1995  \
genre
Mystery         1.072523e+07  2.781307e+08  9.138758e+07  1.499534e+08
Crime           8.962918e+07  7.733952e+07  1.219430e+08  7.811012e+07
Drama           9.141593e+07  7.285734e+07  1.356206e+08  7.533243e+07
Animation       5.040502e+08  6.692760e+05  7.882418e+08  3.598169e+08
Music           2.663520e+08  1.059997e+06           NaN  1.062700e+08
Action          1.594277e+08  5.637173e+07  8.832568e+07  1.178188e+08
Foreign                  NaN           NaN           NaN           NaN
Documentary              NaN           NaN  7.830611e+06           NaN
War             7.550586e+07  1.731828e+08  9.248560e+07  7.500000e+07
History         4.122525e+07  1.342902e+08  5.887457e+06  7.802139e+07
Romance         1.950059e+08  2.854121e+07  2.126254e+08  4.045968e+07
Comedy          1.491277e+08  6.554884e+07  9.474867e+07  7.218928e+07
Family          2.352689e+08  8.547552e+07  2.227296e+08  2.279945e+08
Fantasy         1.624521e+08  3.293630e+07  1.203390e+08  1.282671e+08
Horror          7.415122e+07  5.330757e+06  8.319183e+07  2.671513e+07
Thriller        1.066051e+08  9.739472e+07  1.027076e+08  9.240182e+07
Science Fiction 4.259434e+07  1.390742e+08  7.662750e+07  9.667365e+07
Western         1.591574e+08  5.650506e+07  2.505200e+07  1.855246e+07
TV Movie                 NaN           NaN           NaN           NaN
Adventure       2.520559e+08  1.424342e+08  8.839451e+07  1.401289e+08

                        1996          1997      ...               2009  \
genre                                           ...
Mystery         1.062594e+08  6.935287e+07      ...       6.984452e+07
Crime           4.683539e+07  6.534840e+07      ...       4.865874e+07
Drama           5.836057e+07  7.358007e+07      ...       3.956652e+07
Animation       8.758471e+07  1.009154e+08      ...       2.433655e+08
Music           3.526179e+07  5.178332e+07      ...       8.765727e+07
Action          1.633356e+08  1.053358e+08      ...       1.717490e+08
Foreign                  NaN  0.000000e+00      ...       1.750000e+00
Documentary              NaN  0.000000e+00      ...       7.368583e+06
War             1.664186e+08           NaN      ...       1.104578e+08
History         3.704187e+07  6.848589e+07      ...       5.260018e+07
Romance         5.061994e+07  1.278945e+08      ...       5.463998e+07
Comedy          3.591524e+07  5.855068e+07      ...       6.965731e+07
Family          6.253141e+07  3.930420e+07      ...       2.066505e+08
Fantasy         8.220414e+07  9.090646e+07      ...       2.867183e+08
Horror          4.760999e+07  8.983488e+07      ...       3.082346e+07
Thriller        8.179710e+07  1.315105e+08      ...       5.795111e+07
Science Fiction 1.668067e+08  1.224596e+08      ...       2.381428e+08
Western                  NaN           NaN      ...                NaN
TV Movie                 NaN           NaN      ...                NaN
Adventure       2.065723e+08  1.238979e+08      ...       3.189092e+08

                        2010          2011          2012          2013  \
```

```
genre
Mystery          1.020497e+08  1.169212e+08  7.414954e+07  8.405029e+07
Crime            4.074380e+07  9.365526e+07  9.149609e+07  6.650704e+07
Drama            4.772357e+07  4.533169e+07  9.538976e+07  5.452071e+07
Animation        3.199310e+08  2.466578e+08  2.754644e+08  3.010980e+08
Music            1.763818e+06  1.249970e+08  1.163449e+08  1.223540e+07
Action           1.371655e+08  1.621480e+08  2.529830e+08  1.718815e+08
Foreign          0.000000e+00  0.000000e+00  1.113000e+05           NaN
Documentary      1.846765e+07  1.682173e+07  7.503113e+06  3.223091e+06
War              3.907929e+07  4.650904e+07  6.581907e+07  4.976520e+07
History          5.899821e+07  3.896373e+07  1.170256e+08  5.855735e+07
Romance          7.386076e+07  6.911425e+07  7.524173e+07  4.219857e+07
Comedy           7.815022e+07  8.864117e+07  8.750149e+07  8.276906e+07
Family           2.235535e+08  1.792851e+08  2.302810e+08  2.705075e+08
Fantasy          2.444391e+08  2.578499e+08  3.297305e+08  2.629811e+08
Horror           4.421287e+07  3.788669e+07  3.778651e+07  7.184334e+07
Thriller         7.575624e+07  7.497611e+07  1.017465e+08  8.513178e+07
Science Fiction  1.541972e+08  1.669972e+08  2.280335e+08  2.662696e+08
Western          5.495596e+07  8.211604e+07  2.126841e+08  8.928991e+07
TV Movie                  NaN  0.000000e+00  0.000000e+00  0.000000e+00
Adventure        2.844150e+08  2.606372e+08  4.506673e+08  2.880378e+08

                         2014          2015          2016  2017  \
genre
Mystery          7.715577e+07  3.866913e+07  9.781144e+07   NaN
Crime            4.022622e+07  7.479586e+07  1.388020e+08   NaN
Drama            5.674699e+07  7.293462e+07  6.068936e+07   0.0
Animation        2.201954e+08  3.140907e+08  4.719153e+08   NaN
Music            3.468455e+07  7.920151e+07  0.000000e+00   NaN
Action           2.575422e+08  2.364232e+08  2.108906e+08   NaN
Foreign                   NaN           NaN           NaN   NaN
Documentary      0.000000e+00  0.000000e+00           NaN   NaN
War              1.874737e+08  5.321016e+07  3.148244e+07   NaN
History          8.265211e+07  5.544324e+07  3.744987e+07   NaN
Romance          7.939355e+07  7.118764e+07  4.963900e+07   NaN
Comedy           1.068331e+08  1.199000e+08  1.359984e+08   0.0
Family           2.114126e+08  2.817845e+08  3.477137e+08   0.0
Fantasy          3.657594e+08  1.596482e+08  3.542139e+08   NaN
Horror           4.408987e+07  2.068814e+07  4.222806e+07   NaN
Thriller         7.388507e+07  9.578632e+07  6.597147e+07   NaN
Science Fiction  2.908823e+08  2.588725e+08  3.323677e+08   NaN
Western          1.147618e+06  9.841996e+07  1.397284e+06   NaN
TV Movie                  NaN           NaN           NaN   NaN
Adventure        3.451557e+08  3.377481e+08  3.664628e+08   NaN

                          genre
genre
Mystery                 Mystery
```

```
Crime                        Crime
Drama                        Drama
Animation                Animation
Music                        Music
Action                      Action
Foreign                    Foreign
Documentary            Documentary
War                            War
History                    History
Romance                    Romance
Comedy                      Comedy
Family                      Family
Fantasy                    Fantasy
Horror                      Horror
Thriller                  Thriller
Science Fiction    Science Fiction
Western                    Western
TV Movie                  TV Movie
Adventure                Adventure

[20 rows x 31 columns]
```

0.0.3 Vote Average per genre per year:

```
In [48]: vote_avg_genre.index = vote_avg_genre['genre']
         vote_avg_genre
```

```
Out[48]:                      1988      1989      1990      1991      1992      1993  \
         genre
         Mystery               NaN  6.700000  6.550000       NaN  7.500000  6.700000
         Crime            6.350000  6.166667  6.850000  6.683333  6.490909  6.487500
         Drama            6.408333  6.881818  6.920000  6.446154  6.753846  6.911538
         Animation        7.400000       NaN       NaN       NaN  7.400000  6.800000
         Music                 NaN       NaN       NaN  6.700000  6.300000  6.250000
         Action           6.385714  6.400000  6.500000  5.927273  6.300000  6.247059
         Foreign               NaN       NaN       NaN       NaN       NaN       NaN
         Documentary           NaN  7.400000       NaN       NaN       NaN       NaN
         War              5.700000  7.166667       NaN       NaN  7.100000  7.450000
         History               NaN  7.400000       NaN  7.500000  6.800000  7.433333
         Romance          6.600000  6.966667  6.840000  5.700000  6.700000  6.945455
         Comedy           6.140000  6.358333  6.327273  5.972727  6.575000  6.264286
         Family           6.950000  6.500000  6.250000  6.360000  6.825000  5.900000
         Fantasy          6.900000  6.400000  6.866667  5.950000  6.750000  5.790000
         Horror           6.022222  5.500000  5.300000  5.900000  6.266667  5.100000
         Thriller         6.127273  5.825000  6.455556  6.418182  6.300000  6.150000
         Science Fiction  6.625000  6.540000  6.220000  6.140000  5.740000  5.985714
         Western          6.600000       NaN  7.050000       NaN  7.700000  7.400000
         TV Movie              NaN       NaN       NaN       NaN       NaN       NaN
```

```
Adventure        6.150000  6.370000  6.675000  5.890000  6.600000  6.076923

                     1994      1995      1996      1997       ...            \
genre                                                         ...
Mystery          6.320000  5.975000  6.316667  6.705556       ...
Crime            6.338462  6.300000  6.305882  6.387500       ...
Drama            6.770000  6.564865  6.249123  6.550943       ...
Animation        8.000000  7.200000  6.200000  7.566667       ...
Music                 NaN  6.900000  6.450000  5.900000       ...
Action           5.828571  5.992000  5.904545  5.700000       ...
Foreign               NaN       NaN       NaN  7.300000       ...
Documentary      7.700000       NaN       NaN  6.300000       ...
War              6.550000  7.100000  6.600000       NaN       ...
History          7.300000  6.766667  6.100000  7.166667       ...
Romance          6.533333  6.317647  6.133333  6.176190       ...
Comedy           6.261538  6.273913  6.054054  6.228947       ...
Family           5.833333  6.533333  5.712500  6.033333       ...
Fantasy          6.055556  5.887500  5.740000  5.520000       ...
Horror           6.666667  5.583333  6.000000  6.020000       ...
Thriller         6.055556  6.270833  5.947222  6.134146       ...
Science Fiction  5.450000  5.540000  5.822222  5.721053       ...
Western          6.500000  6.300000       NaN       NaN       ...
TV Movie              NaN       NaN       NaN       NaN       ...
Adventure        5.833333  6.090909  5.900000  5.926087       ...

                     2009      2010      2011      2012      2013      2014  \
genre
Mystery          6.107143  6.329412  6.212500  5.737500  6.240000  5.440000
Crime            6.021875  6.123333  6.295833  5.955556  6.183784  5.762963
Drama            6.300000  6.193043  6.273737  6.256962  6.364545  5.930909
Animation        6.480000  6.300000  5.882353  6.176923  6.323529  6.078571
Music            5.818182  5.100000  5.560000  6.585714  6.675000  6.244444
Action           5.894118  6.038776  5.968966  5.879070  6.044643  5.857407
Foreign          6.350000  5.200000  5.750000  6.900000       NaN       NaN
Documentary      6.540000  6.142857  5.785714  6.711111  6.400000  3.528571
War              7.050000  6.900000  6.200000  6.100000  5.766667  6.790000
History          6.900000  6.700000  5.750000  6.425000  7.025000  6.285714
Romance          6.129825  6.055556  6.180000  6.238462  6.540000  6.270833
Comedy           5.852577  5.779310  5.924390  5.751250  6.073239  5.945161
Family           6.160714  5.762069  5.892857  5.970588  6.013636  6.156522
Fantasy          6.013636  5.909524  5.953333  6.273684  5.947619  6.481250
Horror           5.706667  5.529630  5.412500  5.181818  5.208000  4.914286
Thriller         5.850847  6.066071  6.017391  5.746552  5.926415  5.509091
Science Fiction  5.878125  5.947368  6.065385  6.068182  6.259259  6.088462
Western               NaN  6.220000  5.700000  6.650000  5.900000  5.133333
TV Movie              NaN       NaN  5.000000  5.050000  5.400000       NaN
Adventure        5.955556  6.226667  6.034375  6.164000  6.225000  6.335135
```

```
                     2015      2016  2017            genre
genre
Mystery          5.505000  6.466667   NaN          Mystery
Crime            5.419231  5.550000   NaN            Crime
Drama            5.993684  6.013514   7.4            Drama
Animation        6.476923  6.025000   NaN        Animation
Music            5.687500  6.000000   NaN            Music
Action           5.684783  5.866667   NaN           Action
Foreign               NaN       NaN   NaN          Foreign
Documentary      3.542857       NaN   NaN      Documentary
War              7.250000  6.466667   NaN              War
History          6.566667  6.700000   NaN          History
Romance          6.352174  5.944444   NaN          Romance
Comedy           6.017308  5.592308   7.4           Comedy
Family           5.900000  6.211111   7.4           Family
Fantasy          6.420000  5.846154   NaN          Fantasy
Horror           4.984848  5.600000   NaN           Horror
Thriller         5.444776  5.785185   NaN         Thriller
Science Fiction  5.807143  6.118182   NaN  Science Fiction
Western          5.185714  5.400000   NaN          Western
TV Movie              NaN       NaN   NaN         TV Movie
Adventure        6.268571  6.256522   NaN        Adventure

[20 rows x 31 columns]
```

In [49]:
```
data_profit_genre = data_revenue_genre[data_revenue_genre.columns[0:29]]-data_budget_g
```

0.0.4 Budget

In [50]:
```
fig, ax = plt.subplots(figsize=(9,9))
cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
sns.heatmap(data_budget_genre.ix[:,0:30], xticklabels=3, cmap=cmap, linewidths=0.05)
```

Out[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a33d57c10>
```


```
In [51]: plt.show()
```

0.0.5 Revenue

```
In [52]: fig, ax = plt.subplots(figsize=(9,9))
         cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
         sns.heatmap(data_revenue_genre.ix[:,0:30], xticklabels=3, cmap=cmap, linewidths=0.05)
```

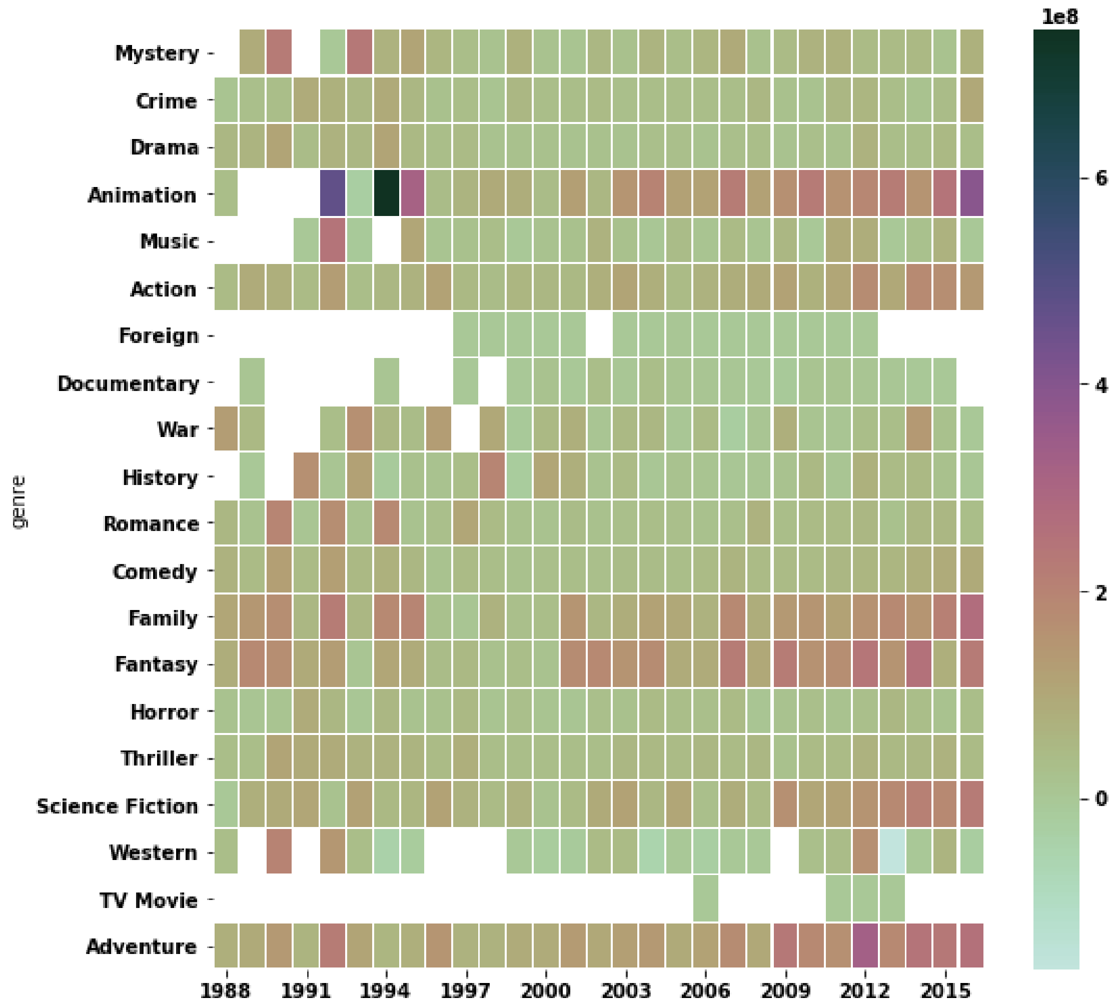
```
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1a342e9ed0>
```


```
In [53]: plt.show()
```

0.0.6 Profit

```
In [54]: fig, ax = plt.subplots(figsize=(9,9))
         cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
         sns.heatmap(data_profit_genre, xticklabels=3, cmap=cmap, linewidths=0.05)
```

```
Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x1a345af6d0>
```

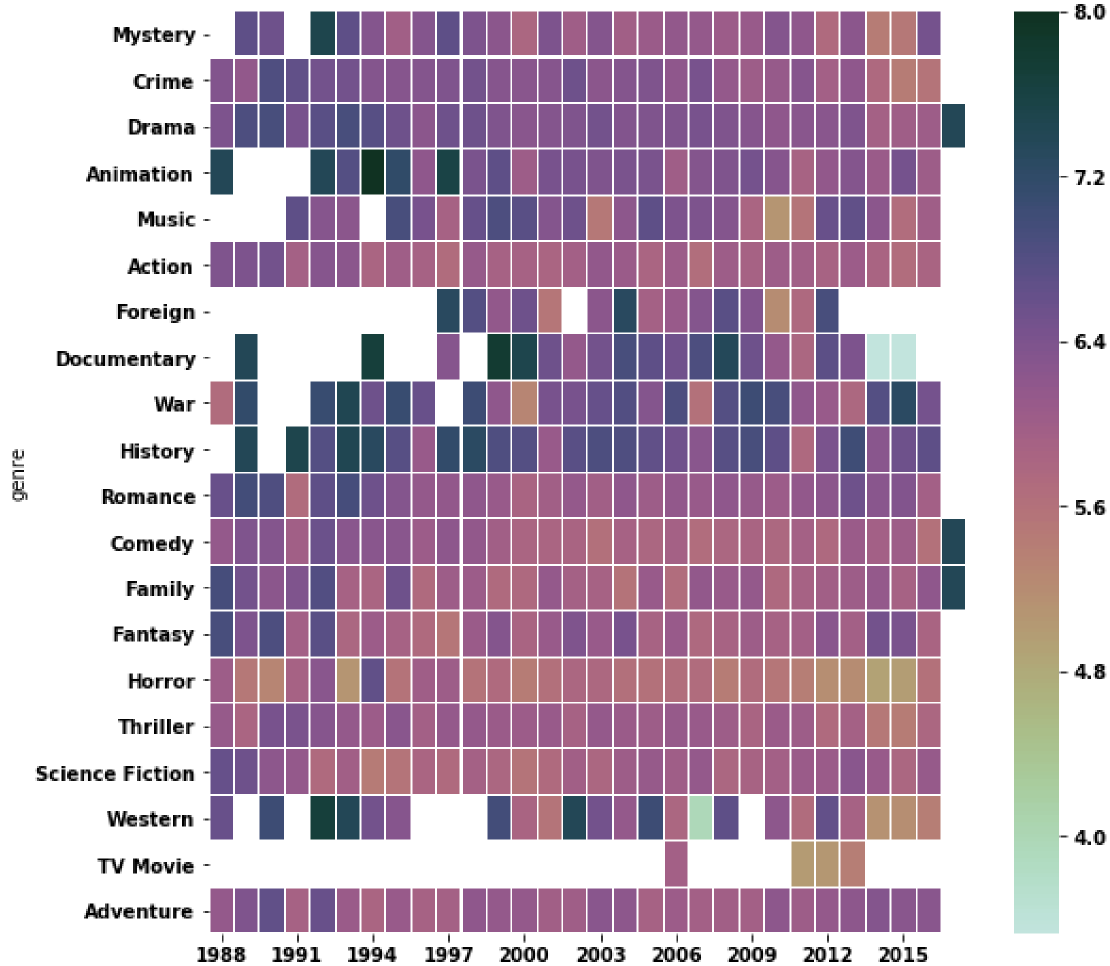


In [55]: `plt.show()`

0.0.7 Vote Average

In [56]:
```
fig, ax = plt.subplots(figsize=(9,9))
cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
sns.heatmap(vote_avg_genre.ix[:,0:30], xticklabels=3, cmap=cmap, linewidths=0.05)
```

Out[56]: `<matplotlib.axes._subplots.AxesSubplot at 0x1a3479f410>`




```
In [57]: plt.show()
```

```
In [58]: temp = data_budget_genre
         temp[2013]=temp[2013].replace(2.550000e+08, 0)
```

Budget

```
In [59]: fig, ax = plt.subplots(figsize=(9,9))
         cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
         sns.heatmap(temp.ix[:,0:30], xticklabels=3, cmap=cmap, linewidths=0.05)
```

```
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1a349f1bd0>
```


```
In [60]: plt.show()
```

```
In [61]: data_revenue_genre[1994]
         temp2 = data_revenue_genre
         temp2[1994] = temp2[1994].replace(788241776.0, 0)
         temp2[1992] = temp2[1992].replace(504050219.0, 0)
         temp2
```

Out[61]:

