The Movies Dataset

dataset : [https://www.kaggle.com/rounakbanik/the-movies-dataset/data (https://www.kaggle.com/rounakbanik/the-movies-dataset/data)](https://www.kaggle.com/rounakbanik/the-movies-dataset/data)
cleaned : [https://drive.google.com/drive/folders/1ZGp7ORu9nA6l3PyNK_H0MGTXNl4sNMsA?usp=sharing (https://drive.google.com/drive/folders/1ZGp7ORu9nA6l3PyNK_H0MGTXNl4sNMsA?usp=sharing)](https://drive.google.com/drive/folders/1ZGp7ORu9nA6l3PyNK_H0MGTXNl4sNMsA?usp=sharing)

In [1]:

```
import warnings
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from wordcloud import wordcloud, STOPWORDS
import glob
import string
import nltk
from nltk.corpus import stopwords
from sklearn.model_selection import train_test_split
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
import seaborn as sns
from sklearn import preprocessing
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.metrics import f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
import scipy.sparse as sp
import matplotlib.pyplot as plt
from sklearn.metrics.pairwise import linear_kernel
from sklearn.metrics.pairwise import cosine_similarity
import itertools
import functools
import operator
```

In [2]:

```
warnings.filterwarnings("ignore")
```

In [3]:
```
movies = pd.read_csv('/Users/davidshi/Downloads/movie/movies.csv', header=0)
movies = movies.replace({np.nan: None}) # replace NaN with None
movies.head()
```

Out[3]:

	id	title	tagline	description	genres	keywords	date	collection	runtime	revenue	...
0	862	Toy Story	None	Led by Woody, Andy's toys live happily in his ...	animation, comedy, family	jealousy, toy, boy, friendship, friends, rival...	1995-10-30	Toy Story Collection	81	3.73554e+08	...
1	8844	Jumanji	Roll the dice and unleash the excitement!	When siblings Judy and Peter discover an encha...	adventure, fantasy, family	board game, disappearance, based on children's...	1995-12-15	None	104	2.62797e+08	...
2	15602	Grumpier Old Men	Still Yelling. Still Fighting. Still Ready for...	A family wedding reignites the ancient feud be...	romance, comedy	fishing, best friend, duringcreditsstinger, ol...	1995-12-22	Grumpy Old Men Collection	101	0	...
3	31357	Waiting to Exhale	Friends are the people who let you be yourself...	Cheated on, mistreated and stepped on, the wom...	comedy, drama, romance	based on novel, interracial relationship, sing...	1995-12-22	None	127	8.14522e+07	...
4	11862	Father of the Bride Part II	Just When His World Is Back To Normal... He's ...	Just when George Banks has recovered from his ...	comedy	baby, midlife crisis, confidence, aging, daugh...	1995-02-10	Father of the Bride Collection	106	7.65789e+07	...

5 rows × 21 columns

In [4]:
```
movies.isnull().sum()
```

Out[4]:
```
id                          0
title                       4
tagline                 25845
description               995
genres                   2524
keywords                14889
date                       88
collection              42054
runtime                   268
revenue                     4
budget                      0
director                  917
cast                     2491
production_companies    12282
production_countries     6496
popularity                  4
average_vote                4
num_votes                   4
language                   11
imdb_id                    17
poster_url                399
dtype: int64
```

In [5]:
```
movies.shape
```

Out[5]:
```
(46628, 21)
```

In [6]:
```
def get_year(date):
    year = None
    if date:
        year = date[:4]
    return year

movies['year'] = movies.date.apply(get_year)
```

Quick Explanatory

Which country have twhe most movies produced?