	1988	1989	1990	1991 \
genre				
Mystery	NaN	1.108795e+08	2.627117e+08	NaN
Crime	2.593798e+07	5.225724e+07	7.694114e+07	1.049300e+08
Drama	6.138733e+07	7.646573e+07	1.279218e+08	5.803509e+07
Animation	4.250701e+07	NaN	NaN	NaN
Music	NaN	NaN	NaN	3.441689e+07
Action	6.098073e+07	1.220110e+08	1.163004e+08	7.159942e+07
Foreign	NaN	NaN	NaN	NaN

```
Documentary              NaN  6.706368e+06           NaN           NaN
War             1.890156e+08  6.261002e+07           NaN           NaN
History                  NaN  3.353184e+06           NaN  2.054055e+08
Romance         6.211316e+07  3.094118e+07  2.074307e+08  1.939886e+07
Comedy          8.140686e+07  6.035897e+07  1.473084e+08  6.829757e+07
Family          1.180648e+08  1.660000e+08  1.841455e+08  8.272960e+07
Fantasy         9.510781e+07  2.056745e+08  1.998274e+08  1.233066e+08
Horror          2.093621e+07  1.754668e+07  3.435932e+07  1.131872e+08
Thriller        4.710995e+07  5.501500e+07  1.470854e+08  1.229121e+08
Science Fiction 8.674738e+06  1.067135e+08  1.279649e+08  1.391539e+08
Western         4.472664e+07           NaN  2.121044e+08           NaN
TV Movie                 NaN           NaN           NaN           NaN
Adventure       1.027466e+08  1.227315e+08  1.738642e+08  9.219372e+07

                        1992          1993          1994          1995  \
genre
Mystery         1.072523e+07  2.781307e+08  9.138758e+07  1.499534e+08
Crime           8.962918e+07  7.733952e+07  1.219430e+08  7.811012e+07
Drama           9.141593e+07  7.285734e+07  1.356206e+08  7.533243e+07
Animation       0.000000e+00  6.692760e+05  0.000000e+00  3.598169e+08
Music           2.663520e+08  1.059997e+06           NaN  1.062700e+08
Action          1.594277e+08  5.637173e+07  8.832568e+07  1.178188e+08
Foreign                  NaN           NaN           NaN           NaN
Documentary              NaN           NaN  7.830611e+06           NaN
War             7.550586e+07  1.731828e+08  9.248560e+07  7.500000e+07
History         4.122525e+07  1.342902e+08  5.887457e+06  7.802139e+07
Romance         1.950059e+08  2.854121e+07  2.126254e+08  4.045968e+07
Comedy          1.491277e+08  6.554884e+07  9.474867e+07  7.218928e+07
Family          2.352689e+08  8.547552e+07  2.227296e+08  2.279945e+08
Fantasy         1.624521e+08  3.293630e+07  1.203390e+08  1.282671e+08
Horror          7.415122e+07  5.330757e+06  8.319183e+07  2.671513e+07
Thriller        1.066051e+08  9.739472e+07  1.027076e+08  9.240182e+07
Science Fiction 4.259434e+07  1.390742e+08  7.662750e+07  9.667365e+07
Western         1.591574e+08  5.650506e+07  2.505200e+07  1.855246e+07
TV Movie                 NaN           NaN           NaN           NaN
Adventure       2.520559e+08  1.424342e+08  8.839451e+07  1.401289e+08

                        1996          1997      ...               2009  \
genre                                           ...
Mystery         1.062594e+08  6.935287e+07      ...       6.984452e+07
Crime           4.683539e+07  6.534840e+07      ...       4.865874e+07
Drama           5.836057e+07  7.358007e+07      ...       3.956652e+07
Animation       8.758471e+07  1.009154e+08      ...       2.433655e+08
Music           3.526179e+07  5.178332e+07      ...       8.765727e+07
Action          1.633356e+08  1.053358e+08      ...       1.717490e+08
Foreign                  NaN  0.000000e+00      ...       1.750000e+00
Documentary              NaN  0.000000e+00      ...       7.368583e+06
War             1.664186e+08           NaN      ...       1.104578e+08
```

```
History          3.704187e+07  6.848589e+07       ...          5.260018e+07
Romance          5.061994e+07  1.278945e+08       ...          5.463998e+07
Comedy           3.591524e+07  5.855068e+07       ...          6.965731e+07
Family           6.253141e+07  3.930420e+07       ...          2.066505e+08
Fantasy          8.220414e+07  9.090646e+07       ...          2.867183e+08
Horror           4.760999e+07  8.983488e+07       ...          3.082346e+07
Thriller         8.179710e+07  1.315105e+08       ...          5.795111e+07
Science Fiction  1.668067e+08  1.224596e+08       ...          2.381428e+08
Western                   NaN           NaN       ...                   NaN
TV Movie                  NaN           NaN       ...                   NaN
Adventure        2.065723e+08  1.238979e+08       ...          3.189092e+08

                         2010          2011          2012          2013  \
genre
Mystery          1.020497e+08  1.169212e+08  7.414954e+07  8.405029e+07
Crime            4.074380e+07  9.365526e+07  9.149609e+07  6.650704e+07
Drama            4.772357e+07  4.533169e+07  9.538976e+07  5.452071e+07
Animation        3.199310e+08  2.466578e+08  2.754644e+08  3.010980e+08
Music            1.763818e+06  1.249970e+08  1.163449e+08  1.223540e+07
Action           1.371655e+08  1.621480e+08  2.529830e+08  1.718815e+08
Foreign          0.000000e+00  0.000000e+00  1.113000e+05           NaN
Documentary      1.846765e+07  1.682173e+07  7.503113e+06  3.223091e+06
War              3.907929e+07  4.650904e+07  6.581907e+07  4.976520e+07
History          5.899821e+07  3.896373e+07  1.170256e+08  5.855735e+07
Romance          7.386076e+07  6.911425e+07  7.524173e+07  4.219857e+07
Comedy           7.815022e+07  8.864117e+07  8.750149e+07  8.276906e+07
Family           2.235535e+08  1.792851e+08  2.302810e+08  2.705075e+08
Fantasy          2.444391e+08  2.578499e+08  3.297305e+08  2.629811e+08
Horror           4.421287e+07  3.788669e+07  3.778651e+07  7.184334e+07
Thriller         7.575624e+07  7.497611e+07  1.017465e+08  8.513178e+07
Science Fiction  1.541972e+08  1.669972e+08  2.280335e+08  2.662696e+08
Western          5.495596e+07  8.211604e+07  2.126841e+08  8.928991e+07
TV Movie                  NaN  0.000000e+00  0.000000e+00  0.000000e+00
Adventure        2.844150e+08  2.606372e+08  4.506673e+08  2.880378e+08

                         2014          2015          2016  2017  \
genre
Mystery          7.715577e+07  3.866913e+07  9.781144e+07   NaN
Crime            4.022622e+07  7.479586e+07  1.388020e+08   NaN
Drama            5.674699e+07  7.293462e+07  6.068936e+07   0.0
Animation        2.201954e+08  3.140907e+08  4.719153e+08   NaN
Music            3.468455e+07  7.920151e+07  0.000000e+00   NaN
Action           2.575422e+08  2.364232e+08  2.108906e+08   NaN
Foreign                   NaN           NaN           NaN   NaN
Documentary      0.000000e+00  0.000000e+00           NaN   NaN
War              1.874737e+08  5.321016e+07  3.148244e+07   NaN
History          8.265211e+07  5.544324e+07  3.744987e+07   NaN
Romance          7.939355e+07  7.118764e+07  4.963900e+07   NaN
```

```
Comedy           1.068331e+08  1.199000e+08  1.359984e+08   0.0
Family           2.114126e+08  2.817845e+08  3.477137e+08   0.0
Fantasy          3.657594e+08  1.596482e+08  3.542139e+08   NaN
Horror           4.408987e+07  2.068814e+07  4.222806e+07   NaN
Thriller         7.388507e+07  9.578632e+07  6.597147e+07   NaN
Science Fiction  2.908823e+08  2.588725e+08  3.323677e+08   NaN
Western          1.147618e+06  9.841996e+07  1.397284e+06   NaN
TV Movie                  NaN           NaN           NaN   NaN
Adventure        3.451557e+08  3.377481e+08  3.664628e+08   NaN

                           genre
genre
Mystery                  Mystery
Crime                      Crime
Drama                      Drama
Animation              Animation
Music                      Music
Action                    Action
Foreign                  Foreign
Documentary          Documentary
War                          War
History                  History
Romance                  Romance
Comedy                    Comedy
Family                    Family
Fantasy                  Fantasy
Horror                    Horror
Thriller                Thriller
Science Fiction  Science Fiction
Western                  Western
TV Movie                TV Movie
Adventure              Adventure

[20 rows x 31 columns]
```

In [62]:
```
temp2[1992][9]
```

Out[62]:
```
41225254.666666664
```

In [63]:
```
fig, ax = plt.subplots(figsize=(9,9))
cmap = sns.cubehelix_palette(start = 1.5, rot = 1.5, as_cmap = True)
sns.heatmap(temp2.ix[:,0:30], xticklabels=3, cmap=cmap, linewidths=0.05)
```

Out[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a34c14d90>
```

In [64]:
```
plt.show()
```

In [65]:
```
from datetime import datetime

data__DataFrame_genre = pd.DataFrame(columns = ['genre', 'cgenres', 'budget', 'gross'
#list(map(datetime.year, DafaFrame_cleaned["release_date"]))
t = df['release_date']
t = pd.to_datetime(t)
t = t.dt.year
data__DataFrame_genre['release_year'] = t

colnames = ['budget', 'genres', 'revenue']
data__DataFrame_clean = df[colnames]
data__DataFrame_clean['release_year'] = t
data__DataFrame_clean = data__DataFrame_clean.dropna()
data__DataFrame_genre = data__DataFrame_genre.dropna()
data__DataFrame_clean.head()
```

Out[65]:
```
      budget                                    genres     revenue  \
0  237000000  Action|Adventure|Fantasy|Science Fiction  2787965087
1  300000000                  Adventure|Fantasy|Action   961000000
2  245000000                    Action|Adventure|Crime   880674609
3  250000000               Action|Crime|Drama|Thriller  1084939099
4  260000000          Action|Adventure|Science Fiction   284139100

   release_year
0        2009.0
1        2007.0
2        2015.0
3        2012.0
4        2012.0
```

In [66]:
```
def clean_genre_and_re_map(row):
    global data__DataFrame_genre
    d = {}
    data_genres = np.array(row['genres'].split('|'))
    n = data_genres.size
    d['budget'] = [row['budget']]*n
    d['revenue'] = [row['revenue']]*n
    d['year'] = [row['release_year']]*n
    d['genre'], d['cgenres'] = [], []
    for genre in data_genres:
        d['genre'].append(genre)
        d['cgenres'].append(data_genres[data_genres != genre])
    data__DataFrame_genre = data__DataFrame_genre.append(pd.DataFrame(d), ignore_inde

data__DataFrame_clean.apply(clean_genre_and_re_map, axis = 1)
data__DataFrame_genre['year'] = data__DataFrame_genre['year'].astype(np.int16)
data__DataFrame_genre = data__DataFrame_genre[['genre', 'budget', 'gross', 'year', 'c
```

In [67]:
```
dict_genres = {}
def connect(row):
    global dict_genres
    genre = row['genre']
    cgenres = row['cgenres']
    if genre not in dict_genres:
        d_cgenres = dict(zip(cgenres, [1]*len(cgenres)))
        dict_genres[genre] = d_cgenres
    else:
        for cgenre in cgenres:
            if cgenre not in dict_genres[genre]:
                dict_genres[genre][cgenre] = 1
            else:
                dict_genres[genre][cgenre] += 1

data__DataFrame_genre.apply(connect, axis = 1)
```

```
list_genres = list(dict_genres.keys())
list_genres.sort()

cmax = 0
for key in dict_genres:
    for e in dict_genres[key]:
        if dict_genres[key][e] > cmax:
            cmax = dict_genres[key][e]
```

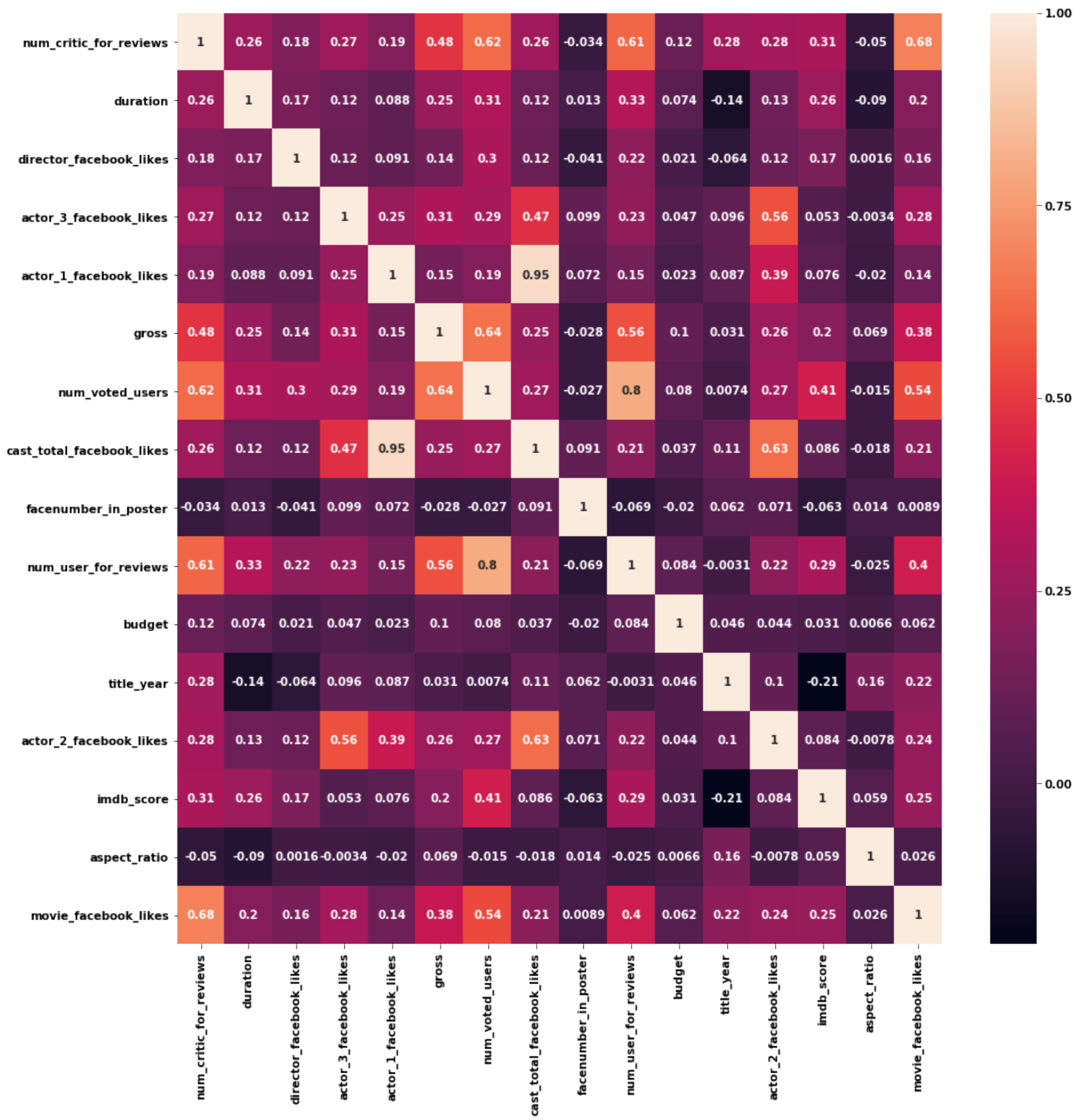
```
Out[67]: "\n#########################\n# visualize connections #\n#########################\nf:
```

```
In [68]: import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         import pandas as pd
         from sklearn.preprocessing import LabelEncoder
         from sklearn.tree import DecisionTreeRegressor
         from sklearn.preprocessing import StandardScaler
         from sklearn.decomposition import PCA as sklearnPCA
```

Let's breakdown the movies_metadata csv file

```
In [69]: data_new = pd.read_csv('movie_metadata.csv')
         DataFrame_new =data_new.drop(['gross','budget'],axis=1).dropna(axis=0)
         fig, ax = plt.subplots(figsize=(15,15))
         sns.heatmap(data=data_new.corr(),annot=True)
```

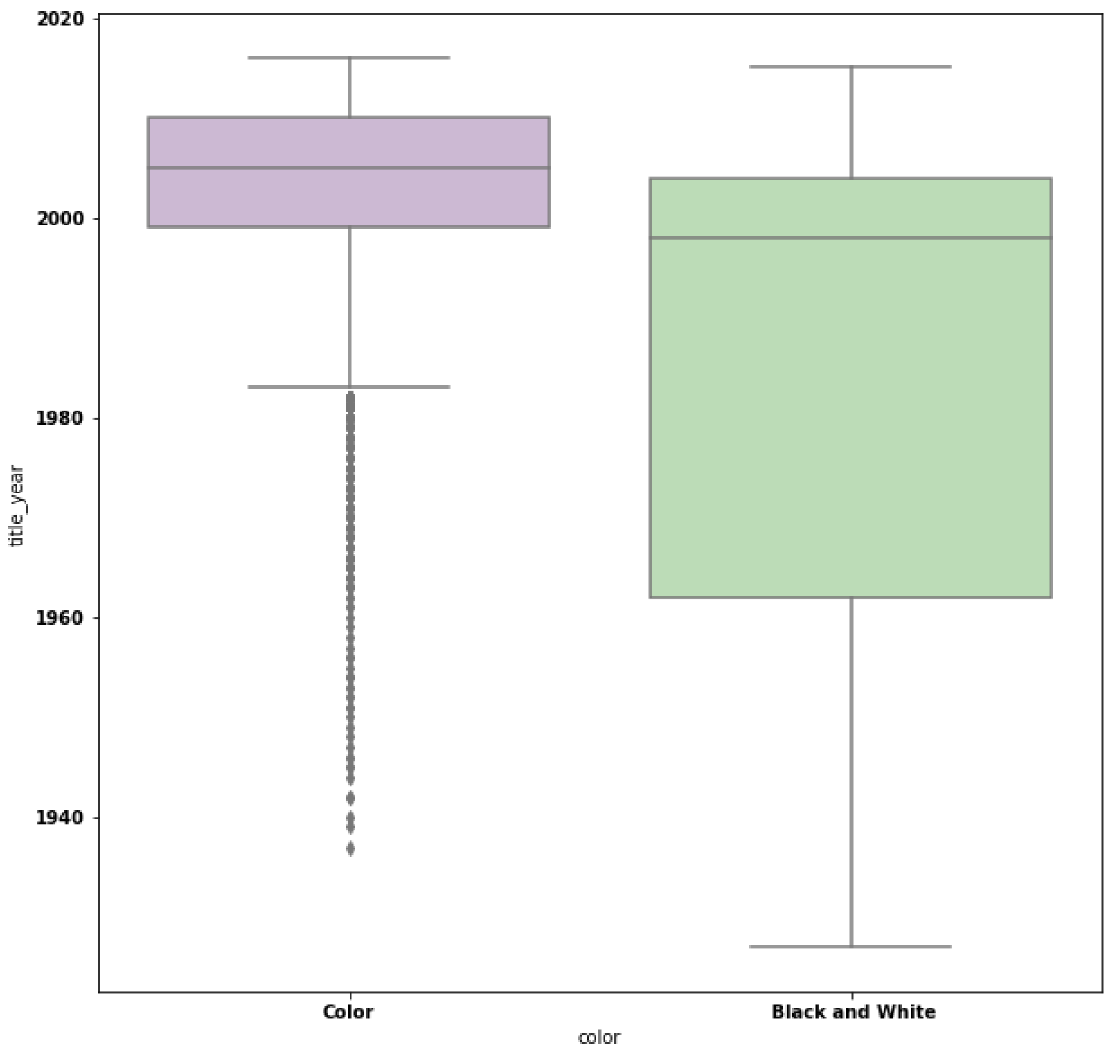
```
Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x1a181e82d0>
```



In [70]:
```
plt.show()
```

In [71]:
```
DataFrame_new = pd.concat([DataFrame_new,data_new.loc[DataFrame_new.index,['gross','bu
DataFrame_new.reset_index(drop=True,inplace=True)
fig, ax = plt.subplots(figsize=(10,10))
sns.boxplot(x="color", y="title_year", data=DataFrame_new, palette="PRGn")
```

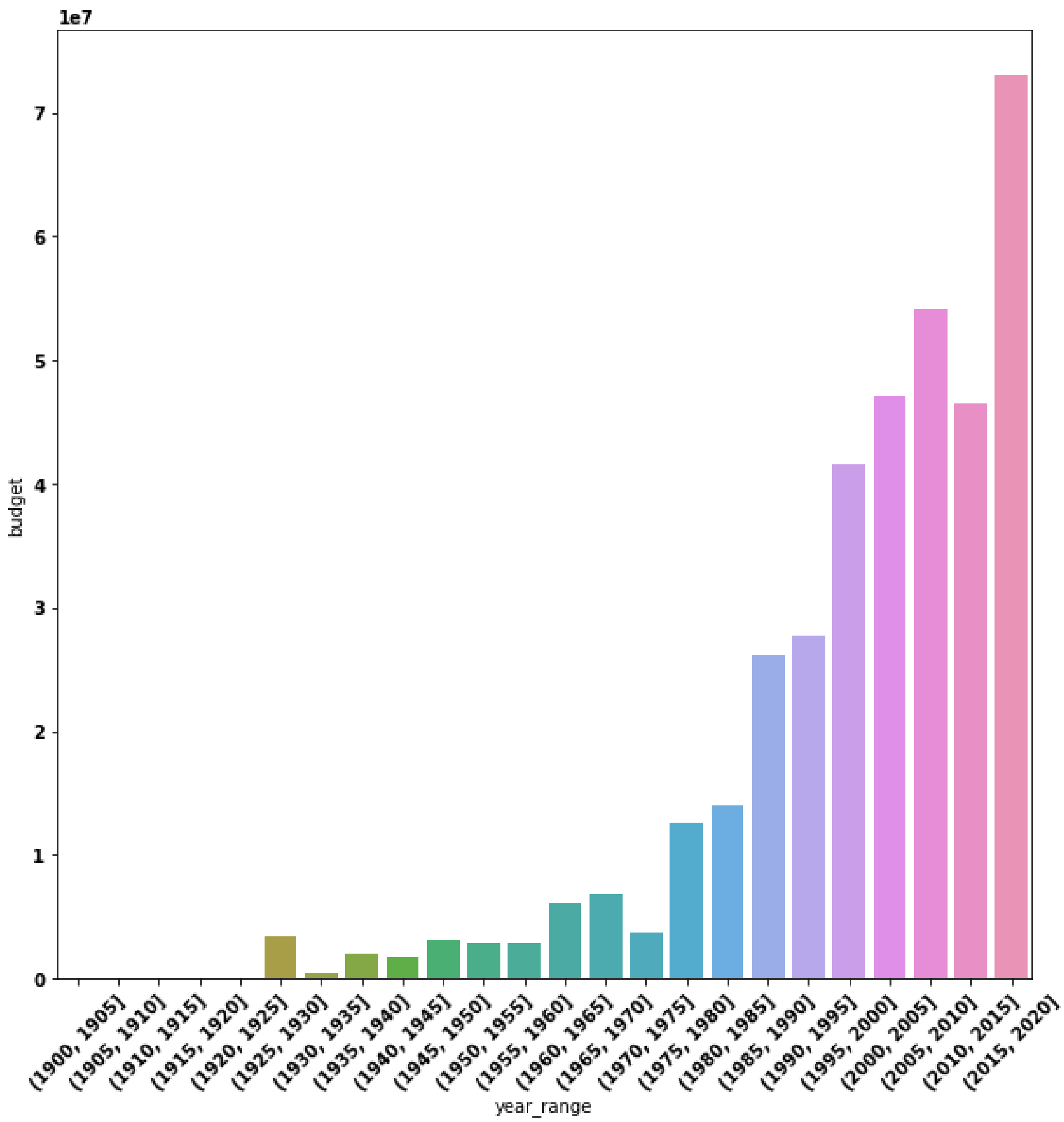
Out[71]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a17fa8450>
```




```
In [72]: plt.show()

In [73]: metadata_cut = pd.cut(DataFrame_new.imdb_score, bins=list(np.arange(1,11)))

         metadata_cut2 = pd.cut(DataFrame_new.title_year, bins=list(5*(np.arange(380,405))))

         metadata_cut3 = pd.cut(DataFrame_new.imdb_score, bins=list([0,4,6,7,8,10]))
         DataFrame_new['imdb_score_bin'] =metadata_cut

         DataFrame_new['year_range'] =metadata_cut2
         DataFrame_new['pc_imdb'] = metadata_cut3

In [74]: label_encoder_metadata = LabelEncoder()
         DataFrame_new['pc_imdb']= label_encoder_metadata.fit_transform(DataFrame_new['pc_imdb
```

In [75]:
```
fig, ax = plt.subplots(figsize=(10,10))
plt.xticks(rotation=45)
sns.barplot(DataFrame_new['year_range'],DataFrame_new['budget'],ci=None)
sns.barplot(DataFrame_new['year_range'],DataFrame_new['budget'],ci=None)
```

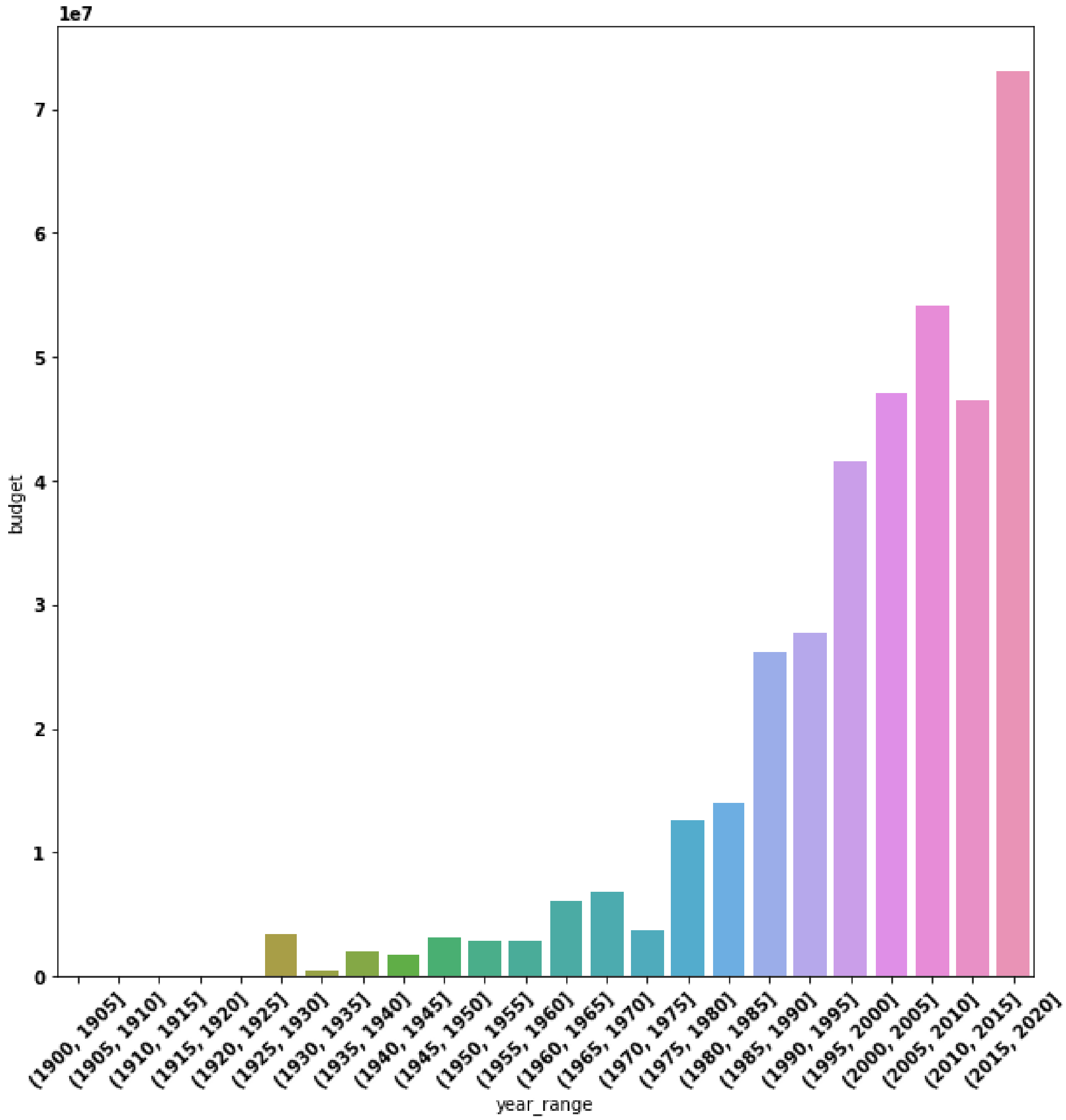
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21aa62d0>



In [76]:
```
plt.show()
```

In [77]:
```
fig, ax = plt.subplots(figsize=(10,10))
plt.xticks(rotation=45)
sns.barplot(DataFrame_new['year_range'],DataFrame_new['budget'],ci=None)
```

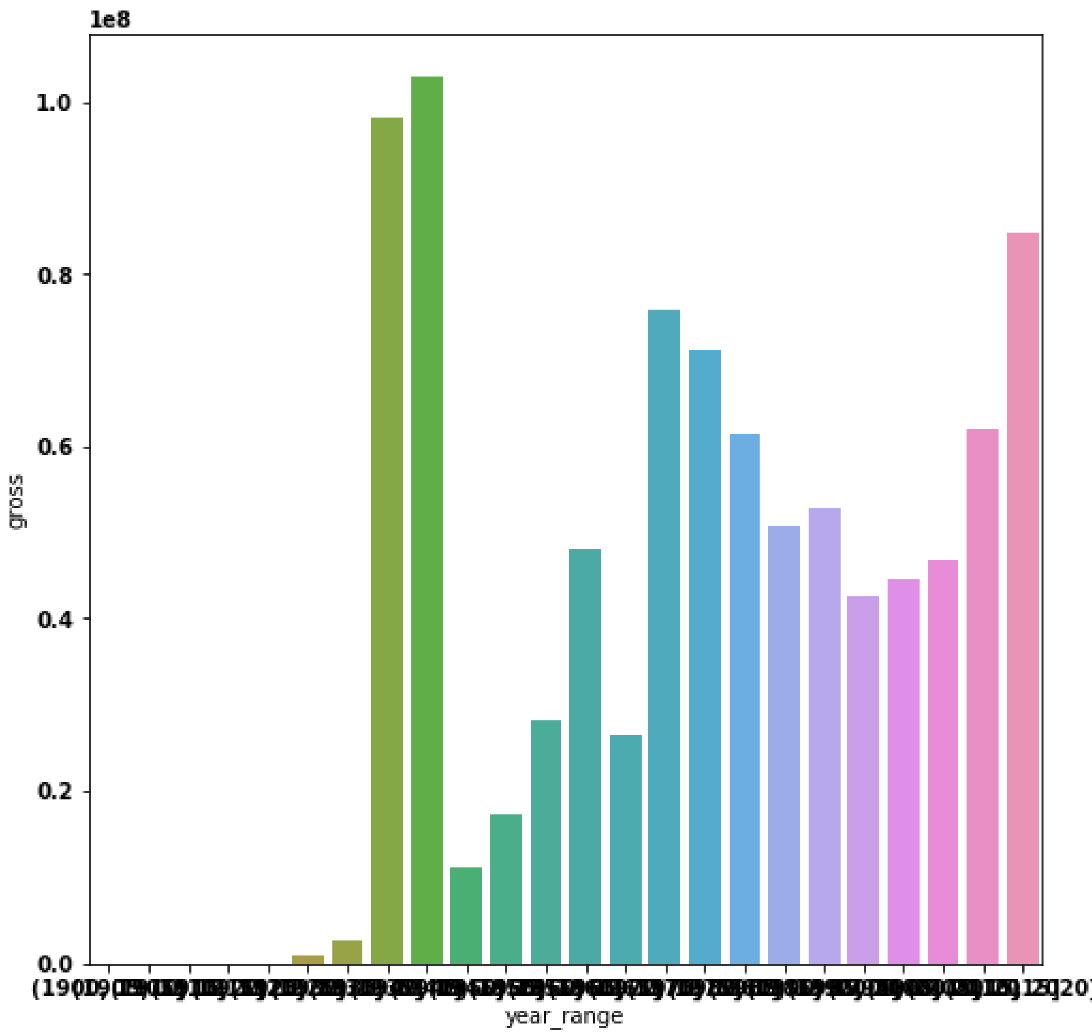
Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21aa6690>



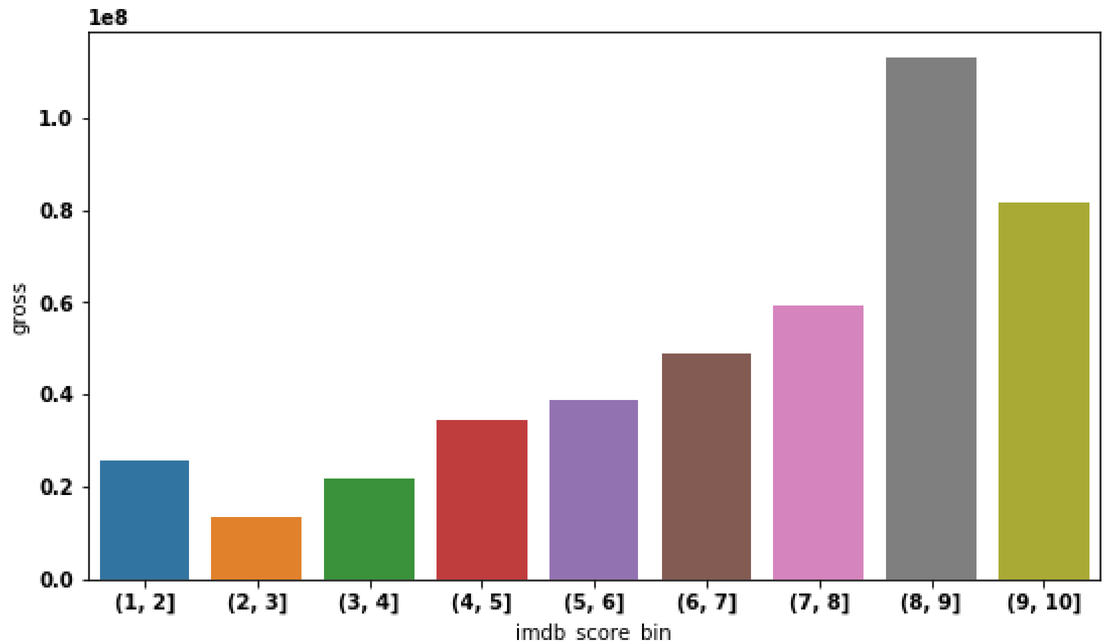
In [78]:
```
plt.show()
```

In [79]:
```
fig, ax = plt.subplots(figsize=(8,8))
sns.barplot(DataFrame_new['year_range'],DataFrame_new['gross'],ci=None)
```

Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21b14b50>



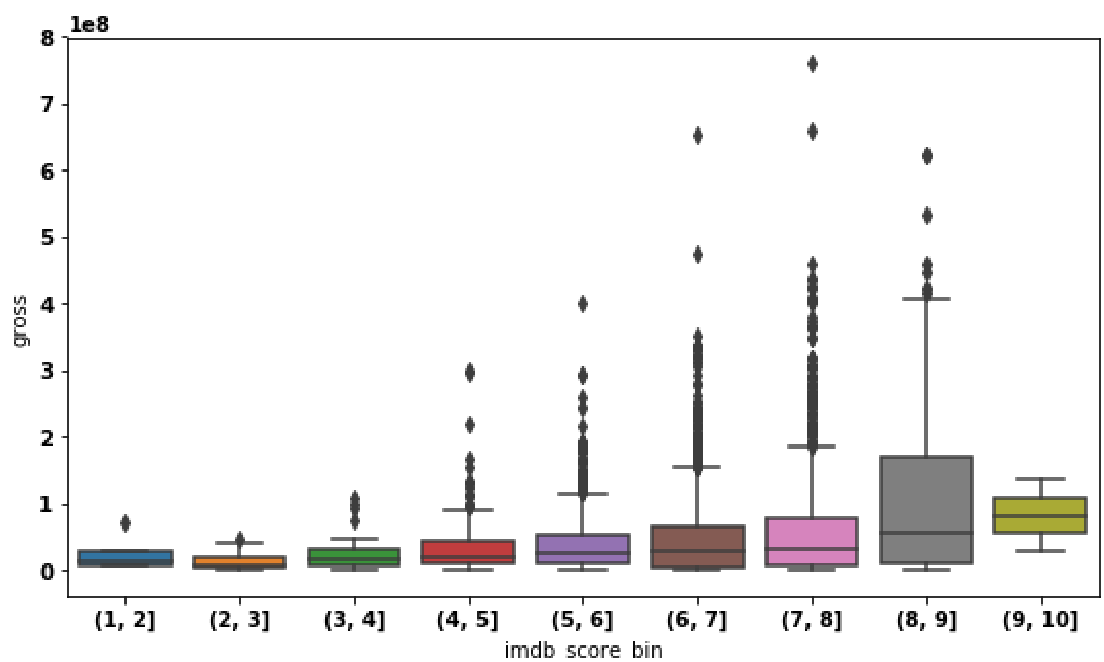

```
In [80]: plt.show()

In [81]: sns.barplot(DataFrame_new['imdb_score_bin'],DataFrame_new['gross'],ci=None)

Out[81]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21fc9990>
```



In [82]:
```
plt.show()
```

In [83]:
```
sns.boxplot(data=DataFrame_new,x='imdb_score_bin',y='gross')
```

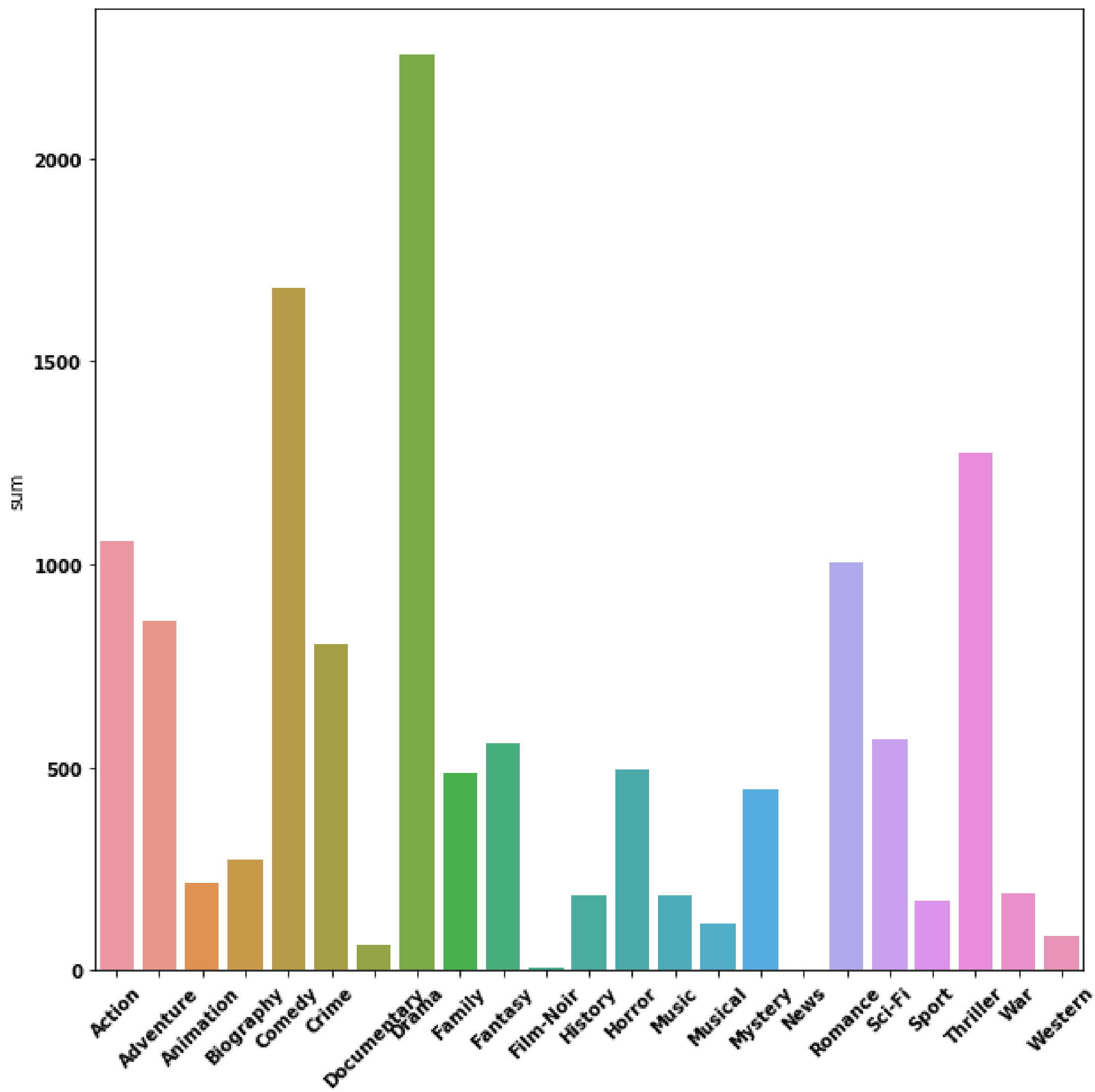
Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21ffa650>



```
In [84]: plt.show()
```

Fill the budget by just using the title year. Here we have considered the fact that the value of $ is a function of time only. But Clearly the graph dosent show any trend for gross because it includes many factor like whether movie was a HIT or a FLOP.

```
In [85]: mean_chart = pd.DataFrame(DataFrame_new.groupby(by=['year_range'])['budget'].mean())
         mean_chart = pd.DataFrame(DataFrame_new.groupby(by=['year_range'])['budget'].mean())

         DataFrame_new = pd.merge(DataFrame_new,mean_chart,left_on='year_range',right_index=Tru

         DataFrame_new.columns

         DataFrame_new['budget_x'].fillna(DataFrame_new['budget_y'],inplace=True)
         DataFrame_new['budget_x'].count()

         df2_new=DataFrame_new

         var_mod=['imdb_score_bin','year_range']
         label_encoder_metadata = LabelEncoder()
         for i in var_mod:
             df2_new[i] = label_encoder_metadata.fit_transform(df2_new[i])

         clf= DecisionTreeRegressor()

         clf.fit(DataFrame_new[DataFrame_new['gross'].notnull()][['imdb_score_bin','year_range

         pred = clf.predict(DataFrame_new[DataFrame_new['gross'].isnull()][['imdb_score_bin','y

         DataFrame_new[DataFrame_new['gross'].isnull()][['imdb_score_bin','year_range']].index

         j=0
         for i in DataFrame_new[DataFrame_new['gross'].isnull()][['imdb_score_bin','year_range
             DataFrame_new['gross'][i] = pred[j]
             j=j+1

         data__DataFrame_genre=DataFrame_new['genres'].str.split('|',expand=True).stack().str.g
         fig, ax = plt.subplots(figsize=(10,10))
         plt.xticks(rotation=45)
         k=pd.DataFrame(data__DataFrame_genre.sum(),columns=['sum'])
         sns.barplot(y='sum',x=k.index,data=k,orient='v')

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x1a33a76210>
```

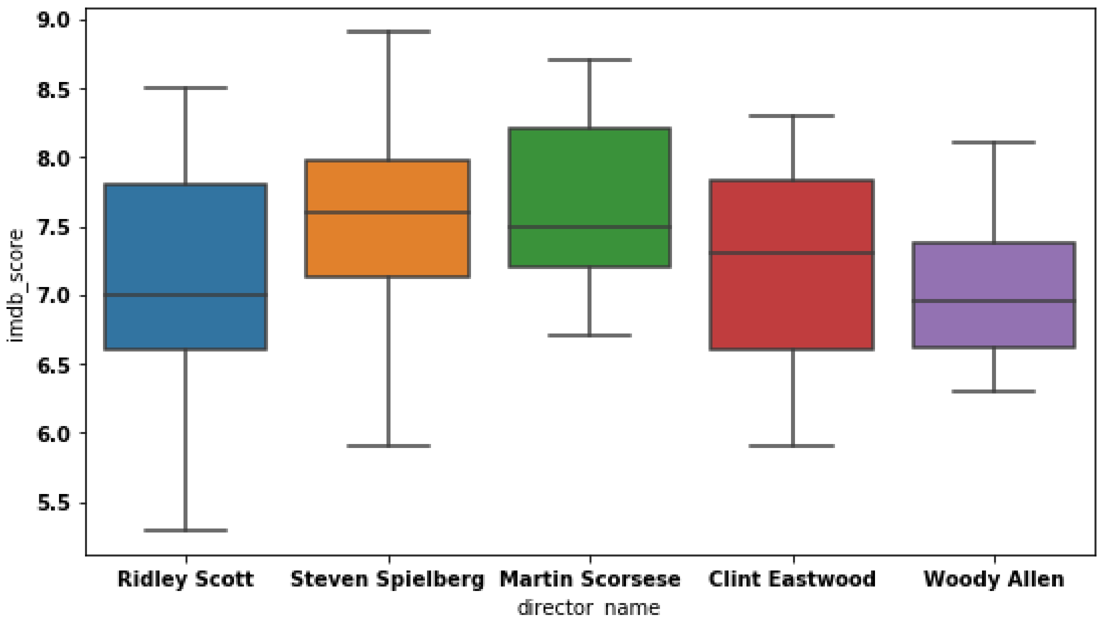


In [86]:
```
plt.show()
```

In [87]:
```
DataFrame_new['age'] = 2017 - DataFrame_new.title_year

k=DataFrame_new.groupby(by='director_name',sort=False).director_facebook_likes.mean()
l=DataFrame_new.groupby(by='director_name',sort=False).imdb_score.sum()
m=DataFrame_new.groupby(by='director_name',sort=False).age.max()
pd.DataFrame(DataFrame_new['director_name'].value_counts())
director_ranking = pd.concat([k,l,m],axis=1)
#Since, Age and imdb score_movie_data are very important factors considered. Because 
#Lets Check which Director has ruled Hollywood?
director_name =list(DataFrame_new['director_name'].value_counts().index[:5])
director_name
```

```
pp = DataFrame_new.loc[(DataFrame_new.director_name == director_name[0])|(DataFrame_ne

sns.boxplot(x='director_name',y='imdb_score',data=pp)
```

Out[87]: <matplotlib.axes._subplots.AxesSubplot at 0x1a35ed1050>



In [88]:
```
plt.show()
```

In [89]:
```
str_list = [] # empty list to contain columns with strings (words)
for colname, colvalue in DataFrame_new.iteritems():
    if type(colvalue[1]) == str:
         str_list.append(colname)
movie_col_list = DataFrame_new.columns.difference(str_list)
X=DataFrame_new[movie_col_list]
X.shape
```

Out[89]: (4411, 21)