In [7]:
```
r = movies[~movies['production_countries'].isnull()]
```

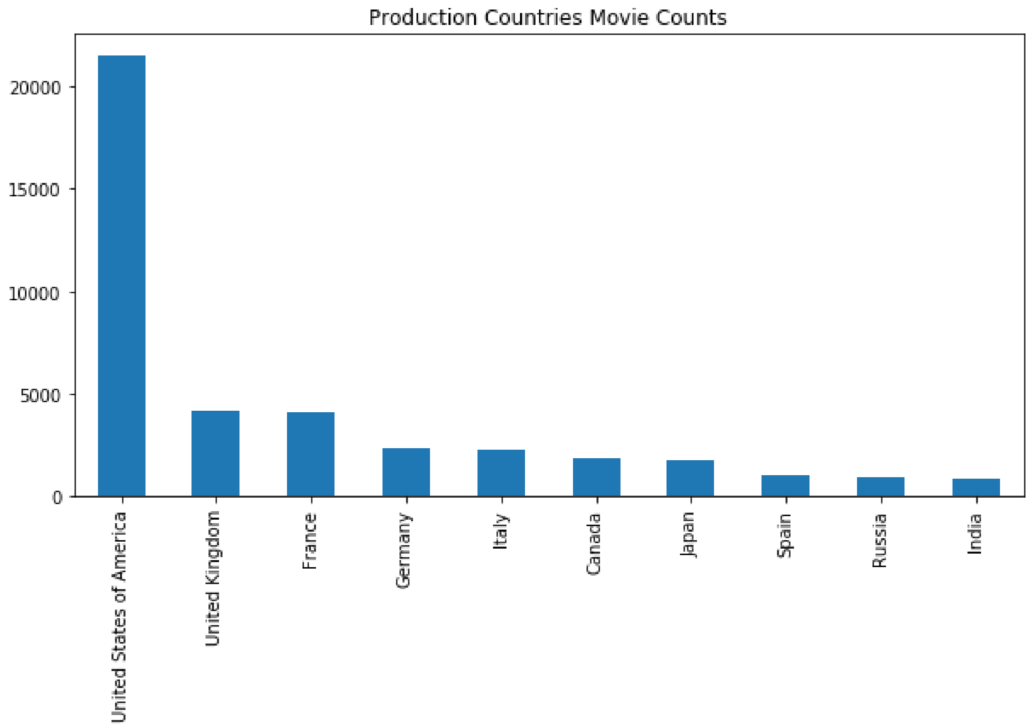
In [8]:
```
r =list(r['production_countries'].str.split(', '))
```

In [9]:
```
flattened_list = functools.reduce(operator.iconcat, r, [])
```

In [10]:
```
dd= pd.Series(flattened_list)
```

In [11]:
```
dd.value_counts().head(10).plot(kind='bar',figsize=(10, 5))
plt.title('Production Countries Movie Counts')
```

Out[11]:
```
Text(0.5, 1.0, 'Production Countries Movie Counts')
```



Multilabel Classification on Genre

Using keywords column to predict Genre

Each movie is classified as mulitple genres. I am going to predict the muliple genres using keywords column. String are cleaned and vectorized.

In [12]:
```
df = movies.dropna(subset = ['title','genres','description'])
```

In [13]:
```
mlb = MultiLabelBinarizer()
mlb.fit(df['genres'])

y = mlb.transform(df['genres'])
```

In [14]:
```
def cleanstring(x):

    x = x.translate(str.maketrans('', '', string.punctuation))
    x = [c for c in x.split() if c.lower() not in stopwords.words('english')]
    return " ".join(x)
```

In [15]:
```
def removepunc(x):

    x = x.translate(str.maketrans('', '', string.punctuation))
    return x
```