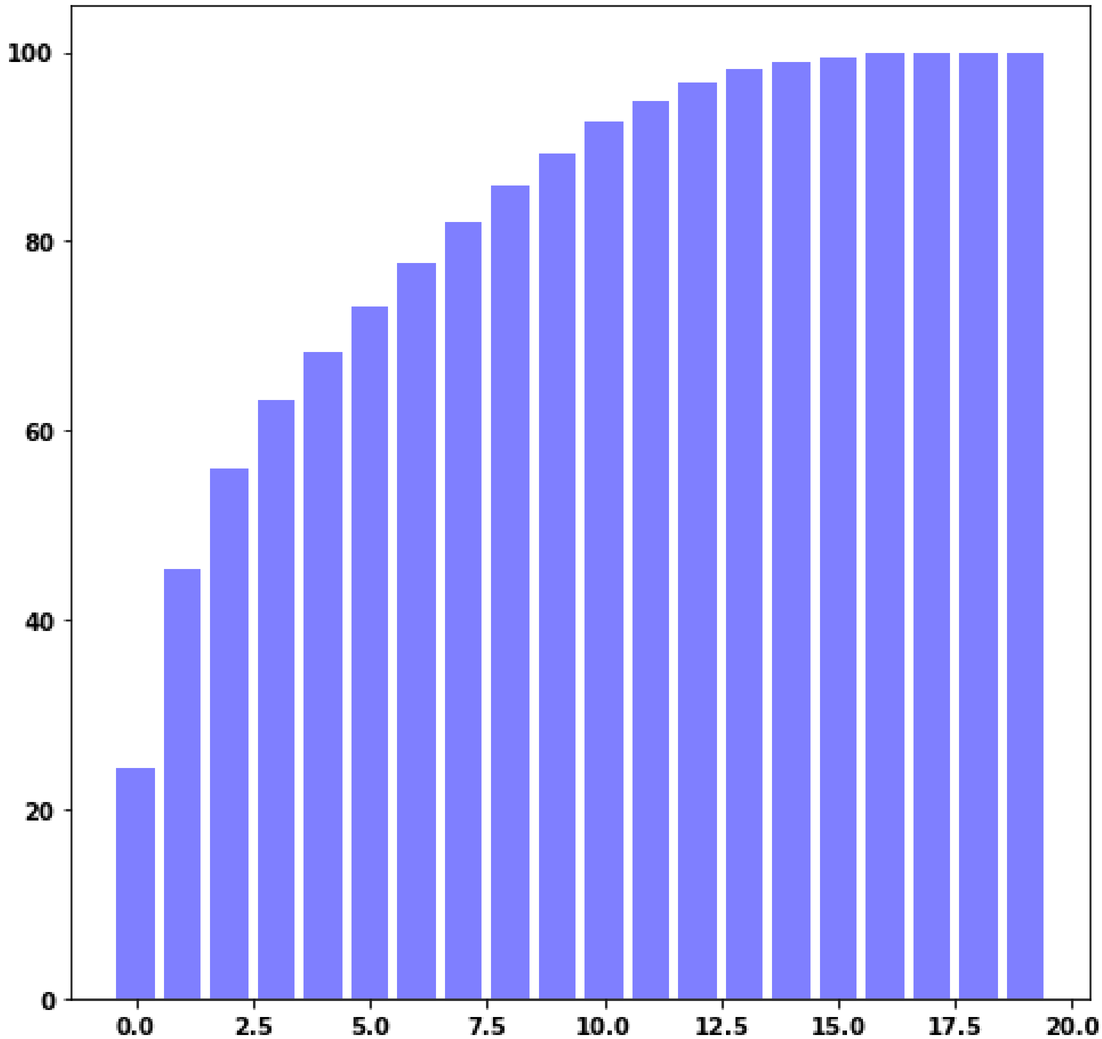
In [90]:
```
X_std = StandardScaler().fit_transform(X)
```

Lets do Principal compoen analysis to get the important features

In [91]:
```
sklearn_pca = sklearnPCA(n_components=20)
Y_sklearn = sklearn_pca.fit_transform(X_std)

cummulative_sum = sklearn_pca.explained_variance_ratio_.cumsum()
```

```
sklearn_pca.explained_variance_ratio_[:10].sum()

cummulative_sum = cummulative_sum*100

fig, ax = plt.subplots(figsize=(8,8))
plt.bar(range(20), cummulative_sum, label='Cumulative _Sum_of_Explained _Varaince', co
```

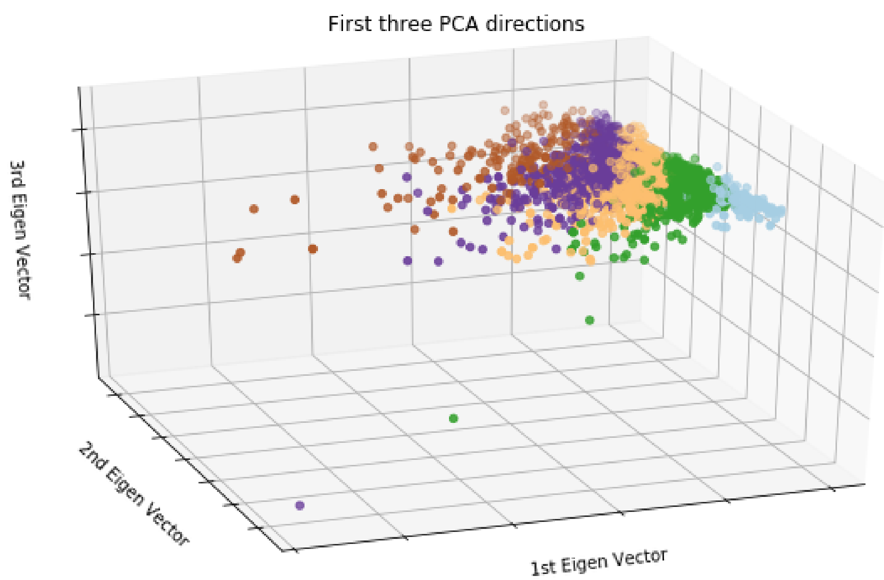
Out[91]: <Container object of 20 artists>



In [92]:
```
plt.show()
```

In [93]:
```
sklearn_pca = sklearnPCA(n_components=3)
X_reduced  = sklearn_pca.fit_transform(X_std)
Y=DataFrame_new['pc_imdb']
```

```
from mpl_toolkits.mplot3d import Axes3D
plt.clf()
fig = plt.figure(1, figsize=(8, 6))
ax = Axes3D(fig, elev=-150, azim=110)
ax.scatter(X_reduced[:, 0], X_reduced[:, 1], X_reduced[:, 2], c=Y,cmap=plt.cm.Paired)
ax.set_title("First three PCA directions")
ax.set_xlabel("1st Eigen Vector")
ax.w_xaxis.set_ticklabels([])
ax.set_ylabel("2nd Eigen Vector")
ax.w_yaxis.set_ticklabels([])
ax.set_zlabel("3rd Eigen Vector")
ax.w_zaxis.set_ticklabels([])
plt.show()
```



Now we have some more insight on the different genres, let's take a look at different keywords. Are there keywords which influence a movie's rating in one way or another? What about the revenue? Let's answer all these questions

```
In [94]: credits_data = load_TMDB_credits_json_data("tmdb_5000_credits.csv")
         movies_data = load_TMDB_movie_json_data("tmdb_5000_movies.csv")

In [95]: del credits_data['title']
         df = pd.concat([movies_data, credits_data], axis=1)

In [96]: df['keywords'] = df['keywords'].apply(pipeline_to_flatten_names)

         list_keywords = set()
         for s in df['keywords'].str.split('|'):
```

```
            list_keywords = set().union(s, list_keywords)
        list_keywords = list(list_keywords)
        list_keywords.remove('')
```

We are interested in which keywords occur the most in our dataset. We use the following function to count them.

```
In [97]: def word_count(df, ref_col, liste):
             keyword_count = dict()
             for s in liste: keyword_count[s] = 0
             for list_keywords in df[ref_col].str.split('|'):
                 if type(list_keywords) == float and pd.isnull(list_keywords): continue
                 for s in [s for s in list_keywords if s in liste]:
                     if pd.notnull(s): keyword_count[s] += 1
             #______________________________________________________________________
             # convert the dictionary_words in a list to sort the keywords by frequency
             keyword_occurences = []
             for k,v in keyword_count.items():
                 keyword_occurences.append([k,v])
             keyword_occurences.sort(key = lambda x:x[1], reverse = True)
             return keyword_occurences, keyword_count

In [98]: keyword_occurences, dum = word_count(df, 'keywords', list_keywords)
         keyword_occurences[:5]

Out[98]: [[u'woman director', 324],
          [u'independent film', 318],
          [u'duringcreditsstinger', 307],
          [u'based on novel', 197],
          [u'murder', 189]]

In [99]: def all_keywords_data(dataframe, colonne = 'keywords'):
             PS = nltk.stem.PorterStemmer()
             keywords_roots  = dict()  # collect the words / root
             keywords_select = dict()  # association: root <-> keyword
             category_keys = []
             icount = 0
             for s in dataframe[colonne]:
                 if pd.isnull(s): continue
                 for t in s.split('|'):
                     t = t.lower() ; racine = PS.stem(t)
                     if racine in keywords_roots:
                         keywords_roots[racine].add(t)
                     else:
                         keywords_roots[racine] = {t}

             for s in keywords_roots.keys():
                 if len(keywords_roots[s]) > 1:
                     min_length = 1000
```

```
                for k in keywords_roots[s]:
                    if len(k) < min_length:
                        clef = k ; min_length = len(k)
                category_keys.append(clef)
                keywords_select[s] = clef
            else:
                category_keys.append(list(keywords_roots[s])[0])
                keywords_select[s] = list(keywords_roots[s])[0]

    print("Number of keywords in variable '{}': {}".format(colonne,len(category_keys)
    return category_keys, keywords_roots, keywords_select
```

```
In [100]: keywords, keywords_roots, keywords_select = all_keywords_data(df, colonne = 'keywords
```

```
Number of keywords in variable 'keywords': 9474
```

Of course, different movies use different keywords for their movies. A problem is, that often a lot of those keywords are the same, although they are communicated in a different form by the different movie producers. The function above inventorizes the different keywords using nltk. The package identifies the 'roots' of different words and groups the different words according to its root. Then, we can replace the words that have a common root with their root. In this way, similar words that are phrased differently are assigned a common 'root'.

When executing the function, it also shows the amount of different keywords, 9474 in our case.

```
In [101]: icount = 0
          for s in keywords_roots.keys():
              if len(keywords_roots[s]) > 1:
                  icount += 1
                  if icount < 15: print(icount, keywords_roots[s], len(keywords_roots[s]))
```

```
(1, set([u'voyeur', u'voyeurism']), 2)
(2, set([u'music', u'musical']), 2)
(3, set([u'mystic', u'mysticism']), 2)
(4, set([u'travel', u'traveller']), 2)
(5, set([u'beautiful', u'beauty']), 2)
(6, set([u'backpacker', u'backpack']), 2)
(7, set([u'coal mining', u'coal mine']), 2)
(8, set([u'spider', u'spiders']), 2)
(9, set([u'whipping', u'whip']), 2)
(10, set([u'immortality', u'immortal']), 2)
(11, set([u'tree', u'trees']), 2)
(12, set([u'supernatural powers', u'supernatural power']), 2)
(13, set([u'addicted', u'addiction', u'addict']), 3)
(14, set([u'singers', u'singer']), 2)
```

The function below replaces the different forms of the words by their root.

In [102]:
```python
def replacement_DataFrame_keywords(df, dico_remplacement, roots = False):
    DataFrame_new = df.copy(deep = True)
    for index, row in DataFrame_new.iterrows():
        chaine = row['keywords']
        if pd.isnull(chaine): continue
        nouvelle_liste = []
        for s in chaine.split('|'):
            clef = PS.stem(s) if roots else s
            if clef in dico_remplacement.keys():
                nouvelle_liste.append(dico_remplacement[clef])
            else:
                nouvelle_liste.append(s)
        DataFrame_new.set_value(index, 'keywords', '|'.join(nouvelle_liste))
    return DataFrame_new
```

In [103]:
```python
df_keywords_cleaned = replacement_DataFrame_keywords(df, keywords_select,roots = True
```

In [104]:
```python
df_keywords_cleaned.head()
```

Out[104]:
```
      budget                                             genres  \
0  237000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...
1  300000000  [{u'id': 12, u'name': u'Adventure'}, {u'id': 1...
2  245000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...
3  250000000  [{u'id': 28, u'name': u'Action'}, {u'id': 80, ...
4  260000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...

                                        homepage      id  \
0                    http://www.avatarmovie.com/   19995
1  http://disney.go.com/disneypictures/pirates/     285
2   http://www.sonypictures.com/movies/spectre/  206647
3            http://www.thedarkknightrises.com/   49026
4          http://movies.disney.com/john-carter   49529

                                            keywords original_language  \
0  culture clash|future|space war|space colony|so...                en
1  ocean|drug abuse|exotic island|east india trad...                en
2  spy|based on novel|secret agent|sequel|mi6|bri...                en
3  dc comics|crime fighter|terrorist|secret ident...                en
4  based on novel|mars|medallion|space travel|pri...                en

                             original_title  \
0                                    Avatar
1  Pirates of the Caribbean: At World's End
2                                   Spectre
3                     The Dark Knight Rises
4                               John Carter

                                            overview  popularity  \
```

```
0  In the 22nd century, a paraplegic Marine is di...  150.437577
1  Captain Barbossa, long believed to be dead, ha...  139.082615
2  A cryptic message from Bonds past sends him o...  107.376788
3  Following the death of District Attorney Harve...  112.312950
4  John Carter is a war-weary, former military ca...   43.926995

                             production_companies  \
0  [{u'name': u'Ingenious Film Partners', u'id': ...
1  [{u'name': u'Walt Disney Pictures', u'id': 2},...
2  [{u'name': u'Columbia Pictures', u'id': 5}, {u...
3  [{u'name': u'Legendary Pictures', u'id': 923},...
4     [{u'name': u'Walt Disney Pictures', u'id': 2}]

                         ...                         runtime  \
0                        ...                           162.0
1                        ...                           169.0
2                        ...                           148.0
3                        ...                           165.0
4                        ...                           132.0

                                 spoken_languages    status  \
0  [{u'iso_639_1': u'en', u'name': u'English'}, {...  Released
1       [{u'iso_639_1': u'en', u'name': u'English'}]  Released
2  [{u'iso_639_1': u'fr', u'name': u'Français'}, ...  Released
3       [{u'iso_639_1': u'en', u'name': u'English'}]  Released
4       [{u'iso_639_1': u'en', u'name': u'English'}]  Released

                                         tagline  \
0                    Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                           A Plan No One Escapes
3                                 The Legend Ends
4           Lost in our world, found in another.

                                      title vote_average vote_count movie_id  \
0                                    Avatar          7.2      11800    19995
1  Pirates of the Caribbean: At World's End          6.9       4500      285
2                                   Spectre          6.3       4466   206647
3                     The Dark Knight Rises          7.6       9106    49026
4                               John Carter          6.1       2124    49529

                                               cast  \
0  [{u'name': u'Sam Worthington', u'gender': 2, u...
1  [{u'name': u'Johnny Depp', u'gender': 2, u'cha...
2  [{u'name': u'Daniel Craig', u'gender': 2, u'ch...
3  [{u'name': u'Christian Bale', u'gender': 2, u'...
4  [{u'name': u'Taylor Kitsch', u'gender': 2, u'c...
```

```
                                              crew
0  [{u'name': u'Stephen E. Rivkin', u'gender': 0,...
1  [{u'name': u'Dariusz Wolski', u'gender': 2, u'...
2  [{u'name': u'Thomas Newman', u'gender': 2, u'd...
3  [{u'name': u'Hans Zimmer', u'gender': 2, u'dep...
4  [{u'name': u'Andrew Stanton', u'gender': 2, u'...

[5 rows x 23 columns]
```

Next, we will use the nltk package to get rid of synonyms. The function below take a word as a parameter and returns all of the synonyms of that word according to the nltk package.

```
In [105]: def data_synonyms(word):
              lemma = set()
              for ss in wordnet.synsets(word):
                  for w in ss.lemma_names():
                      #_______________________________
                      # We just get the 'nouns':
                      index = ss.name().find('.')+1
                      if ss.name()[index] == 'n': lemma.add(w.lower().replace('_',' '))
              return lemma
```

```
In [106]: def check_keyword(mot, key_count, threshold):
              return (False , True)[key_count.get(mot, 0) >= threshold]
```

```
In [107]: keyword_occurences.sort(key = lambda x:x[1], reverse = False)
          key_count = dict()
          for s in keyword_occurences:
              key_count[s[0]] = s[1]
          #__________________________________________________________________________
          # Creation of a dictionary_words to replace keywords by higher frequency keywords
          replacement_dict = dict()
          icount = 0
          for index, [mot, nb_apparitions] in enumerate(keyword_occurences):
              if nb_apparitions > 5: continue  # only the keywords that appear less than 5 tim
              lemma = data_synonyms(mot)
              if len(lemma) == 0: continue     # case of the plurals
              #_________________________________________________________________
              liste_mots = [(s, key_count[s]) for s in lemma
                            if check_keyword(s, key_count, key_count[mot])]
              liste_mots.sort(key = lambda x:(x[1],x[0]), reverse = True)
              if len(liste_mots) <= 1: continue       # no replacement
              if mot == liste_mots[0][0]: continue    # replacement by himself
              icount += 1
              if  icount < 8:
                  print('{:<12} -> {:<12} (init: {})'.format(mot, liste_mots[0][0], liste_mots
              replacement_dict[mot] = liste_mots[0][0]

          print(90*'_'+'\n'+'The replacement concerns {}% of the keywords.'.format(round(len(re
```

```
aggression   -> hostility    (init: [(u'hostility', 12), (u'aggression', 1)])
glass        -> ice          (init: [(u'ice', 5), (u'methamphetamine', 1), (u'glass', 1), (u'c
hole         -> trap         (init: [(u'trap', 3), (u'jam', 1), (u'hole', 1)])
household    -> family       (init: [(u'family', 69), (u'house', 11), (u'home', 4), (u'househo
artillery    -> gun          (init: [(u'gun', 27), (u'weapon', 16), (u'artillery', 1)])
enchantress  -> witch        (init: [(u'witch', 42), (u'femme fatale', 6), (u'siren', 1), (u'e
homoeroticism -> homosexuality (init: [(u'homosexuality', 17), (u'homoeroticism', 1)])
-------------------------------------------------------------------------------------------
The replacement concerns 0.0% of the keywords.
```

```
In [108]: print('Keywords that appear both in Keys and Values:'.upper()+'\n'+45*'-')
          icount = 0
          for s in replacement_dict.values():
              if s in replacement_dict.keys():
                  icount += 1
                  if icount < 10: print('{:<20} -> {:<20}'.format(s, replacement_dict[s]))

          for key, value in replacement_dict.items():
              if value in replacement_dict.keys():
                  replacement_dict[key] = replacement_dict[value]
```

```
KEYWORDS THAT APPEAR BOTH IN KEYS AND VALUES:
---------------------------------------------
record                -> book
bum                   -> tramp
fatherhood            -> father
heart                 -> spirit
camp                  -> summer camp
destruction           -> death
heart                 -> spirit
pin                   -> fall
trap                  -> ambush
```

```
In [109]: keywords_DataFrame_synonyms = replacement_DataFrame_keywords(df_keywords_cleaned, re
          keywords, keywords_roots, keywords_select = all_keywords_data(keywords_DataFrame_syn
```

```
Number of keywords in variable 'keywords': 8886
```

```
In [110]: keywords.remove('')
          new_keyword_occurences, keywords_count = word_count(keywords_DataFrame_synonyms,'key
          new_keyword_occurences[:5]
```

```
Out[110]: [[u'woman director', 324],
           [u'independent film', 318],
           [u'duringcreditsstinger', 307],
           [u'based on novel', 197],
           [u'murder', 197]]
```

```
In [111]: def replacement_df_low_frequency_keywords(df, keyword_occurences):
              DataFrame_new = df.copy(deep = True)
              key_count = dict()
              for s in keyword_occurences:
                  key_count[s[0]] = s[1]
              for index, row in DataFrame_new.iterrows():
                  chaine = row['keywords']
                  if pd.isnull(chaine): continue
                  nouvelle_liste = []
                  for s in chaine.split('|'):
                      if key_count.get(s, 4) > 3: nouvelle_liste.append(s)
                  DataFrame_new.set_value(index, 'keywords', '|'.join(nouvelle_liste))
              return DataFrame_new
```

```
In [112]: keywords_DataFrame_occurence = replacement_df_low_frequency_keywords(keywords_DataFra
          keywords, keywords_roots, keywords_select = all_keywords_data(keywords_DataFrame_occu
```

```
Number of keywords in variable 'keywords': 2110
```

```
In [113]: keywords_DataFrame_occurence.head()
```

```
Out[113]:       budget                                             genres  \
          0  237000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...
          1  300000000  [{u'id': 12, u'name': u'Adventure'}, {u'id': 1...
          2  245000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...
          3  250000000  [{u'id': 28, u'name': u'Action'}, {u'id': 80, ...
          4  260000000  [{u'id': 28, u'name': u'Action'}, {u'id': 12, ...

                                                   homepage      id  \
          0                     http://www.avatarmovie.com/   19995
          1  http://disney.go.com/disneypictures/pirates/     285
          2   http://www.sonypictures.com/movies/spectre/  206647
          3            http://www.thedarkknightrises.com/   49026
          4          http://movies.disney.com/john-carter   49529

                                                      keywords original_language  \
          0  culture clash|future|space colony|society|spac...                en
          1  ocean|drug abuse|exotic island|east india trad...                en
          2  spy|based on novel|secret agent|sequel|british...                en
          3  dc comics|crime fighter|terrorist|secret ident...                en
          4  based on novel|mars|medallion|space travel|pri...                en

                                    original_title  \
          0                                 Avatar
          1  Pirates of the Caribbean: At World's End
          2                                Spectre
          3                  The Dark Knight Rises
          4                            John Carter
```

```
                                            overview  popularity  \
0  In the 22nd century, a paraplegic Marine is di...  150.437577
1  Captain Barbossa, long believed to be dead, ha...  139.082615
2  A cryptic message from Bonds past sends him o...  107.376788
3  Following the death of District Attorney Harve...  112.312950
4  John Carter is a war-weary, former military ca...   43.926995

                                production_companies  \
0  [{u'name': u'Ingenious Film Partners', u'id': ...
1  [{u'name': u'Walt Disney Pictures', u'id': 2},...
2  [{u'name': u'Columbia Pictures', u'id': 5}, {u...
3  [{u'name': u'Legendary Pictures', u'id': 923},...
4     [{u'name': u'Walt Disney Pictures', u'id': 2}]

                         ...                         runtime  \
0                        ...                           162.0
1                        ...                           169.0
2                        ...                           148.0
3                        ...                           165.0
4                        ...                           132.0

                                    spoken_languages    status  \
0  [{u'iso_639_1': u'en', u'name': u'English'}, {...  Released
1       [{u'iso_639_1': u'en', u'name': u'English'}]  Released
2  [{u'iso_639_1': u'fr', u'name': u'Français'}, ...  Released
3       [{u'iso_639_1': u'en', u'name': u'English'}]  Released
4       [{u'iso_639_1': u'en', u'name': u'English'}]  Released

                                         tagline  \
0                    Enter the World of Pandora.
1  At the end of the world, the adventure begins.
2                           A Plan No One Escapes
3                                 The Legend Ends
4           Lost in our world, found in another.

                                      title vote_average vote_count movie_id  \
0                                    Avatar          7.2      11800    19995
1  Pirates of the Caribbean: At World's End          6.9       4500      285
2                                   Spectre          6.3       4466   206647
3                     The Dark Knight Rises          7.6       9106    49026
4                               John Carter          6.1       2124    49529

                                                cast  \
0  [{u'name': u'Sam Worthington', u'gender': 2, u...
1  [{u'name': u'Johnny Depp', u'gender': 2, u'cha...
2  [{u'name': u'Daniel Craig', u'gender': 2, u'ch...
3  [{u'name': u'Christian Bale', u'gender': 2, u'...
```

```
4  [{u'name': u'Taylor Kitsch', u'gender': 2, u'c...

                                                crew
0  [{u'name': u'Stephen E. Rivkin', u'gender': 0,...
1  [{u'name': u'Dariusz Wolski', u'gender': 2, u'...
2  [{u'name': u'Thomas Newman', u'gender': 2, u'd...
3  [{u'name': u'Hans Zimmer', u'gender': 2, u'dep...
4  [{u'name': u'Andrew Stanton', u'gender': 2, u'...

[5 rows x 23 columns]
```

In [114]:
```
df_keywords= keywords_DataFrame_occurence
keyword_list = set()
for s in df_keywords['keywords'].str.split('|'):
    keyword_list = set().union(s, keyword_list)
keyword_list = list(keyword_list)
keyword_list.remove('')
keyword_list[:5]
```

Out[114]:
```
[u'racial segregation',
 u'computer hacker',
 u'chaos',
 u'shark attack',
 u'protest']
```

In [115]:
```
DafaFrame_cleaned = df_keywords[['title','vote_average','release_date','runtime','bud

for keyword in keyword_list:
    DafaFrame_cleaned[keyword] = df['keywords'].str.contains(keyword).apply(lambda x
DafaFrame_cleaned[:5]

DafaFrame_cleaned.head()
```

Out[115]:
```
                                       title  vote_average release_date  \
0                                     Avatar           7.2   2009-12-10
1  Pirates of the Caribbean: At World's End           6.9   2007-05-19
2                                    Spectre           6.3   2015-10-26
3                      The Dark Knight Rises           7.6   2012-07-16
4                                John Carter           6.1   2012-03-07

   runtime     budget     revenue  racial segregation  computer hacker  chaos  \
0    162.0  237000000  2787965087                   0                0      0
1    169.0  300000000   961000000                   0                0      0
2    148.0  245000000   880674609                   0                0      0
3    165.0  250000000  1084939099                   0                0      0
4    132.0  260000000   284139100                   0                0      0

   shark attack   ...    mental institution  mountain climber  \
0             0   ...                     0                 0
```

```
1              0   ...                     0                 0
2              0   ...                     0                 0
3              0   ...                     0                 0
4              0   ...                     0                 0

   american football  ghost  mephisto  atheist  dying and death  mercenary  \
0                  0      0         0        0                0          0
1                  0      0         0        0                0          0
2                  0      0         0        0                0          0
3                  0      0         0        0                0          0
4                  0      0         0        0                0          0

   rural  parole
0      0       0
1      0       0
2      0       0
3      0       0
4      0       0

[5 rows x 2129 columns]
```

In [116]:
```python
mean_per_keyword = pd.DataFrame(keyword_list)
```

In [117]:
```python
#Mean votes average
Array_Keyword_list = []*len(keyword_list)
for keyword in keyword_list:
    Array_Keyword_list.append(DafaFrame_cleaned.groupby(keyword, as_index=True)['vote

#Mean budget
new_array_genre_data2 = []*len(keyword_list)
for keyword in keyword_list:
    new_array_genre_data2.append(DafaFrame_cleaned.groupby(keyword, as_index=True)['

#Mean revenue
Array_Keyword_list3 = []*len(keyword_list)
for keyword in keyword_list:
    Array_Keyword_list3.append(DafaFrame_cleaned.groupby(keyword, as_index=True)['re

mean_per_keyword['mean_vote_average']=list(pd.DataFrame(Array_Keyword_list)[1])
mean_per_keyword['mean_budget']=list(pd.DataFrame(new_array_genre_data2)[1])
mean_per_keyword['mean_revenue']=list(pd.DataFrame(Array_Keyword_list3)[1])
```

In [118]:
```python
mean_per_keyword.sort_values('mean_vote_average', ascending=False).head()
```

Out[118]:
```
                          0  mean_vote_average  mean_budget  mean_revenue
1010              brazilian               7.68    2040000.0  7.247696e+06
1105                   jedi               7.65   45337500.0  6.339741e+08
1694            bittersweet               7.60   15100000.0  1.252883e+08
```

```
1868  loss of sense of reality               7.60    4200054.5  7.319838e+06
656                        fascism               7.58   20450000.0  3.614916e+07
```

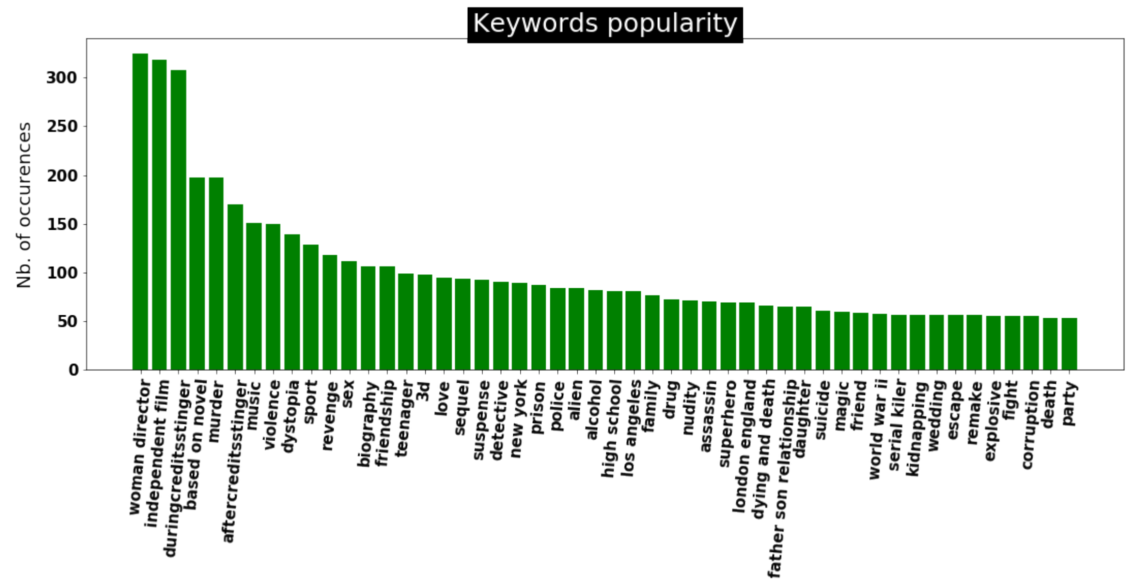
In [119]:
```
mean_per_keyword.sort_values('mean_budget', ascending=False).head()
```

Out[119]:
```
                                0  mean_vote_average   mean_budget  \
1645                 swashbuckler           7.080000  2.072000e+08
1856           based on fairy tale          6.650000  1.850000e+08
1190                       hobbit           7.540000  1.844000e+08
710     marvel cinematic universe           7.015385  1.823077e+08
581   east india trading company           6.950000  1.787500e+08

      mean_revenue
1645  7.516485e+08
1856  4.537670e+08
1190  9.466358e+08
710   7.798770e+08
581   6.704178e+08
```

In [120]:
```
mean_per_keyword.sort_values('mean_revenue', ascending=False).head()
```

Out[120]:
```
                          0  mean_vote_average   mean_budget  mean_revenue
2114        mountain climber           7.300000  1.500000e+08  1.274219e+09
1190                  hobbit           7.540000  1.844000e+08  9.466358e+08
980             transformers           6.125000  1.762500e+08  9.402898e+08
979                    broom           7.483333  1.508333e+08  9.018436e+08
34      school of witchcraft           7.480000  1.560000e+08  8.869172e+08
```

In [121]:
```
fig = plt.figure(1, figsize=(18,13))
trunc_occurences = new_keyword_occurences[0:50]
# LOWER PANEL: HISTOGRAMS
ax2 = fig.add_subplot(2,1,2)
y_axis = [i[1] for i in trunc_occurences]
x_axis = [k for k,i in enumerate(trunc_occurences)]
x_label = [i[0] for i in trunc_occurences]
plt.xticks(rotation=85, fontsize = 15)
plt.yticks(fontsize = 15)
plt.xticks(x_axis, x_label)
plt.ylabel("Nb. of occurences", fontsize = 18, labelpad = 10)
ax2.bar(x_axis, y_axis, align = 'center', color='g')
#_______________________
plt.title("Keywords popularity",bbox={'facecolor':'k', 'pad':5},color='w',fontsize =
plt.show()
```




```
In [122]: Df1 = pd.DataFrame(trunc_occurences)
          Df2 = mean_per_keyword
          result = Df1.merge(Df2, left_on=0, right_on=0, how='inner')

In [123]: result = result.rename(columns ={0:'keyword', 1:'occurences'})

In [124]: result.sort_values('mean_vote_average', ascending= False)

Out[124]:                   keyword  occurences  mean_vote_average   mean_budget  \
          40            serial kiler          57           7.400000  2.000000e+04
          39            world war ii          58           6.943333  3.953675e+07
          12               biography         106           6.685981  2.452445e+07
          34  father son relationship          65           6.666154  4.004557e+07
          47              corruption          55           6.628333  3.713630e+07
          33         dying and death          66           6.627273  3.607249e+07
          45               explosive          55           6.606667  4.732000e+07
          3           based on novel         197           6.602538  4.532546e+07
          24                 alcohol          82           6.567470  2.185181e+07
          35                daughter          65           6.537500  3.354488e+07
          21                  prison          87           6.522581  3.824056e+07
          43                  escape          57           6.518310  4.565310e+07
          36                 suicide          61           6.496296  2.407074e+07
          16                    love          95           6.471388  3.098239e+07
          48                   death          53           6.454455  3.616768e+07
          6                    music         151           6.436585  2.094051e+07
          13              friendship         106           6.428472  2.994101e+07
          32          london england          69           6.423188  3.513928e+07
          41              kidnapping          57           6.417241  2.888621e+07
```

28	drug	72	6.393333	2.040123e+07
37	magic	60	6.391045	7.525896e+07
22	police	84	6.388824	2.823271e+07
8	dystopia	139	6.373381	5.862790e+07
27	family	77	6.370558	3.099732e+07
26	los angeles	81	6.332927	3.160159e+07
7	violence	150	6.328022	3.157138e+07
30	assassin	70	6.322535	4.676056e+07
38	friend	59	6.294932	3.076485e+07
9	sport	128	6.285714	2.546307e+07
18	suspense	93	6.251087	2.577715e+07
19	detective	90	6.249091	3.459194e+07
20	new york	89	6.248571	3.351962e+07
1	independent film	318	6.245912	4.221864e+06
4	murder	197	6.232971	2.460980e+07
5	aftercreditsstinger	170	6.215882	6.222303e+07
11	sex	112	6.213559	1.497524e+07
31	superhero	69	6.205333	1.070320e+08
15	3d	98	6.191837	1.079490e+08
46	fight	55	6.176433	4.638382e+07
29	nudity	71	6.166957	1.614908e+07
10	revenge	118	6.146721	3.889385e+07
49	party	53	6.141837	2.129166e+07
2	duringcreditsstinger	307	6.102280	5.222324e+07
14	teenager	99	6.076238	1.458614e+07
42	wedding	57	6.068657	3.203188e+07
23	alien	84	6.027434	6.868983e+07
25	high school	81	6.017822	1.375000e+07
0	woman director	324	5.998148	1.712953e+07
17	sequel	94	5.987234	7.423197e+07
44	remake	56	5.786207	3.928534e+07

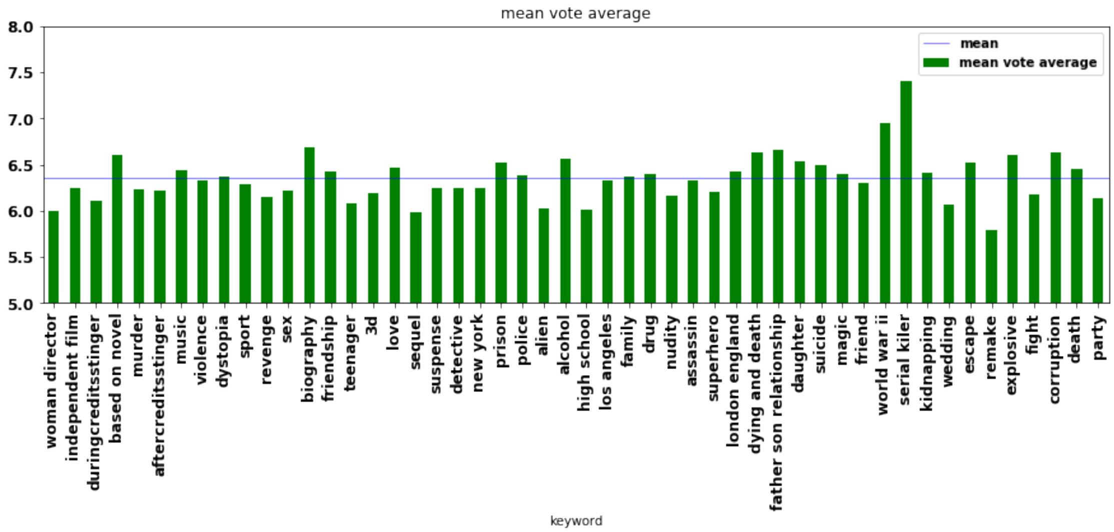
	mean_revenue
40	9.900000e+04
39	9.807107e+07
12	6.053863e+07
34	1.151591e+08
47	1.025770e+08
33	1.455099e+08
45	1.735899e+08
3	1.438100e+08
24	7.047892e+07
35	1.260095e+08
21	9.654383e+07
43	1.382031e+08
36	6.208187e+07
16	1.089839e+08
48	1.284936e+08

```
6     6.984209e+07
13    1.068130e+08
32    1.103393e+08
41    8.739728e+07
28    5.213815e+07
37    2.551707e+08
22    8.555389e+07
8     1.589433e+08
27    9.376477e+07
26    9.507014e+07
7     9.435216e+07
30    1.156094e+08
38    1.045227e+08
9     6.665445e+07
18    8.831605e+07
19    8.986268e+07
20    8.953728e+07
1     4.611131e+06
4     5.843215e+07
5     2.219717e+08
11    4.267742e+07
31    3.653859e+08
15    3.961385e+08
46    1.362612e+08
29    4.125465e+07
10    1.064460e+08
49    7.815954e+07
2     1.883636e+08
14    6.009193e+07
42    1.101635e+08
23    2.062562e+08
25    4.789369e+07
0     4.981613e+07
17    2.810250e+08
44    9.373569e+07
```

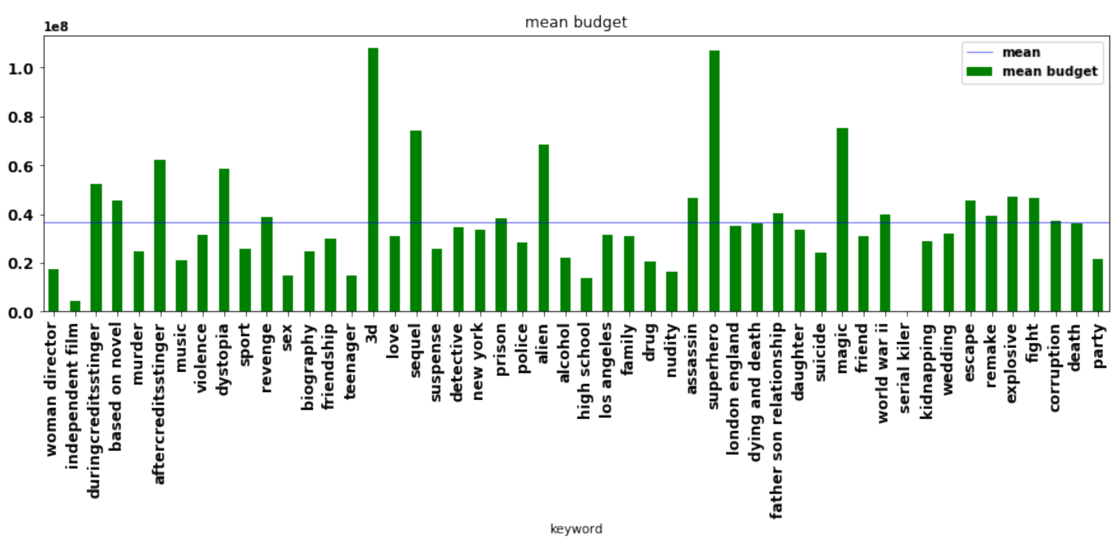
In [125]:
```python
result['mean_vote_average'].mean()
```

Out[125]: 6.353304991835236

In [126]:
```python
ax = result.plot.bar(x = 'keyword', y='mean_vote_average', title="mean vote average"
                     figsize=(15,4), legend=True, fontsize=12, color='green', label =
ax.set_ylim(5, 8)
ax.axhline(y=result['mean_vote_average'].mean(),c="blue",linewidth=0.5, label='mean')
ax.legend()
plt.show()
```




```
In [127]: ax = result.plot.bar(x = 'keyword', y='mean_budget', title="mean budget",
                               figsize=(15,4), legend=True, fontsize=12, color='green', label='
          ax.axhline(y=result['mean_budget'].mean(),c="blue",linewidth=0.5, label='mean')
          ax.legend()
          plt.show()
```



So superhero movies do have a high revenue and serial killer movies do not. Let's take a look at the differences

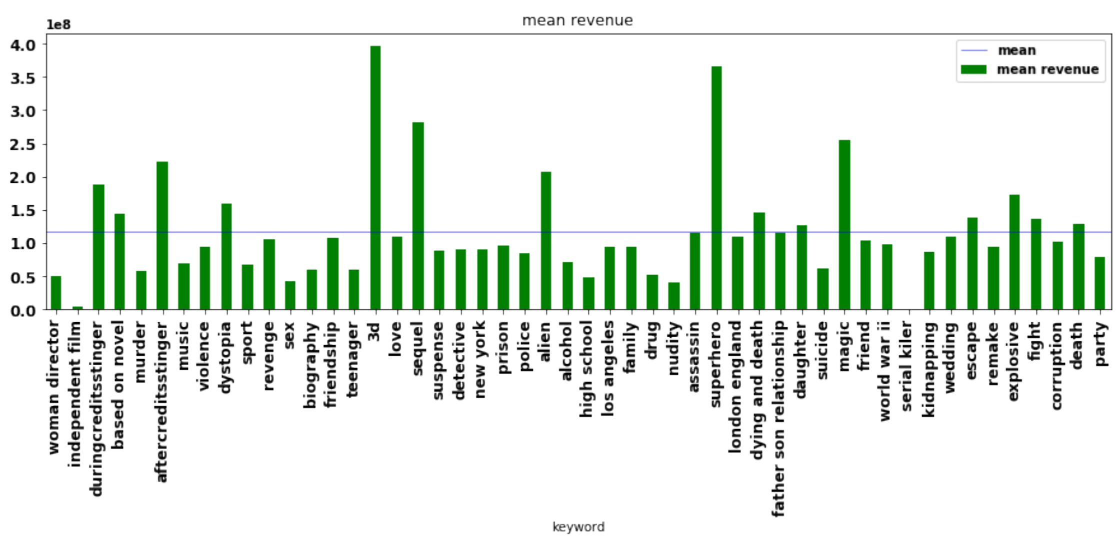
```
In [128]: result.sort_values('mean_budget').head()
```

Out[128]:

	keyword	occurences	mean_vote_average	mean_budget
40	serial kiler	57	7.400000	2.000000e+04
1	independent film	318	6.245912	4.221864e+06
25	high school	81	6.017822	1.375000e+07
14	teenager	99	6.076238	1.458614e+07
11	sex	112	6.213559	1.497524e+07

	mean_revenue
40	9.900000e+04
1	4.611131e+06
25	4.789369e+07
14	6.009193e+07
11	4.267742e+07

In [129]:
```
ax = result.plot.bar(x = 'keyword', y='mean_revenue', title="mean revenue",
                        figsize=(15,4), legend=True, fontsize=12, color='green', label='
ax.axhline(y=result['mean_revenue'].mean(),c="blue",linewidth=0.5, label='mean')
ax.legend()
plt.show()
```



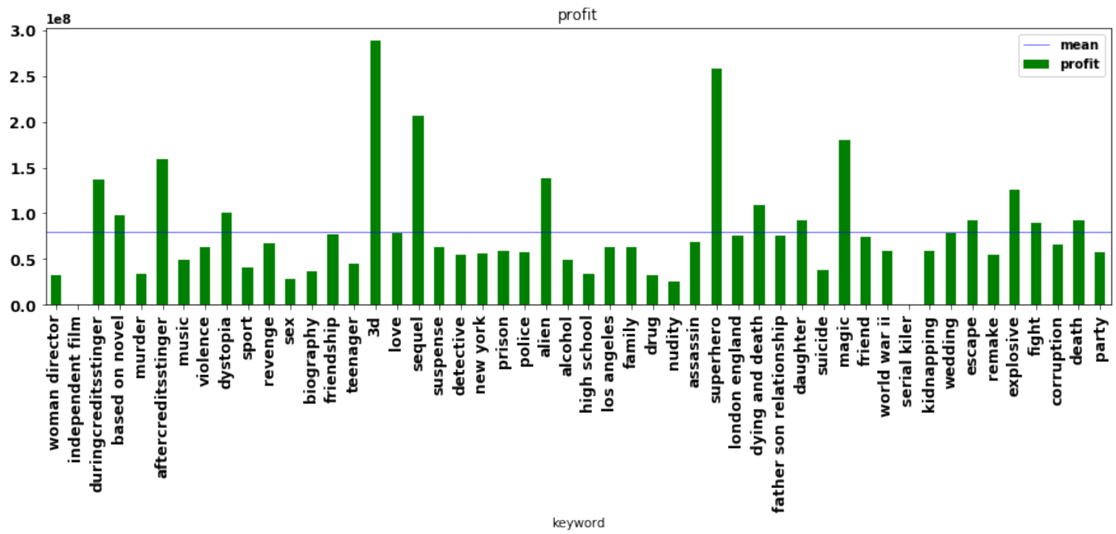
In [130]:
```
result['profit'] = result['mean_revenue'] - result['mean_budget']
result.head()
```

Out[130]:

	keyword	occurences	mean_vote_average	mean_budget
0	woman director	324	5.998148	1.712953e+07
1	independent film	318	6.245912	4.221864e+06
2	duringcreditsstinger	307	6.102280	5.222324e+07
3	based on novel	197	6.602538	4.532546e+07
4	murder	197	6.232971	2.460980e+07

```
   mean_revenue        profit
0  4.981613e+07  3.268660e+07
1  4.611131e+06  3.892670e+05
2  1.883636e+08  1.361403e+08
3  1.438100e+08  9.848457e+07
4  5.843215e+07  3.382235e+07
```

```
In [131]: ax = result.plot.bar(x = 'keyword', y='profit', title="profit",
                               figsize=(15,4), legend=True, fontsize=12, color='green', label='
          ax.axhline(y=result['profit'].mean(),c="blue",linewidth=0.5, label='mean')
          ax.legend()
          plt.show()
```



0.1 Cast analysis

A previous version of this dataset only contained the top three actors per movie. Since we only want to analyze the most important actors of a movie and since the old dataset was a bit more suited to do that, we convert the dataset back to its previous state using Sohier Dane's method.

```
In [132]: LOST_COLUMNS = [
              'actor_1_facebook_likes',
              'actor_2_facebook_likes',
              'actor_3_facebook_likes',
              'aspect_ratio',
              'cast_total_facebook_likes',
              'color',
              'content_rating',
              'director_facebook_likes',
              'facenumber_in_poster',
```

```
                'movie_facebook_likes',
                'movie_imdb_link',
                'num_critic_for_reviews',
                'num_user_for_reviews'
                            ]
```

```
In [133]: TMDB_TO_IMDB_SIMPLE_EQUIVALENCIES = {
                'budget': 'budget',
                'data_genres': 'data_genres',
                'revenue': 'gross',
                'title': 'movie_title',
                'runtime': 'duration',
                'original_language': 'language',  # it's possible that spoken_languages would be
                'keywords': 'plot_keywords',
                'vote_count': 'num_voted_users',
                                                    }

          IMDB_COLUMNS_TO_REMAP = {'imdb_score': 'vote_average'}
```

```
In [134]: def type_check_normalize(container, index_values):
              # return a missing value rather than an error upon indexing/key failure
              result = container
              try:
                  for idx in index_values:
                      result = result[idx]
                  return result
              except IndexError or KeyError:
                  return pd.np.nan


          def get_director(crew_data):
              directors = [x['name'] for x in crew_data if x['job'] == 'Director']
              return type_check_normalize(directors, [0])


          def pipeline_to_flatten_names(keywords):
              return '|'.join([x['name'] for x in keywords])


          def clearning_afterJSON_data(movies_data, credits_data):
              # Converts TMDb data to make it as compatible as possible with kernels built on
              tmdb_movies = movies_data.copy()
              tmdb_movies.rename(columns=TMDB_TO_IMDB_SIMPLE_EQUIVALENCIES, inplace=True)
              tmdb_movies['title_year'] = pd.to_datetime(tmdb_movies['release_date']).apply(lam
              # I'm assuming that the first production country is equivalent, but have not bee
              tmdb_movies['country'] = tmdb_movies['production_countries'].apply(lambda x: type
              tmdb_movies['language'] = tmdb_movies['spoken_languages'].apply(lambda x: type_ch
              tmdb_movies['director_name'] = credits_data['crew'].apply(get_director)
```

```
        tmdb_movies['actor_1_name'] = credits_data['cast'].apply(lambda x: type_check_no
        tmdb_movies['actor_2_name'] = credits_data['cast'].apply(lambda x: type_check_no
        tmdb_movies['actor_3_name'] = credits_data['cast'].apply(lambda x: type_check_no
        tmdb_movies['genres'] = tmdb_movies['genres'].apply(pipeline_to_flatten_names)
        tmdb_movies['plot_keywords'] = tmdb_movies['plot_keywords'].apply(pipeline_to_fla
        return tmdb_movies
```

```
In [135]: credits_data = load_TMDB_credits_json_data("tmdb_5000_credits.csv")
          movies_data = load_TMDB_movie_json_data("tmdb_5000_movies.csv")
          df = clearning_afterJSON_data(movies_data, credits_data)
```

```
In [136]: movie_DataFrame3 = df
```

```
In [137]: columns = ['homepage', 'plot_keywords', 'language', 'overview', 'popularity', 'taglin
                      'original_title', 'num_voted_users', 'country', 'spoken_languages', 'dura
                     'production_companies', 'production_countries', 'status']
```

```
In [138]: df = df.drop(columns, axis=1)
```

We are interested in the same descriptives for the actors, as we were for keywords and the genres. To do that, we first have to, once again, restructure the dataframe.