In [16]:
```
df['keywords'] = df['keywords'].astype(str)
```

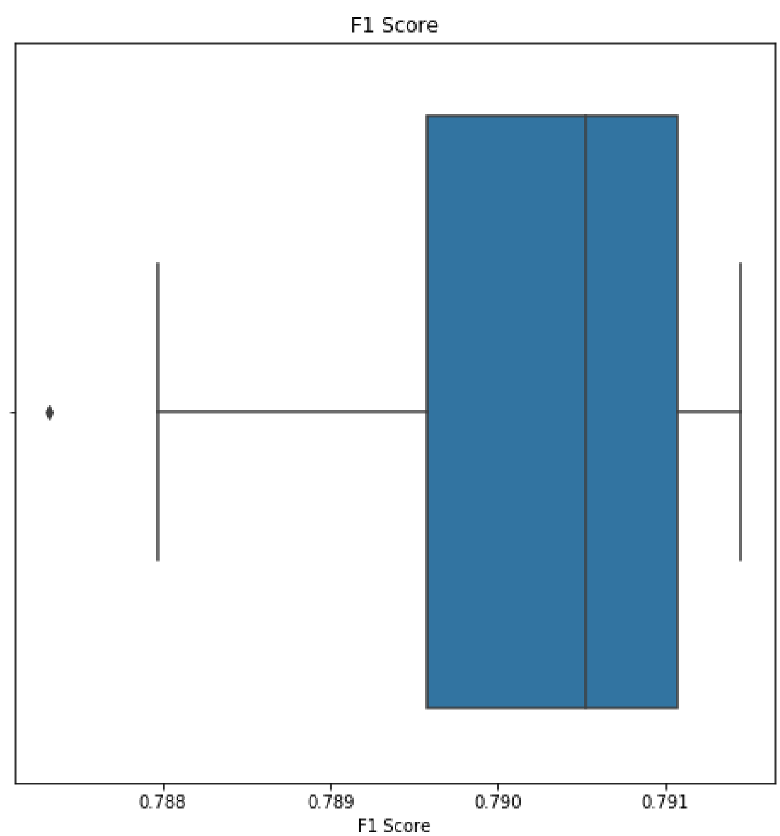
In [17]:
```
X=df['keywords'].apply(removepunc)
X=TfidfVectorizer('english',max_df=0.8,lowercase=True).fit_transform(X)
Xtrain,Xtest,ytrain,ytest = train_test_split(X,y,test_size=0.2,random_state=0)
```

In [18]:
```
lr = LogisticRegression()
clf = OneVsRestClassifier(lr)
results = pd.DataFrame(columns = ['F1 Score'])
```

In [19]:
```
for i in range (10):
    Xtrain,Xtest,ytrain,ytest = train_test_split(X,y,test_size=0.2,random_state=i)
    clf.fit(Xtrain,ytrain)
    pred=clf.predict(Xtest)
    results=results.append({'F1 Score' : f1_score(ytest,pred,average="micro")}, ignore_inde
```

In [20]:
```
plt.figure(figsize=(8,8))
plt.title('F1 Score')
sns.boxplot(x=results['F1 Score'])
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fde60ee7ed0>
```

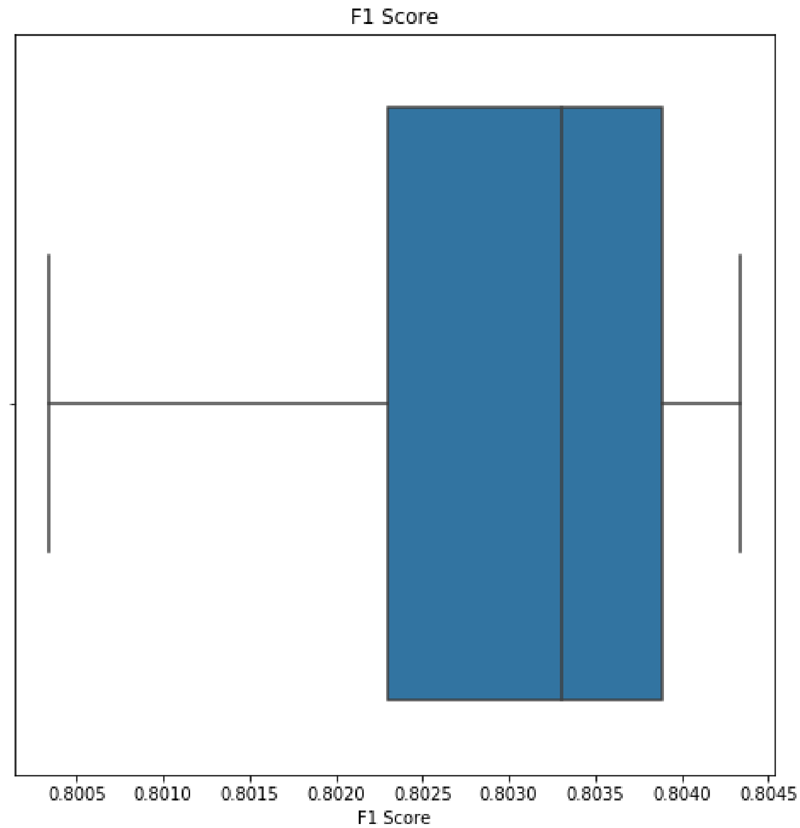


Using description column to predict Genre

In [21]:
```
X2 = df['description'].astype(str)
X2 = TfidfVectorizer('english',max_df=0.8,lowercase=True).fit_transform(X2)
```