We first create a seperate dataframe for each of the three actors, after which we can combine them to get one dataframe with all three types of actor.

```
In [139]: genres_data = set()
          for s in df['genres'].str.split('|'):
              genres_data = set().union(s, genres_data)
          genres_data = list(genres_data)
          genres_data.remove('')
```

```
In [140]: DafaFrame_cleaned = df[['actor_1_name', 'vote_average','title_year', 'movie_title',
          for genre in genres_data:
              DafaFrame_cleaned[genre] = df['genres'].str.contains(genre).apply(lambda x:1 if x

          DataFrame_Actor2 = df[['actor_2_name', 'vote_average','title_year', 'movie_title', 'g
          for genre in genres_data:
              DataFrame_Actor2[genre] = df['genres'].str.contains(genre).apply(lambda x:1 if x

          DataFrame_Actor3 = df[['actor_3_name', 'vote_average','title_year', 'movie_title', 'g
          for genre in genres_data:
              DataFrame_Actor3[genre] = df['genres'].str.contains(genre).apply(lambda x:1 if x
```

```
In [141]: DafaFrame_cleaned = DafaFrame_cleaned.rename(columns={'actor_1_name': 'actor'})
          DataFrame_Actor2 = DataFrame_Actor2.rename(columns={'actor_2_name': 'actor'})
          DataFrame_Actor3 = DataFrame_Actor3.rename(columns={'actor_3_name': 'actor'})

          total = [DafaFrame_cleaned, DataFrame_Actor2, DataFrame_Actor3]
          DataFrame_total = pd.concat(total)
          DataFrame_total.head()
```

Out[141]:
```
               actor  vote_average  title_year  \
0        Zoe Saldana           7.2      2009.0
1      Orlando Bloom           6.9      2007.0
2  Christoph Waltz           6.3      2015.0
3      Michael Caine           7.6      2012.0
4       Lynn Collins           6.1      2012.0

                                 movie_title       gross     budget  Mystery  \
0                                     Avatar  2787965087  237000000        0
1  Pirates of the Caribbean: At World's End   961000000  300000000        0
2                                    Spectre   880674609  245000000        0
3                      The Dark Knight Rises  1084939099  250000000        0
4                                John Carter   284139100  260000000        0

   Crime  Drama  Animation    ...      Romance  Comedy  Family  Fantasy  \
0      0      0          0    ...            0       0       0        1
1      0      0          0    ...            0       0       0        1
2      1      0          0    ...            0       0       0        0
3      1      1          0    ...            0       0       0        0
4      0      0          0    ...            0       0       0        0

   Horror  Thriller  Science Fiction  Western  TV Movie  Adventure
0       0         0                1        0         0          1
1       0         0                0        0         0          1
2       0         0                0        0         0          1
3       0         1                0        0         0          0
4       0         0                1        0         0          1

[5 rows x 26 columns]
```

In [142]:
```
DataFrame_actors = DataFrame_total.groupby('actor').mean()
DataFrame_actors.loc[:, 'favored_genre'] = DataFrame_actors[genres_data].idxmax(axis
DataFrame_actors.drop(genres_data, axis = 1, inplace = True)
DataFrame_actors = DataFrame_actors.reset_index()
```

In [143]:
```
DataFrame_total.loc[DataFrame_total['actor'] == "Gary Oldman"].sort_values('vote_ave
```

Out[143]:
```
            actor  vote_average  title_year  \
2460  Gary Oldman           4.8      2009.0
990   Gary Oldman           5.5      1995.0
1132  Gary Oldman           5.6      2011.0
224   Gary Oldman           5.7      2014.0
1528  Gary Oldman           5.7      2016.0
1013  Gary Oldman           6.1      2015.0
387   Gary Oldman           6.2      1997.0
2080  Gary Oldman           6.6      2011.0
449   Gary Oldman           6.6      2010.0
3934  Gary Oldman           6.6      1996.0
```

```
137   Gary Oldman          6.7      2011.0
1246  Gary Oldman          6.9      1998.0
322   Gary Oldman          7.3      1997.0
82    Gary Oldman          7.3      2014.0
1181  Gary Oldman          7.5      1991.0
3     Gary Oldman          7.6      2012.0
191   Gary Oldman          7.7      2004.0

                                 movie_title       gross     budget  \
2460                              The Unborn    76514050   16000000
990                         The Scarlet Letter    10382407   50000000
1132                           Red Riding Hood    89162162   42000000
224                                   RoboCop   242688965  120000000
1528                                 Criminal    14708696   31500000
1013                                 Child 44     3324330   50000000
387                              Air Force One   315156409   85000000
2080                  Tinker Tailor Soldier Spy           0   30000000
449                            The Book of Eli   157107755   80000000
3934                                 Basquiat     3011195    2962051
137                            Kung Fu Panda 2   665692281  150000000
1246                         Quest for Camelot    38172500   40000000
322                          The Fifth Element   263920180   90000000
82             Dawn of the Planet of the Apes   710644566  170000000
1181                                      JFK   205405498   40000000
3                        The Dark Knight Rises  1084939099  250000000
191   Harry Potter and the Prisoner of Azkaban   789804554  130000000

      Mystery  Crime  Drama  Animation    ...      Romance  Comedy  Family  \
2460        1      0      0          0    ...            0       0       0
990         0      0      1          0    ...            1       0       0
1132        0      0      0          0    ...            0       0       0
224         0      0      0          0    ...            0       0       0
1528        0      0      0          0    ...            0       0       0
1013        0      1      0          0    ...            0       0       0
387         0      0      0          0    ...            0       0       0
2080        1      0      1          0    ...            0       0       0
449         0      0      0          0    ...            0       0       0
3934        0      0      1          0    ...            0       0       0
137         0      0      0          1    ...            0       0       1
1246        0      0      1          1    ...            1       0       1
322         0      0      0          0    ...            0       0       0
82          0      0      1          0    ...            0       0       0
1181        0      0      1          0    ...            0       0       0
3           0      1      1          0    ...            0       0       0
191         0      0      0          0    ...            0       0       1

      Fantasy  Horror  Thriller  Science Fiction  Western  TV Movie  Adventure
2460        0       1         1                0        0         0          0
```

```
990     0   0   0     0   0   0   0
1132    1   1   1     0   0   0   0
224     0   0   0     1   0   0   0
1528    0   0   0     0   0   0   0
1013    0   0   1     0   0   0   0
387     0   0   1     0   0   0   0
2080    0   0   1     0   0   0   0
449     0   0   1     1   0   0   0
3934    0   0   0     0   0   0   0
137     0   0   0     0   0   0   0
1246    1   0   0     0   0   0   0
322     1   0   1     1   0   0   1
82      0   0   1     1   0   0   0
1181    0   0   1     0   0   0   0
3       0   0   1     0   0   0   0
191     1   0   0     0   0   0   1

[17 rows x 26 columns]
```

In [144]:
```python
DataFrame_actors.loc[DataFrame_actors['actor'] == "Gary Oldman"]
```

Out[144]:
```
            actor  vote_average   title_year         gross        budget  \
2197  Gary Oldman      6.494118  2005.941176  2.747432e+08  8.102718e+07

     favored_genre
2197      Thriller
```

In [145]:
```python
DataFrame_appearance = DataFrame_total[['actor', 'title_year']].groupby('actor').cou
DataFrame_appearance = DataFrame_appearance.reset_index(drop = True)
DataFrame_selection = DataFrame_appearance['title_year'] > 9
DataFrame_selection = DataFrame_selection.reset_index(drop = True)
best_actors = DataFrame_actors[DataFrame_selection]
```

In [146]:
```python
best_actors.sort_values('vote_average', ascending=False).head()
```

Out[146]:
```
                actor  vote_average   title_year         gross        budget  \
2549      Ian McKellen      7.120000  2005.400000  6.826655e+08  1.435000e+08
1931      Emily Watson      6.990000  2007.800000  5.639998e+07  2.180000e+07
1943       Emma Watson      6.930000  2007.700000  5.875647e+08  1.103000e+08
3581   Keira Knightley      6.870000  2008.600000  3.146037e+08  7.795002e+07
749          Brad Pitt      6.842857  2004.714286  2.281057e+08  7.457143e+07

     favored_genre
2549     Adventure
1931         Drama
1943     Adventure
3581         Drama
749       Thriller
```

```
In [147]: best_actors.sort_values('gross', ascending=False).head()
```

```
Out[147]:                actor  vote_average   title_year         gross        budget  \
          2549     Ian McKellen      7.120000  2005.400000  6.826655e+08  1.435000e+08
          1943      Emma Watson      6.930000  2007.700000  5.875647e+08  1.103000e+08
          413     Anne Hathaway      6.825000  2010.750000  4.475747e+08  1.021667e+08
          6672      Zoe Saldana      6.554545  2008.545455  3.984685e+08  7.136364e+07
          3330  Josh Hutcherson      6.250000  2011.300000  3.497807e+08  7.460000e+07

                  favored_genre
          2549        Adventure
          1943        Adventure
          413             Drama
          6672        Adventure
          3330  Science Fiction
```

```
In [148]: best_actors.sort_values('budget', ascending=False).head()
```

```
Out[148]:                     actor  vote_average   title_year         gross  \
          2549          Ian McKellen         7.120  2005.400000  6.826655e+08
          1943           Emma Watson         6.930  2007.700000  5.875647e+08
          413          Anne Hathaway         6.825  2010.750000  4.475747e+08
          2778            Jamie Foxx         6.270  2008.700000  2.171006e+08
          2468  Helena Bonham Carter         6.575  2006.416667  2.788076e+08

                      budget favored_genre
          2549  1.435000e+08     Adventure
          1943  1.103000e+08     Adventure
          413   1.021667e+08         Drama
          2778  9.568000e+07         Drama
          2468  9.091667e+07         Drama
```

Looks like Sir Ian McKellen has had quite a career.

He came out on top on all three of our attributes.

He plays in the movies with the highsest budget, but returns this with the highest average revenues.

It makes sense that these enormous budgets lead to good movies.

This is reflected by him having the highest average score on IMDB.

We can now develop several plots to analyze our actors.

Let us start by plotting the average budget per actor and the average revenue per actor.

```
In [149]: genre_data_count = []
          for genre in genres_data:
              genre_data_count.append([genre, DafaFrame_cleaned[genre].values.sum()])
          genre_data_count.sort(key = lambda x:x[1], reverse = True)
          labels_ForGenre, sizes_ForGenre = zip(*genre_data_count)
          labels_selected = [n if v > sum(sizes_ForGenre) * 0.01 else '' for n, v in genre_data
          reduced_genre_list = labels_ForGenre[:19]
          trace=[]
```

```
for genre in reduced_genre_list:
    trace.append({'type':'scatter',
                  'mode':'markers',
                  'y':best_actors.loc[best_actors['favored_genre']==genre,'gross'],
                  'x':best_actors.loc[best_actors['favored_genre']==genre,'budget'],
                  'name':genre,
                  'text': best_actors.loc[best_actors['favored_genre']==genre,'actor
                  'marker':{'size':10,'opacity':0.7,
                            'line':{'width':1.25,'color':'black'}}})
layout={'title':'Actors favored data_genres',
       'xaxis':{'title':'mean year of activity'},
       'yaxis':{'title':'mean score_movie_data'}}
fig=Figure(data=trace,layout=layout)
pyo.iplot(fig)
```

We can also use this data to highlight single actors.
Let us take a look at actors for who we have data of more than 20 movies.

In [150]:
```
DataFrame_selection = DataFrame_appearance['title_year'] > 20
best_actors = DataFrame_actors[DataFrame_selection]
best_actors
```

Out[150]:

	actor	vote_average	title_year	gross	\
1179	Christopher Plummer	6.642857	1996.571429	1.001847e+08	
4698	Morgan Freeman	6.622727	2002.909091	1.425407e+08	
5448	Robert De Niro	6.277273	2001.409091	9.379787e+07	
5678	Samuel L. Jackson	6.275000	2003.083333	1.716997e+08	
6075	Susan Sarandon	6.095238	2004.571429	3.342379e+07	
6595	Woody Harrelson	6.450000	2008.458333	1.816275e+08	

	budget	favored_genre
1179	3.159524e+07	Drama
4698	4.509091e+07	Thriller
5448	2.781364e+07	Drama
5678	6.266667e+07	Action
6075	2.502381e+07	Drama
6595	4.899167e+07	Comedy

In [151]:
```
class Trace():
    #____________________
    def __init__(self, color):
        self.mode = 'markers'
        self.name = 'default'
        self.title = 'default title'
        self.marker = dict(color=color, size=110,
                           line=dict(color='white'), opacity=0.7)
        self.r = []
        self.t = []
    #______________________________
```

```
    def set_color(self, color):
        self.marker = dict(color = color, size=110,
                           line=dict(color='white'), opacity=0.7)
    #_____________________________
    def set_name(self, name):
        self.name = name
    #_____________________________
    def set_title(self, title):
        self.na = title
    #____________________________
    def set_actor(self, actor):
        self.actor = actor

    #___________________________
    def set_values(self, r, t):
        self.r = np.array(r)
        self.t = np.array(t)
```

So let's have a look at Morgan Freeman.

We would like to have a clear overview of all the movies he played in and what his movies scored on IMDB. We can do this using a polar chart.

```
In [152]: names =['Morgan Freeman']
          movie_DataFrame2 = DafaFrame_cleaned[DafaFrame_cleaned['actor'] == 'Morgan Freeman']
          total_count  = 0
          years = []
          imdb_score = []
          genre = []
          titles = []
          actor = []
          for s in genres_data:
              icount = movie_DataFrame2[s].sum()
              #__________________________________________________________________
              # Here, we set the limit to 3 because of a bug in plotly's package
              if icount > 3:
                  total_count += 1
                  genre.append(s)
                  actor.append(list(movie_DataFrame2[movie_DataFrame2[s] ==1 ]['actor']))
                  years.append(list(movie_DataFrame2[movie_DataFrame2[s] == 1]['title_year']))
                  imdb_score.append(list(movie_DataFrame2[movie_DataFrame2[s] == 1]['vote_avera
                  titles.append(list(movie_DataFrame2[movie_DataFrame2[s] == 1]['movie_title']
          max_y = max([max(s) for s in years])
          min_y = min([min(s) for s in years])
          year_range = max_y - min_y

          years_normed = []
          for i in range(total_count):
              years_normed.append( [360/total_count*((an-min_y)/year_range+i) for an in years[
```

```
In [153]: color = ('royalblue', 'grey', 'wheat', 'c', 'firebrick', 'seagreen', 'lightskyblue',
                    'lightcoral', 'yellowgreen', 'gold', 'tomato', 'violet', 'aquamarine', 'cha
```

```
In [154]: trace = [Trace(color[i]) for i in range(total_count)]
          tr    = []
          for i in range(total_count):
              trace[i].set_name(genre[i])
              trace[i].set_title(titles[i])
              trace[i].set_values(np.array(imdb_score[i]),
                                  np.array(years_normed[i]))
              tr.append(go.Scatter(r      = trace[i].r,
                                   t      = trace[i].t,
                                   mode   = trace[i].mode,
                                   name   = trace[i].name,
                                   marker = trace[i].marker,
          #                         text   = ['default title' for j in range(len(trace[i].r))]
                                   hoverinfo = 'all'
                                  ))
          layout = go.Layout(
              title='Morgan Freeman',
              font=dict(
                  size=15
              ),
              plot_bgcolor='rgb(223, 223, 223)',
              angularaxis=dict(
                  tickcolor='rgb(253,253,253)'
              ),
              hovermode='Closest',
          )
          fig = go.Figure(data = tr, layout=layout)
          pyo.iplot(fig)
```

0.2 MACHINE LEARNING AND PREDICTION

```
In [155]: movie_DataFrame2 = Early_movie_DataFrame
```

```
In [156]: movie_DataFrame2['log_budget'] = np.log(movie_DataFrame2['budget'])
          movie_DataFrame2['log_popularity'] = np.log(movie_DataFrame2['popularity'])
          movie_DataFrame2['log_revenue']= np.log(movie_DataFrame2['revenue'])
          movie_DataFrame2['log_runtime']= np.log(movie_DataFrame2['runtime'])
          movie_DataFrame2['log_vote_average'] = np.log(movie_DataFrame2['vote_average'])
          movie_DataFrame2['log_vote_count'] = np.log(movie_DataFrame2['vote_count'])

          movie_DataFrame3=movie_DataFrame2[movie_DataFrame2.columns[-6:]]

          movie_DataFrame3=movie_DataFrame3[movie_DataFrame3.replace([np.inf, -np.inf], np.nan
          movie_DataFrame3=movie_DataFrame3.dropna(axis=1)
```

```
column_order = ['log_budget', 'log_popularity','log_revenue','log_runtime',
              'log_vote_average','log_vote_count']
movie_DataFrame3 = movie_DataFrame3[column_order]
```

In [157]:
```
movie_DataFrame3.head()
```

Out[157]:
```
   log_budget  log_popularity  log_revenue  log_runtime  log_vote_average  \
0   19.283571        5.013548    21.748578     5.087596          1.974081
1   19.519293        4.935068    20.683485     5.129899          1.931521
2   19.316769        4.676344    20.596199     4.997212          1.840550
3   19.336971        4.721289    20.804790     5.105945          2.028148
4   19.376192        3.782529    19.464974     4.882802          1.808289

   log_vote_count
0        9.375855
1        8.411833
2        8.404248
3        9.116689
4        7.661056
```

In [158]:
```
movie_col_list = ['budget','popularity','revenue','runtime','vote_average','vote_cou
movie_num = movie_DataFrame2[movie_col_list]
movie_num.head()
```

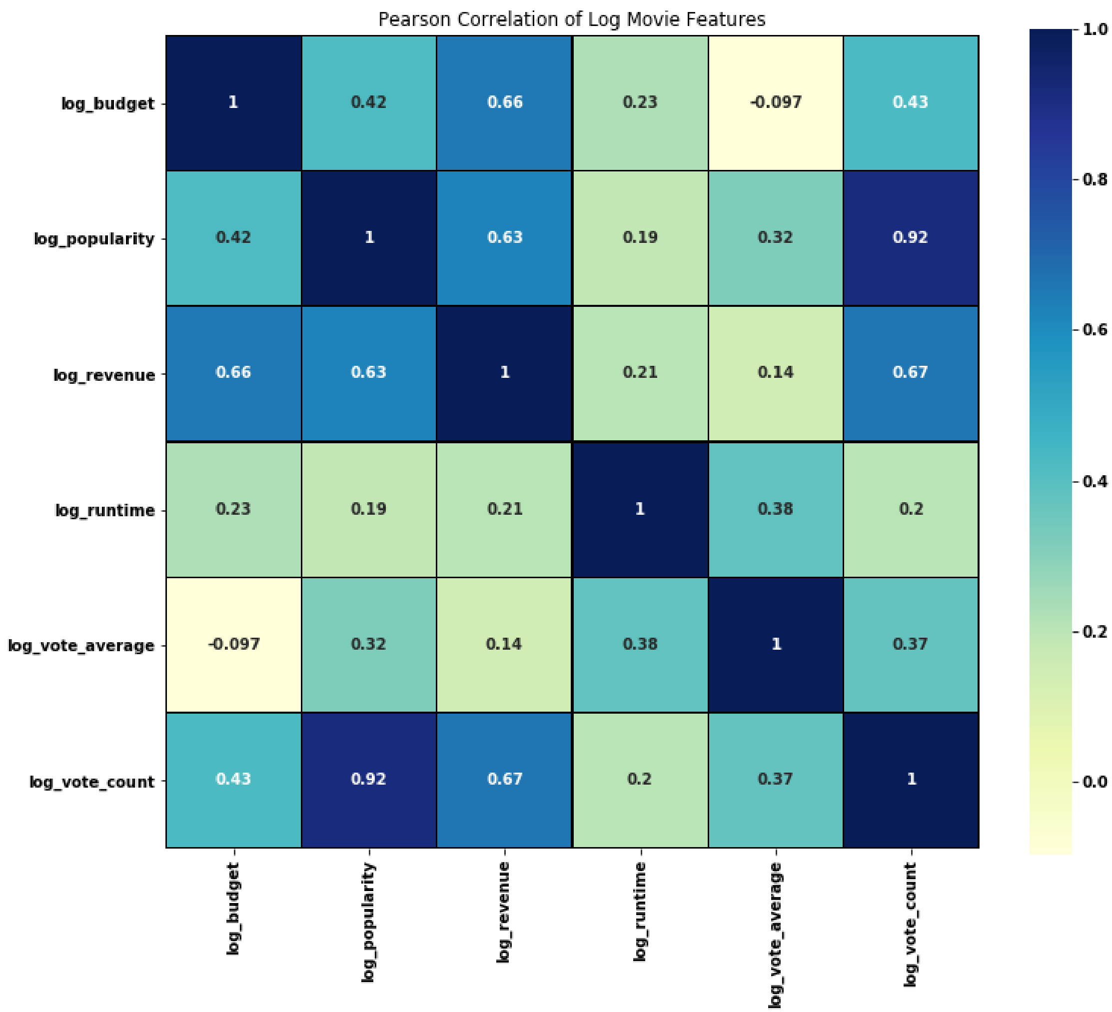
Out[158]:
```
      budget  popularity     revenue  runtime  vote_average  vote_count
0  237000000  150.437577  2787965087    162.0           7.2       11800
1  300000000  139.082615   961000000    169.0           6.9        4500
2  245000000  107.376788   880674609    148.0           6.3        4466
3  250000000  112.312950  1084939099    165.0           7.6        9106
4  260000000   43.926995   284139100    132.0           6.1        2124
```