In [22]:
```
results = pd.DataFrame(columns = ['F1 Score'])
for i in range (10):
    Xtrain,Xtest,ytrain,ytest = train_test_split(X2,y,test_size=0.2,random_state=i)
    clf.fit(Xtrain,ytrain)
    pred=clf.predict(Xtest)
    results=results.append({'F1 Score' : f1_score(ytest,pred,average="micro")}, ignore_inde
plt.figure(figsize=(8,8))
plt.title('F1 Score')
sns.boxplot(x=results['F1 Score'])
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fde68bd0a90>



Demographic Filtering

movie recommendations by rating and popularity

Although data already provides average rating, this can be quite misleading. When comparing two average ratings the consideration of number of votes is very important. Movie 1 can have a rating of 9.0 with only 3 votes compared to Movie 2 having a rating of 8.0 with 50 votes. In this situation Movie 1's rating is very biased due to the low amount of voters. To tackle this problem IMBD have a weight rating formula.

Weighted Rating = (vR)/(v+m) + (mC)/(v+m)

m = minimum votes to be listed in chart (we will assume movies with 85 percentile number of voters to be relevant)
C = mean of average rating for all movies
R = average rating for specific movie
v = number of votes for specific movie

In [23]:
```
m=df['num_votes'].quantile(0.85)
C=df['average_vote'].mean()
df2=df[df['num_votes']>m]
```

In [24]:
```
def weightedrating(j,m=m,C=C):
    v=j['num_votes']
    R=j['average_vote']

    return (v*R)/(v+m) + (m*C)/(v+m)
```

In [25]:
```
df2['imbd_wr']=df.apply(weightedrating,axis=1)
```

In [26]:
```
df.shape
```

Out[26]: (43372, 22)

In [27]:
```
df2.shape
```

Out[27]: (6482, 23)

In [28]:
```
df.set_index('id')
df2.set_index('id')
df['imbd_wr']=df2['imbd_wr']
```

In [29]:
```
df['genres']=df['genres'].str.split(', ')
s = df.apply(lambda x: pd.Series(x['genres']),axis=1).stack().reset_index(level=1, drop=Tru
s.name = 'genre'
gen_df = df.drop('genres', axis=1).join(s)
```

This seperates the genre column by listing movies duplicately in dataframe. Example would be:

--before--
movie 1 : [comedy,dance]

--after--
movie 1 : [comedy]
movie 1 : [dance]

In [30]:
```
def genre_rec(genre,method):
    if(method == 'popularity'):
        x = gen_df[gen_df['genre']==genre]
        x=x.reset_index(drop=True)
        return x[['title','year',method]].sort_values(by=[method],ascending=False).head(20)

    if(method =='imbd_wr'):
        x = gen_df[gen_df['genre']==genre]
        x=x.reset_index(drop=True)
        return x[['title','year',method]].sort_values(by=[method],ascending=False).head(20)
```

In [31]:
```
genre_rec('horror','imbd_wr')
```

Out[31]:

	title	year	imbd_wr
53	Psycho	1960	8.206322
56	The Shining	1980	8.045797
51	Alien	1979	7.857514
168	The Thing	1982	7.690211
50	Aliens	1986	7.646700
4230	Train to Busan	2016	7.532656
4679	Black Mirror: White Christmas	2014	7.523496
87	Jaws	1975	7.440498
834	Shaun of the Dead	2004	7.437046
140	The Exorcist	1973	7.424285
2173	The Conjuring	2013	7.353137
1343	Let the Right One In	2008	7.351216
159	Rosemary's Baby	1968	7.335308
1707	I Saw the Devil	2010	7.326398
479	The Others	2001	7.315057
83	Nosferatu	1922	7.311819
57	Evil Dead II	1987	7.309732
178	King Kong	1933	7.287780
125	Halloween	1978	7.267883
42	Night of the Living Dead	1968	7.262514

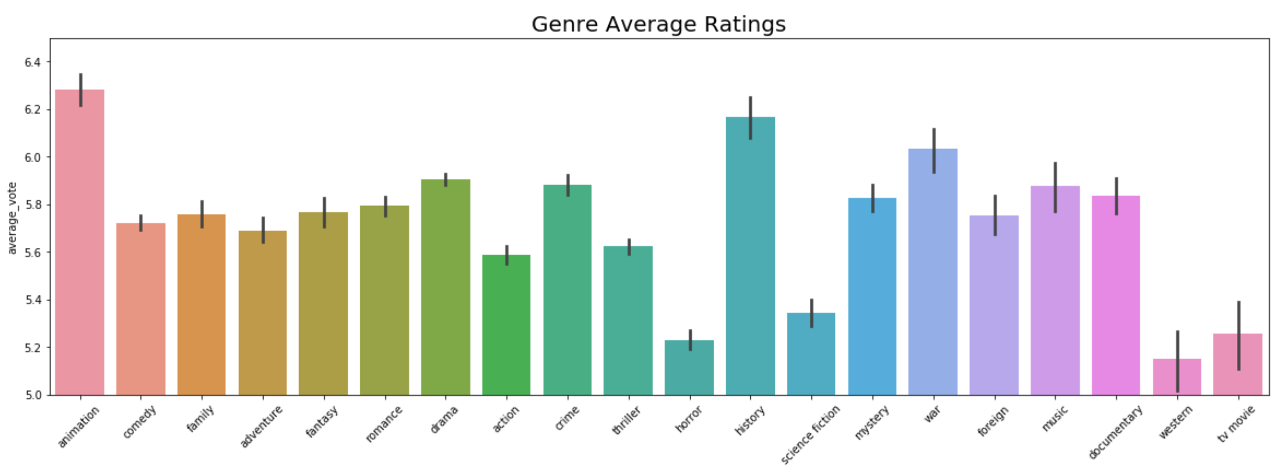
In [32]:
```
genre_rec('comedy','popularity')
```

Out[32]:

	title	year	popularity
9119	Minions	2015	547.488
7437	Big Hero 6	2014	213.85
8025	Deadpool	2016	187.86
8026	Guardians of the Galaxy Vol. 2	2017	185.331
8024	Pirates of the Caribbean: Dead Men Tell No Tales	2017	133.828
12415	Captain Underpants: The First Epic Movie	2017	88.5612
127	Forrest Gump	1994	48.3072
9113	Ted 2	2015	42.0615
11283	Now You See Me 2	2016	39.5407
785	Life Is Beautiful	1997	39.395
12990	Girls Trip	2017	37.9649
12685	Despicable Me 3	2017	36.6315
12397	Baywatch	2017	35.6377
3664	Dilwale Dulhania Le Jayenge	1995	34.457
12969	The Emoji Movie	2017	33.6946
12918	The House	2017	30.1468
7733	Kingsman: The Secret Service	2015	28.2242
12394	Diary of a Wimpy Kid: The Long Haul	2017	28.177
7263	Sex Tape	2014	27.4707
1767	Monsters, Inc.	2001	26.42

In [33]:
```
plt.figure(figsize=(20,6))
plt.ylim(5,6.5)
sns.barplot(x='genre',y='average_vote',data=gen_df)
plt.xticks(rotation=45)
plt.title('Genre Average Ratings', fontsize=20)
```

Out[33]:
```
Text(0.5, 1.0, 'Genre Average Ratings')
```



Content Based Filtering

movie recommendations by plot similarity

In [34]:
```
tfidf_matrix = TfidfVectorizer(stop_words='english').fit_transform(df['description'])
```

In [35]:
```
tfidf_matrix.shape
```

Out[35]:
```
(43372, 73186)
```

description column is vectorized and transformed into TF-IDF matrix. 70000+ words describing 40000+ movies.

In [36]:
```
df = df.reset_index(drop=True)
```

In [37]:
```
indices = pd.Series(df.index, index=df['title'])
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

In [38]:
```
indices ##movie array
```

Out[38]:
```
title
Toy Story                          0
Jumanji                            1
Grumpier Old Men                   2
Waiting to Exhale                  3
Father of the Bride Part II        4
                               ...
Caged Heat 3000                43367
Robin Hood                     43368
Subdue                         43369
Century of Birthing            43370
Betrayal                       43371
Length: 43372, dtype: int64
```

redoing index so index can match between movie array and cosine similiarty matrix. Calculating the dot product / scalar product of TF-IDF vectorized data will give cosine similiarity score.