In [159]:
```
movie_DataFrame2.columns
```

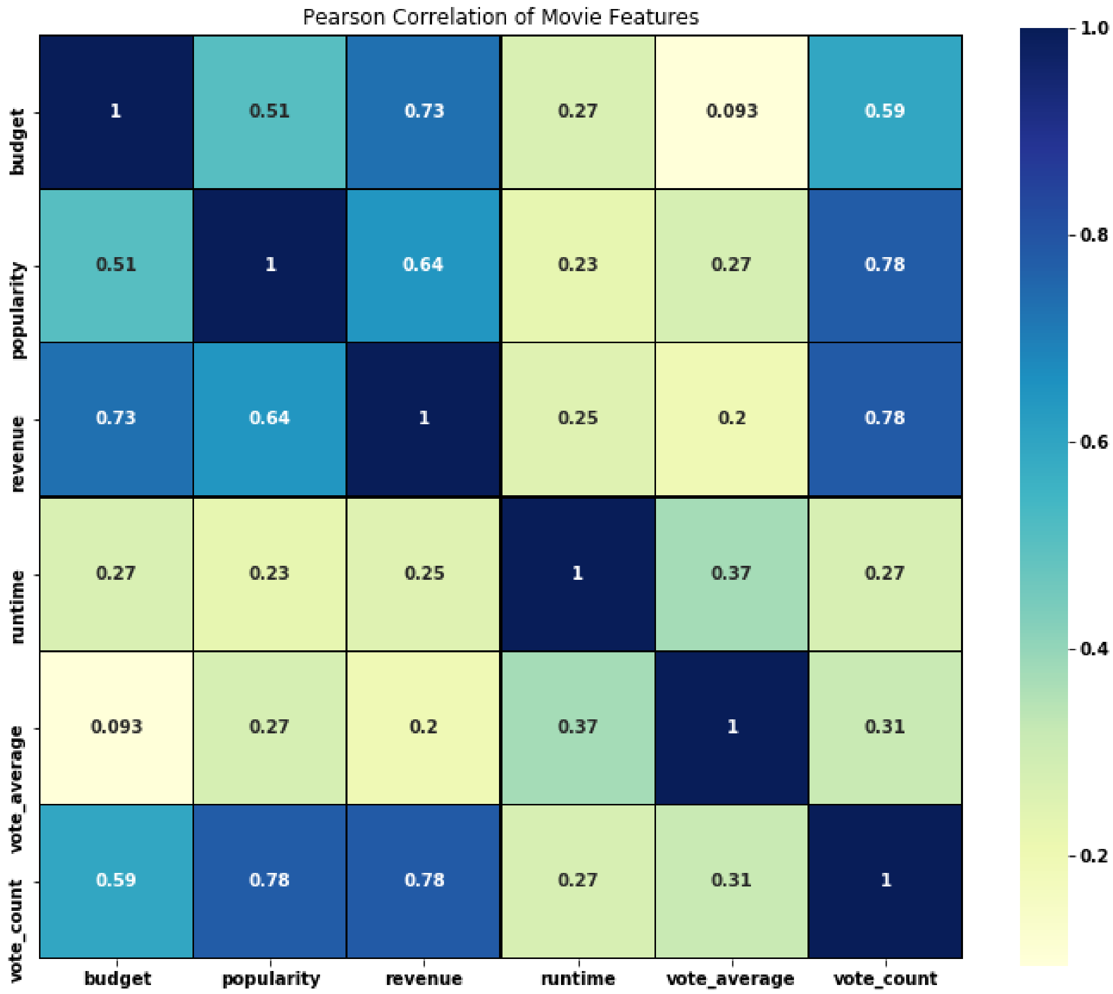
Out[159]:
```
Index([u'title', u'release_date', u'popularity', u'vote_average',
       u'vote_count', u'budget', u'revenue', u'genres', u'keywords', u'cast',
       u'crew', u'tagline', u'runtime', u'production_companies',
       u'production_countries', u'status', u'log_budget', u'log_popularity',
       u'log_revenue', u'log_runtime', u'log_vote_average', u'log_vote_count'],
      dtype='object')
```

In [160]:
```
f, ax = plt.subplots(figsize=(12,10))
plt.title('Pearson Correlation of Log Movie Features')
sns.heatmap(movie_DataFrame3.astype(float).corr(), linewidths=0.25, vmax=1.0, square=
           cmap="YlGnBu", linecolor='black', annot=True)
```

Out[160]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a4c8dd0d0>
```




```
In [161]: plt.show()

In [162]: f, ax = plt.subplots(figsize=(12,10))
          plt.title('Pearson Correlation of Movie Features')
          sns.heatmap(movie_num.astype(float).corr(), linewidths=0.25, vmax=1.0, square=True,
                      cmap="YlGnBu", linecolor='black', annot=True)

Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0x1a3b02fcd0>
```



In [163]:
```
from sklearn.model_selection import train_test_split

training_list = ['popularity','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']

X = training.values
Y = target.values

X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)
```

In [164]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import preprocessing
from sklearn import utils
```

In [165]:
```
label_encoder_data = preprocessing.LabelEncoder()
label_encoded_data = label_encoder_data.fit_transform(Y_train)
```

In [166]:
```
X_train.shape, Y_train.shape, X_test.shape, Y_test.shape, label_encoded_data.shape
```

Out[166]:
```
((3218, 3), (3218,), (1585, 3), (1585,), (3218,))
```

In [167]:
```
#Logistic regression

logreg = LogisticRegression()
logreg.fit(X_train, label_encoded_data)
Y_pred = logreg.predict(X_test)
acc_log = round(logreg.score(X_train, label_encoded_data) * 100, 2)
print('logistic regression:', acc_log)

#SVM
svc = SVC()
svc.fit(X_train, label_encoded_data)
Y_pred = svc.predict(X_test)
acc_svc = round(svc.score(X_train, label_encoded_data)*100,2)
print('Support Vector Machine:', acc_svc)

#Knearestneighbors

knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, label_encoded_data)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, label_encoded_data) * 100, 2)
print('KNN:', acc_knn)

# Gaussian Naive Bayes

gaussian = GaussianNB()
gaussian.fit(X_train, label_encoded_data)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(X_train, label_encoded_data) * 100, 2)
print('Gaussian Naive Bayes:', acc_gaussian)

# Perceptron

perceptron = Perceptron()
perceptron.fit(X_train, label_encoded_data)
```

```
Y_pred = perceptron.predict(X_test)
acc_perceptron = round(perceptron.score(X_train, label_encoded_data) * 100, 2)
print('Perceptron:', acc_perceptron)

# Linear SVC

linear_svc = LinearSVC()
linear_svc.fit(X_train, label_encoded_data)
Y_pred = linear_svc.predict(X_test)
acc_linear_svc = round(linear_svc.score(X_train, label_encoded_data) * 100, 2)
print('linear SVC:', acc_linear_svc)

# Stochastic Gradient Descent

sgd = SGDClassifier()
sgd.fit(X_train, label_encoded_data)
Y_pred = sgd.predict(X_test)
acc_sgd = round(sgd.score(X_train, label_encoded_data) * 100, 2)
print('Stochastic Gradient Descent:', acc_sgd)

# Decision Tree

decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, label_encoded_data)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(X_train, label_encoded_data) * 100, 2)
print("Decision Tree:", acc_decision_tree)

# Random Forest

random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, label_encoded_data)
Y_pred = random_forest.predict(X_test)
random_forest.score(X_train, label_encoded_data)
acc_random_forest = round(random_forest.score(X_train, label_encoded_data) * 100, 2)
print("Random forest:", acc_random_forest)
```

```
('logistic regression:', 6.65)
('Support Vector Machine:', 92.14)
('KNN:', 38.25)
('Gaussian Naive Bayes:', 5.78)
('Perceptron:', 1.21)
('linear SVC:', 1.65)
('Stochastic Gradient Descent:', 4.66)
('Decision Tree:', 100.0)
('Random forest:', 100.0)
```

```
In [168]: movie_num.head()
```

Out[168]:

	budget	popularity	revenue	runtime	vote_average	vote_count
0	237000000	150.437577	2787965087	162.0	7.2	11800
1	300000000	139.082615	961000000	169.0	6.9	4500
2	245000000	107.376788	880674609	148.0	6.3	4466
3	250000000	112.312950	1084939099	165.0	7.6	9106
4	260000000	43.926995	284139100	132.0	6.1	2124

In [169]:
```
from matplotlib import pyplot as plt
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
import numpy as np
print(__doc__)
```

```
Automatically created module for IPython interactive environment
```

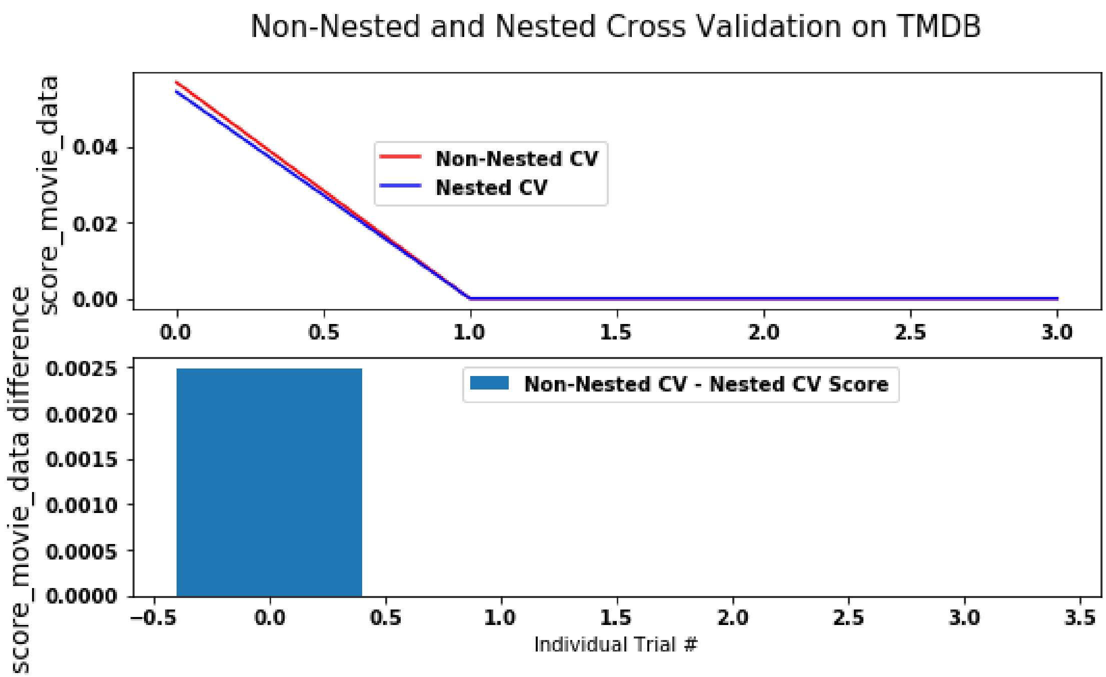
In [170]:
```
NUM_RANDOM_TRIALS = 4 #30

# Load the dataset
training_list = ['budget','popularity','revenue','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']

X = training.values
Y = target.values

X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)

label_encoder_data = preprocessing.LabelEncoder()
label_encoded_data = label_encoder_data.fit_transform(Y_train)

# Set up possible values of parameters to optimize over
p_grid = {"C": [1, 10, 100],
          "gamma": [.01, .1]}

# We will use a Support Vector Classifier with "rbf" kernel
svm = SVC(kernel="rbf")

# Arrays to store scores_data
non_nested_scores = np.zeros(NUM_RANDOM_TRIALS)
nested_scores = np.zeros(NUM_RANDOM_TRIALS)
```

In [171]:
```
#for i in range(NUM_RANDOM_TRIALS):
for i in range(1):
    print('Trial Number : ',i)
    # Choose cross-validation techniques for the inner and outer loops,
    # independently of the dataset.
    # E.g "LabelKFold", "LeaveOneOut", "LeaveOneLabelOut", etc.
```

```
        inner_cv = KFold(n_splits=4, shuffle=True, random_state=i)
        outer_cv = KFold(n_splits=4, shuffle=True, random_state=i)

        # Non_nested parameter search and scoring
        clf = GridSearchCV(estimator=svm, param_grid=p_grid, cv=inner_cv)
        clf.fit(X_train, label_encoded_data)
        non_nested_scores[i] = clf.best_score_

        # Nested CV with parameter optimization
        nested_score = cross_val_score(clf, X=X_train, y=label_encoded_data, cv=outer_cv)
        nested_scores[i] = nested_score.mean()
        print('Score of', i, ' : ',nested_score[i])

    score_difference = non_nested_scores - nested_scores

    print("Average difference of {0:6f} with std. dev. of {1:6f}."
          .format(score_difference.mean(), score_difference.std()))
```

```
('Trial Number : ', 0)
('Score of', 0, ' : ', 0.055900621118012424)
Average difference of 0.000621 with std. dev. of 0.001076.
```

In [172]:
```
plt.figure()
plt.subplot(211)
non_nested_scores_line, = plt.plot(non_nested_scores, color='r')
nested_line, = plt.plot(nested_scores, color='b')
plt.ylabel("score_movie_data", fontsize="14")
plt.legend([non_nested_scores_line, nested_line],
           ["Non-Nested CV", "Nested CV"],
           bbox_to_anchor=(0, .4, .5, 0))
plt.title("Non-Nested and Nested Cross Validation on TMDB",
          x=.5, y=1.1, fontsize="15")

# Plot bar chart of the difference.
plt.subplot(212)
difference_plot = plt.bar(range(NUM_RANDOM_TRIALS), score_difference)
plt.xlabel("Individual Trial #")
plt.legend([difference_plot],
           ["Non-Nested CV - Nested CV Score"],
           bbox_to_anchor=(0, 1, .8, 0))
plt.ylabel("score_movie_data difference", fontsize="14")

plt.show()
```



In [173]: Y_pred

Out[173]: array([47, 40, 40, ..., 48, 38, 47])

In [174]:
```
Machine_Learning_Models_List_Pipeline2 = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'Stochastic Gradient Decent', 'Linear SVC',
              'Decision Tree'],
    'Score': [acc_svc, acc_knn, acc_log,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, acc_linear_svc, acc_decision_tree]})
Machine_Learning_Models_List_Pipeline2.sort_values(by='Score', ascending=False)
```

Out[174]:

	Model	Score
3	Random Forest	100.00
8	Decision Tree	100.00
0	Support Vector Machines	92.14
1	KNN	38.25
2	Logistic Regression	6.65
4	Naive Bayes	5.78
6	Stochastic Gradient Decent	4.66
7	Linear SVC	1.65
5	Perceptron	1.21

In [175]:
```
from sklearn.model_selection import train_test_split
```

```
training_list = ['popularity','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']

X = training.values
Y = target.values

X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)

Y_train = pd.cut(Y_train,10, labels=["1", "2","3","4","5","6","7","8","9","10"])
```

In [176]:
```
#Logistic regression

logreg = LogisticRegression()
logreg.fit(X_train, Y_train)
Y_pred = logreg.predict(X_test)
acc_log = round(logreg.score(X_train, Y_train) * 100, 2)
print('logistic regression:', acc_log)

#SVM
svc = SVC()
svc.fit(X_train, Y_train)
Y_pred = svc.predict(X_test)
acc_svc = round(svc.score(X_train, Y_train)*100,2)
print('Support Vector Machine:', acc_svc)

#Knearestneighbors

knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
print('KNN:', acc_knn)

# Gaussian Naive Bayes

gaussian = GaussianNB()
gaussian.fit(X_train, Y_train)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(X_train, Y_train) * 100, 2)
print('Gaussian Naive Bayes:', acc_gaussian)

# Perceptron

perceptron = Perceptron()
perceptron.fit(X_train, Y_train)
Y_pred = perceptron.predict(X_test)
```

```
    acc_perceptron = round(perceptron.score(X_train, Y_train) * 100, 2)
    print('Perceptron:', acc_perceptron)

    # Linear SVC

    linear_svc = LinearSVC()
    linear_svc.fit(X_train, Y_train)
    Y_pred = linear_svc.predict(X_test)
    acc_linear_svc = round(linear_svc.score(X_train, Y_train) * 100, 2)
    print('linear SVC:', acc_linear_svc)

    # Stochastic Gradient Descent

    sgd = SGDClassifier()
    sgd.fit(X_train, Y_train)
    Y_pred = sgd.predict(X_test)
    acc_sgd = round(sgd.score(X_train, Y_train) * 100, 2)
    print('Stochastic Gradient Descent:', acc_sgd)

    # Decision Tree

    decision_tree = DecisionTreeClassifier()
    decision_tree.fit(X_train, Y_train)
    Y_pred = decision_tree.predict(X_test)
    acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)
    print("Decision Tree:", acc_decision_tree)

    # Random Forest

    random_forest = RandomForestClassifier(n_estimators=100)
    random_forest.fit(X_train, Y_train)
    Y_pred = random_forest.predict(X_test)
    random_forest.score(X_train, Y_train)
    acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
    print("Random forest:", acc_random_forest)
```

```
('logistic regression:', 43.51)
('Support Vector Machine:', 93.47)
('KNN:', 63.3)
('Gaussian Naive Bayes:', 29.96)
('Perceptron:', 34.12)
('linear SVC:', 6.25)
('Stochastic Gradient Descent:', 38.04)
('Decision Tree:', 100.0)
('Random forest:', 100.0)
```

```
In [177]: Machine_Learning_Models_List_Pipeline = pd.DataFrame({
              'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
```

```
                    'Random Forest', 'Naive Bayes', 'Perceptron',
                    'Stochastic Gradient Decent', 'Linear SVC',
                    'Decision Tree'],
          'Score': [acc_svc, acc_knn, acc_log,
                    acc_random_forest, acc_gaussian, acc_perceptron,
                    acc_sgd, acc_linear_svc, acc_decision_tree]})
Machine_Learning_Models_List_Pipeline.sort_values(by='Score', ascending=False)
```

Out[177]:

	Model	Score
3	Random Forest	100.00
8	Decision Tree	100.00
0	Support Vector Machines	93.47
1	KNN	63.30
2	Logistic Regression	43.51
6	Stochastic Gradient Decent	38.04
5	Perceptron	34.12
4	Naive Bayes	29.96
7	Linear SVC	6.25

In [178]:

```
Machine_Learning_Models_List_Pipeline2.sort_values(by='Score', ascending=False)
```

Out[178]:

	Model	Score
3	Random Forest	100.00
8	Decision Tree	100.00
0	Support Vector Machines	92.14
1	KNN	38.25
2	Logistic Regression	6.65
4	Naive Bayes	5.78
6	Stochastic Gradient Decent	4.66
7	Linear SVC	1.65
5	Perceptron	1.21

In [179]:

```
import os
import pandas as pd
from pandas import DataFrame,Series
from sklearn import tree
import matplotlib
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.preprocessing import StandardScaler
import statsmodels.formula.api as smf
import statsmodels.api as sm
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
from sklearn import neighbors
from sklearn import linear_model
get_ipython().magic(u'matplotlib inline')
```

In [180]: movie_num.head()

Out[180]:

	budget	popularity	revenue	runtime	vote_average	vote_count
0	237000000	150.437577	2787965087	162.0	7.2	11800
1	300000000	139.082615	961000000	169.0	6.9	4500
2	245000000	107.376788	880674609	148.0	6.3	4466
3	250000000	112.312950	1084939099	165.0	7.6	9106
4	260000000	43.926995	284139100	132.0	6.1	2124

In [181]:
```
correlation_data = []
for i in range(0,6):
    correlation_data.append(movie_num.ix[:,i].corr(movie_num['vote_average']))
```

In [182]: correlation_data

Out[182]:
```
[0.093145745348164069,
 0.27395182861902773,
 0.19714966581130883,
 0.37398853534941218,
 1.0,
 0.3129974039957597]
```

In [183]:
```
from sklearn.model_selection import train_test_split

training_list = ['popularity','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']

X = training.values
Y = target.values

X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)
```

In [184]:
```
#Revenue
from sklearn.model_selection import train_test_split

training_list = ['budget','popularity','vote_average','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['revenue']

X = training.values
Y = target.values

X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)
```

In [185]:
```
from sklearn import preprocessing
from sklearn import utils
```

```
label_encoder_data = preprocessing.LabelEncoder()
label_encoded_data = label_encoder_data.fit_transform(Y_train)
```

In [186]:
```
'''
# TAKES TIME

#Logistic regression

logreg = LogisticRegression()
logreg.fit(X_train, label_encoded_data)
Y_pred = logreg.predict(X_test)
acc_log = round(logreg.score(X_train, label_encoded_data) * 100, 2)
print('logistic regression:', acc_log)

#SVM
svc = SVC()
svc.fit(X_train, label_encoded_data)
Y_pred = svc.predict(X_test)
acc_svc = round(svc.score(X_train, label_encoded_data)*100,2)
print('Support Vector Machine:', acc_svc)

#Knearestneighbors

knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, label_encoded_data)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, label_encoded_data) * 100, 2)
print('KNN:', acc_knn)

# Gaussian Naive Bayes

gaussian = GaussianNB()
gaussian.fit(X_train, label_encoded_data)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(X_train, label_encoded_data) * 100, 2)
print('Gaussian Naive Bayes:', acc_gaussian)

# Perceptron

perceptron = Perceptron()
perceptron.fit(X_train, label_encoded_data)
Y_pred = perceptron.predict(X_test)
acc_perceptron = round(perceptron.score(X_train, label_encoded_data) * 100, 2)
print('Perceptron:', acc_perceptron)

# Linear SVC
```

```
linear_svc = LinearSVC()
linear_svc.fit(X_train, label_encoded_data)
Y_pred = linear_svc.predict(X_test)
acc_linear_svc = round(linear_svc.score(X_train, label_encoded_data) * 100, 2)
print('linear SVC:', acc_linear_svc)

# Stochastic Gradient Descent

sgd = SGDClassifier()
sgd.fit(X_train, label_encoded_data)
Y_pred = sgd.predict(X_test)
acc_sgd = round(sgd.score(X_train, label_encoded_data) * 100, 2)
print('Stochastic Gradient Descent:', acc_sgd)

# Decision Tree

decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, label_encoded_data)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(X_train, label_encoded_data) * 100, 2)
print("Decision Tree:", acc_decision_tree)

# Random Forest

random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, label_encoded_data)
Y_pred = random_forest.predict(X_test)
random_forest.score(X_train, label_encoded_data)
acc_random_forest = round(random_forest.score(X_train, label_encoded_data) * 100, 2)
print("Random forest:", acc_random_forest)
'''
```

Out[186]: '\n# TAKES TIME\n\n#Logistic regression\n\nlogreg = LogisticRegression()\nlogreg.fit

In [187]:
```
Machine_Learning_Models_List_Pipeline2 = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'Stochastic Gradient Decent', 'Linear SVC',
              'Decision Tree'],
    'Score': [acc_svc, acc_knn, acc_log,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, acc_linear_svc, acc_decision_tree]})
Machine_Learning_Models_List_Pipeline2.sort_values(by='Score', ascending=False)
```

Out[187]:

	Model	Score
3	Random Forest	100.00
8	Decision Tree	100.00
0	Support Vector Machines	93.47

```
1                          KNN   63.30
2          Logistic Regression   43.51
6  Stochastic Gradient Decent   38.04
5                   Perceptron   34.12
4                  Naive Bayes   29.96
7                   Linear SVC    6.25
```

1 Comparing different regression techniques

We want to compare a few regression techniques to help us in making predictions. We'll use linear regression and random forest, as treated in the lectures. We start by recreating our numerical data frame.

```
In [188]: from sklearn.model_selection import train_test_split

          training_list = ['budget','popularity','revenue','runtime','vote_count']
          training = movie_num[training_list]
          target = movie_num['vote_average']

          X = training.values
          Y = target.values

          X_train, X_test, Y_train, Y_test = train_test_split(
          X, Y, test_size=0.33, random_state=42)
```

```
In [191]: from sklearn import tree
          clf = tree.DecisionTreeRegressor()
          clf = clf.fit(X_train, Y_train)
          Y_pred = clf.predict(X_test)
          acc_decision_tree = round(clf.score(X_train, Y_train) * 100, 2)
          print("Decision Tree:", acc_decision_tree)

          #Linear regression
          from sklearn import linear_model
          from sklearn import metrics

          lin_regression = linear_model.LinearRegression()
          lin_regression.fit(X_train, Y_train)
          Y_pred = lin_regression.predict(X_test)
          acc_linReg = round(lin_regression.score(X_train, Y_train)*100,2)
          print("Linear Regression:", acc_linReg)
```

```
('Decision Tree:', 100.0)
('Linear Regression:', 20.34)
```

```
In [194]: movie_col_list = ['budget','popularity','revenue','runtime','vote_average','vote_cou
          movie_num = movie_DataFrame2[movie_col_list]
          movie_num.head()
```

Out[194]:

	budget	popularity	revenue	runtime	vote_average	vote_count
0	237000000	150.437577	2787965087	162.0	7.2	11800
1	300000000	139.082615	961000000	169.0	6.9	4500
2	245000000	107.376788	880674609	148.0	6.3	4466
3	250000000	112.312950	1084939099	165.0	7.6	9106
4	260000000	43.926995	284139100	132.0	6.1	2124

In [195]:
```
correlation_data = []
for i in range(0,6):
    correlation_data.append(movie_num.ix[:,i].corr(movie_num['vote_average']))
correlation_data
```

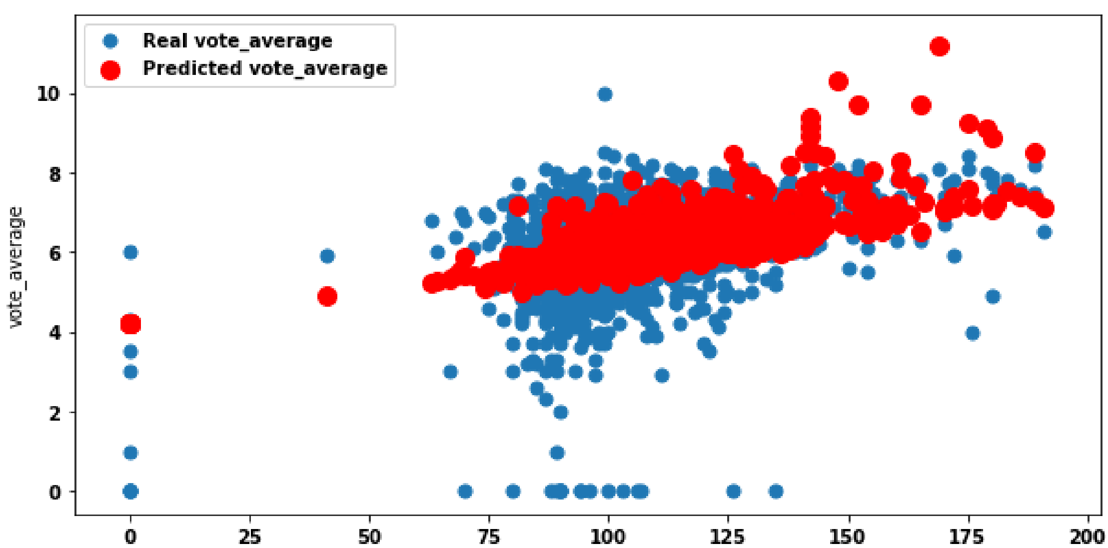
Out[195]:
```
[0.093145745348164069,
 0.27395182861902773,
 0.19714966581130883,
 0.37398853534941218,
 1.0,
 0.3129974039957597]
```

In [196]:
```
training_list = ['popularity','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']
```

In [197]:
```
X = training.values
y = target.values
```

In [198]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_sta
```

In [199]:
```
f = plt.figure(figsize=(10,5))
plt.scatter(X_test[:,1], y_test, s=50,label="Real vote_average");
plt.scatter(X_test[:,1], Y_pred,s=100, c='r',label="Predicted vote_average");
plt.ylabel("vote_average");
plt.legend(loc=2);
```



In [200]:
```
training_list = ['budget','popularity','revenue','runtime','vote_count']
training = movie_num[training_list]
target = movie_num['vote_average']
```

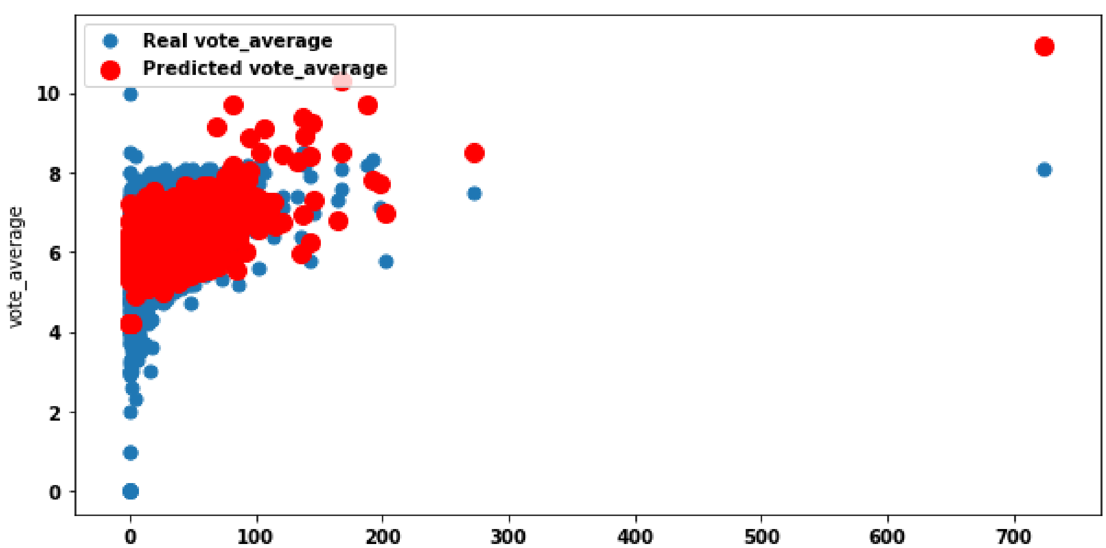
In [201]:
```
from sklearn import linear_model
regr = linear_model.LinearRegression()

regr.fit(X_train, y_train)

y_pred_lr = regr.predict(X_test)
```

In [202]:
```
X = training.values
y = target.values
```

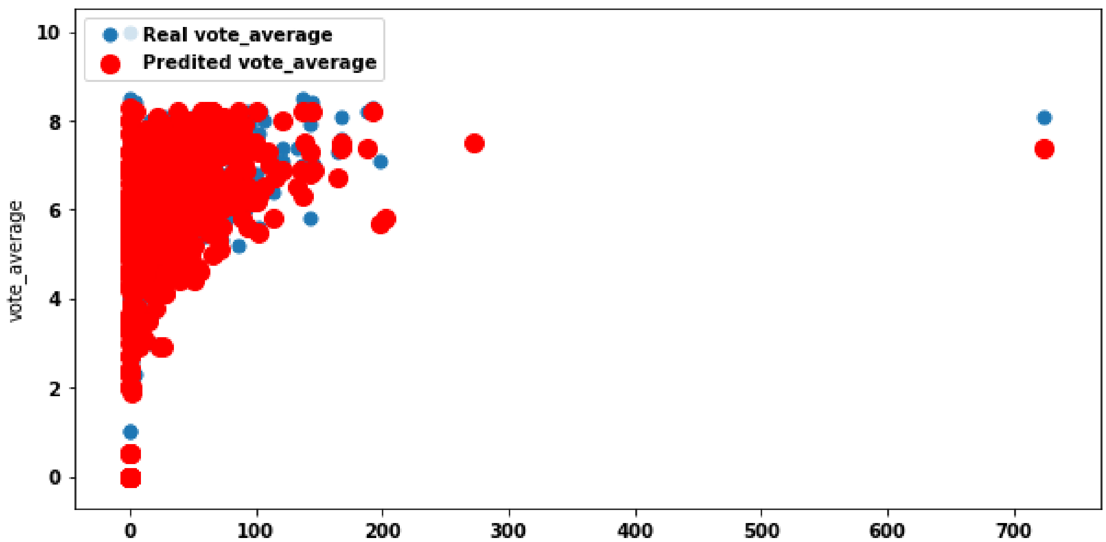
In [203]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_sta
```

In [204]:
```
from sklearn import linear_model
# Create linear regression object
regr = linear_model.LinearRegression()

# Train the model using the training sets
regr.fit(X_train, y_train)

# Make predictions using the testing set
y_pred_lr = regr.predict(X_test)
```

In [205]:
```
f = plt.figure(figsize=(10,5))
plt.scatter(X_test[:,1], y_test, s=50,label="Real vote_average");
plt.scatter(X_test[:,1], y_pred_lr,s=100, c='r',label="Predicted vote_average");
plt.ylabel("vote_average");
plt.legend(loc=2);
```

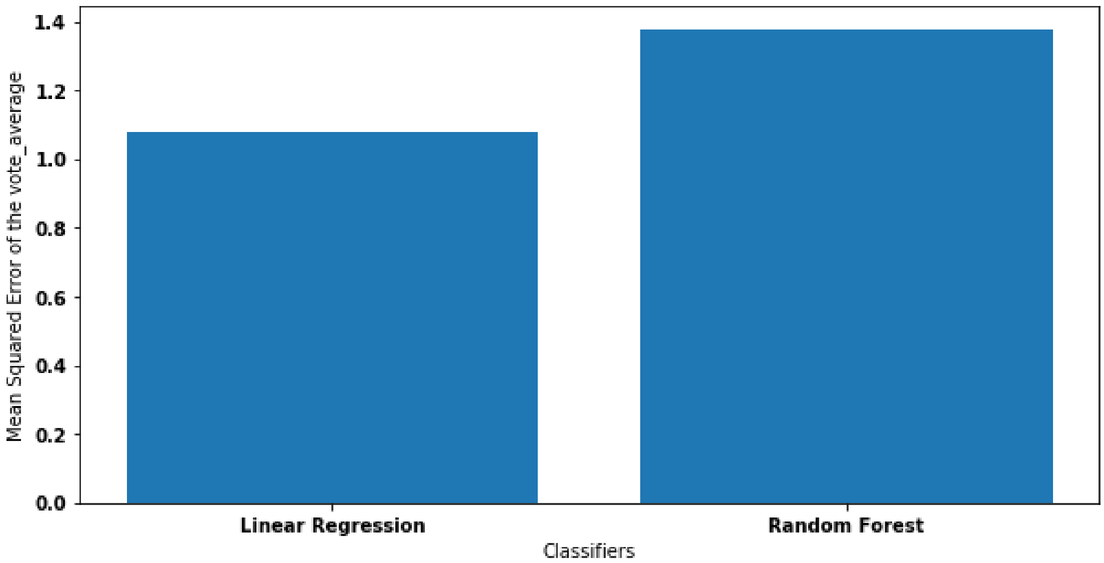


```
In [206]: from sklearn.ensemble import RandomForestRegressor
          # Create linear regression object
          rf = RandomForestRegressor(1)

          # Train the model using the training sets
          rf.fit(X_train, y_train)

          # Make predictions using the testing set
          y_pred_rf = rf.predict(X_test)

In [207]: f = plt.figure(figsize=(10,5))
          plt.scatter(X_test[:,1], y_test, s=50,label="Real vote_average");
          plt.scatter(X_test[:,1], y_pred_rf,s=100, c='r',label="Predited vote_average");
          plt.ylabel("vote_average");
          plt.legend(loc=2);
```




```
In [208]: from sklearn.metrics import mean_squared_error

          error_lr = mean_squared_error(y_test,y_pred_lr)
          error_rf = mean_squared_error(y_test,y_pred_rf)

          print(error_lr)
          print(error_rf)

1.08038126837
1.37682649842
```

In [216]:
```
f = plt.figure(figsize=(10,5))
plt.bar(range(2),[error_lr,error_rf], yerr=np.std(0))
plt.xlabel("Classifiers");
plt.ylabel("Mean Squared Error of the vote_average");
plt.xticks(range(2),['Linear Regression','Random Forest'])
plt.legend(loc=2);
```

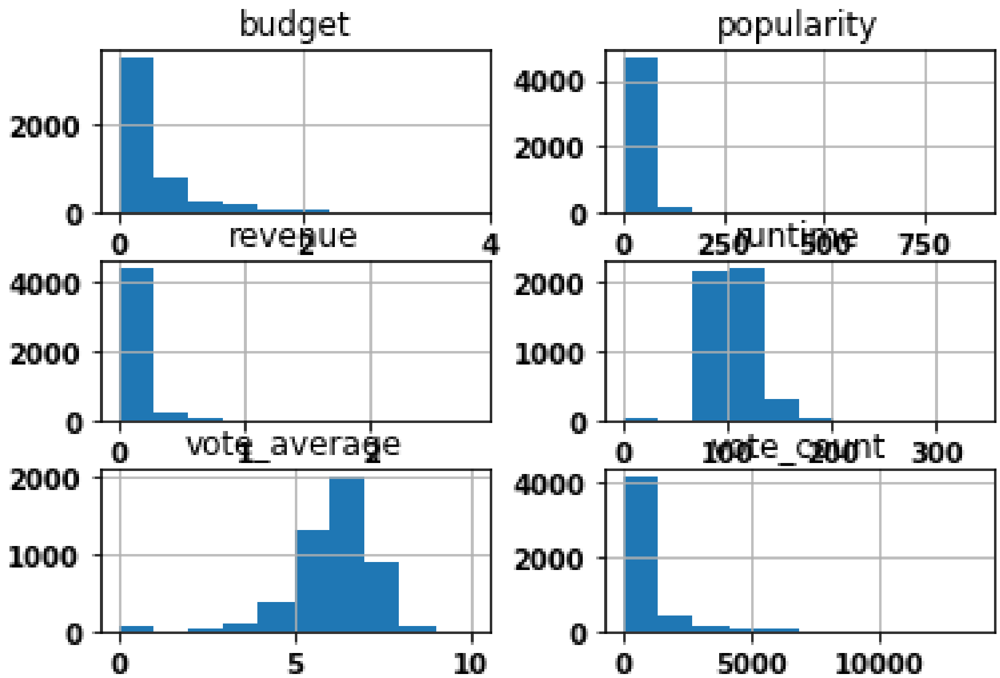


In [210]:
```
np.std(error_rf)
```

Out[210]: 0.0

In [211]:
```
import matplotlib.pyplot
movie_num.hist()
```

Out[211]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1a396df9d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a4b4b3710>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a4c7db0d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a4c6d6a50>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a4c806410>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a3a1d05d0>]], dtype=obje
```



2 SENTIMENT ANALYSIS USING LSTM

```
In [213]: import numpy as np
          import pandas as pd

          from gensim import corpora
          from nltk.corpus import stopwords
          from nltk.tokenize import word_tokenize
          from nltk.stem import SnowballStemmer

          from keras.preprocessing import sequence
          from keras.utils import np_utils
          from keras.models import Sequential
          from keras.layers import Dense, Dropout, Activation, Embedding
          from keras.layers import LSTM
          np.random.seed(0)

In [214]: if __name__ == "__main__":

              #load data
              DataFrame_train_data = pd.read_csv('./data/train.tsv', sep='\t', header=0)
              DataFrame_test_data = pd.read_csv('./data/test.tsv', sep='\t', header=0)

              DataFrame_raw_train_docs = DataFrame_train_data['Phrase'].values
```

```
DataFrame_raw_test_docs = DataFrame_test_data['Phrase'].values
train_sentiment = DataFrame_train_data['Sentiment'].values
data_labelling_len = len(np.unique(train_sentiment))

#text pre-processing
stop_words = set(stopwords.words('english'))
stop_words.update(['.', ',', '"', "'", ':', ';', '(', ')', '[', ']', '{', '}'])
stemmer = SnowballStemmer('english')

###print 'pre-processing train docs...'
list_processed_docs_train = []
for doc in DataFrame_raw_train_docs:
   all_tokens = word_tokenize(doc)
   all_filtered_words = [word for word in all_tokens if word not in stop_words]
   after_stemming_of_words = [stemmer.stem(word) for word in all_filtered_words]
   list_processed_docs_train.append(after_stemming_of_words)

###print 'pre-processing test docs...'
processed_docs_test = []
for doc in DataFrame_raw_test_docs:
   all_tokens = word_tokenize(doc)
   all_filtered_words = [word for word in all_tokens if word not in stop_words]
   after_stemming_of_words = [stemmer.stem(word) for word in all_filtered_words]
   processed_docs_test.append(after_stemming_of_words)

processed_docs_all = np.concatenate((list_processed_docs_train, processed_docs_te

dictionary_words = corpora.Dictionary(processed_docs_all)
dictionary_size = len(dictionary_words.keys())
###print 'dictionary_words size: ', dictionary_size
#dictionary_words.save('dictionary_words.dict')
#corpus = [dictionary_words.doc2bow(doc) for doc in processed_docs]

###print 'converting to token ids...'
word_id_train, word_id_len = [], []
for doc in list_processed_docs_train:
    word_ids = [dictionary_words.token2id[word] for word in doc]
    word_id_train.append(word_ids)
    word_id_len.append(len(word_ids))

word_id_test, word_ids = [], []
for doc in processed_docs_test:
    word_ids = [dictionary_words.token2id[word] for word in doc]
    word_id_test.append(word_ids)
    word_id_len.append(len(word_ids))

sequence_length = np.round((np.mean(word_id_len) + 2*np.std(word_id_len))).astype
```

```
#pad sequences
word_id_train = sequence.pad_sequences(np.array(word_id_train), maxlen=sequence_l
word_id_test = sequence.pad_sequences(np.array(word_id_test), maxlen=sequence_len
y_train_enc = np_utils.to_categorical(train_sentiment, data_labelling_len)

#LSTM
###print 'fitting LSTM ...'
model = Sequential()
model.add(Embedding(dictionary_size, 128, dropout=0.2))
model.add(LSTM(128, dropout_W=0.2, dropout_U=0.2))
model.add(Dense(data_labelling_len))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accura
model.fit(word_id_train, y_train_enc, nb_epoch=1, batch_size=256, verbose=1)

test_pred = model.predict_classes(word_id_test)

#Output a csv file to check output
DataFrame_test_data['Sentiment'] = test_pred.reshape(-1,1)
header = ['PhraseId', 'Sentiment']
DataFrame_test_data.to_csv('./lstm_sentiment.csv', columns=header, index=False, h
```

```
Epoch 1/1
156060/156060 [==============================] - 112s 718us/step - loss: 0.9981 - acc: 0.5982
```

In [215]:
```
DataFrame_test_data
```

Out[215]:

	PhraseId	SentenceId	\
0	156061	8545	
1	156062	8545	
2	156063	8545	
3	156064	8545	
4	156065	8545	
5	156066	8545	
6	156067	8545	
7	156068	8545	
8	156069	8545	
9	156070	8545	
10	156071	8545	
11	156072	8545	
12	156073	8545	
13	156074	8545	
14	156075	8545	
15	156076	8546	
16	156077	8546	
17	156078	8546	

```
18        156079        8546
19        156080        8546
20        156081        8546
21        156082        8546
22        156083        8546
23        156084        8546
24        156085        8546
25        156086        8546
26        156087        8546
27        156088        8546
28        156089        8546
29        156090        8546
...          ...         ...
66262     222323       11853
66263     222324       11853
66264     222325       11853
66265     222326       11853
66266     222327       11853
66267     222328       11853
66268     222329       11853
66269     222330       11853
66270     222331       11853
66271     222332       11853
66272     222333       11853
66273     222334       11853
66274     222335       11853
66275     222336       11853
66276     222337       11853
66277     222338       11853
66278     222339       11853
66279     222340       11853
66280     222341       11854
66281     222342       11854
66282     222343       11854
66283     222344       11854
66284     222345       11854
66285     222346       11854
66286     222347       11854
66287     222348       11855
66288     222349       11855
66289     222350       11855
66290     222351       11855
66291     222352       11855

                                                   Phrase  Sentiment
0       An intermittently pleasing but mostly routine ...          3
1       An intermittently pleasing but mostly routine ...          3
2                                                      An          2
```

3	intermittently pleasing but mostly routine effort	3
4	intermittently pleasing but mostly routine	3
5	intermittently pleasing but	3
6	intermittently pleasing	3
7	intermittently	2
8	pleasing	3
9	but	2
10	mostly routine	2
11	mostly	2
12	routine	2
13	effort	2
14	.	2
15	Kidman is really the only thing that 's worth ...	2
16	Kidman	2
17	is really the only thing that 's worth watchin...	2
18	is really the only thing that 's worth watchin...	2
19	is really	2
20	is	2
21	really	2
22	the only thing that 's worth watching in Birth...	2
23	the only thing	2
24	the	2
25	only thing	2
26	only	2
27	thing	2
28	that 's worth watching in Birthday Girl , a fi...	2
29	that	2
...	...	...
66262	organized	2
66263	efficiency	3
66264	numerous flashbacks	2
66265	a constant edge of tension	2
66266	a constant edge	2
66267	constant edge	2
66268	, Miller 's film is one of 2002 's involvingly...	3
66269	Miller 's film is one of 2002 's involvingly a...	3
66270	Miller 's film	2
66271	is one of 2002 's involvingly adult surprises .	3
66272	is one of 2002 's involvingly adult surprises	3
66273	one of 2002 's involvingly adult surprises	3
66274	of 2002 's involvingly adult surprises	2
66275	2002 's involvingly adult surprises	2
66276	2002 's	2
66277	involvingly adult surprises	3
66278	involvingly	2
66279	adult surprises	2
66280	They should have called it Gutterball .	2
66281	should have called it Gutterball .	2

```
66282                    should have called it Gutterball           2
66283                           have called it Gutterball           2
66284                                called it Gutterball           2
66285                                       it Gutterball           2
66286                                          Gutterball           2
66287             A long-winded , predictable scenario .           1
66288               A long-winded , predictable scenario           1
66289                                    A long-winded ,           2
66290                                      A long-winded           2
66291                               predictable scenario           1

[66292 rows x 4 columns]
```

2.1 THE END [Nikesh-nrs113, Anirudh-ab1721]