In [39]:
```
def get_recommendations(title, cosine_sim=cosine_sim):
    # Get the index of movie
    idx = indices[title]

    # pair similarity scores
    sim_scores = list(enumerate(cosine_sim[idx]))

    # Sort the movies based on similarity scores
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)


    sim_scores = sim_scores[1:11]
    movie_indices = [i[0] for i in sim_scores]
    return df['title'].iloc[movie_indices]
```

In [40]:
```
get_recommendations('Minions')
```

Out[40]:
```
20713                           Despicable Me 2
18175                       What's Up, Scarlet?
10463                 A Story of Floating Weeds
30034                   The Mother Of Invention
16020                               Madam Satan
30908                          The Invisible Boy
302                     Stuart Saves His Family
43091                                    Banana
5618                              Soul Assassin
7958      Sherlock Holmes and the Secret Weapon
Name: title, dtype: object
```

In [41]:
```
get_recommendations('Toy Story')
```

Out[41]:
```
15210                                     Toy Story 3
2938                                      Toy Story 2
23852                                       Small Fry
10200                            The 40 Year Old Virgin
23218                         Andy Hardy's Blonde Trouble
37146    Superstar: The Life and Times of Andy Warhol
40952    Andy Peters: Exclamation Mark Question Point
8243                                        The Champ
1047                              Rebel Without a Cause
26371                        Life Begins for Andy Hardy
Name: title, dtype: object
```

movie recommendation by cast, keywords, genre. Using count vectorizer to weigh frequency of repeating cast and repeating keywords in multiple movies.

In [42]:
```
df.isnull().sum()
```

Out[42]:
```
id                          0
title                       0
tagline                 22870
description                 0
genres                      0
keywords                    0
date                       23
collection              38914
runtime                     0
revenue                     0
budget                      0
director                  539
cast                     1713
production_companies     9744
production_countries     4687
popularity                  0
average_vote                0
num_votes                   0
language                    9
imdb_id                    10
poster_url                168
year                       23
imbd_wr                 36890
dtype: int64
```

In [43]:
```
df = df.dropna(subset = ['cast'])
df = df.reset_index(drop=True)
indices = pd.Series(df.index, index=df['title'])
```

In [44]:
```
df['cast'].apply(removepunc)
```

Out[44]:
```
0        Tom Hanks Tim Allen Don Rickles Jim Varney Wal...
1        Robin Williams Jonathan Hyde Kirsten Dunst Bra...
2        Walter Matthau Jack Lemmon AnnMargret Sophia L...
3        Whitney Houston Angela Bassett Loretta Devine ...
4        Steve Martin Diane Keaton Martin Short Kimberl...
                               ...
41654    Lisa Boyle Kena Land Zaneta Polard Don Yanan D...
41655    Patrick Bergin Uma Thurman David Morrissey Jür...
41656              Leila Hatami Kourosh Tahami Elham Korda
41657    Angel Aquino Perry Dizon Hazel Orencio Joel To...
41658    Erika Eleniak Adam Baldwin Julie du Page James...
Name: cast, Length: 41659, dtype: object
```

In [45]:
```
df['keywords'].apply(removepunc)
```

Out[45]:
```
0        jealousy toy boy friendship friends rivalry bo...
1        board game disappearance based on childrens bo...
2         fishing best friend duringcreditsstinger old men
3        based on novel interracial relationship single...
4        baby midlife crisis confidence aging daughter ...
                               ...
41654                                                 None
41655                                                 None
41656                                          tragic love
41657                                    artist play pinoy
41658                                                 None
Name: keywords, Length: 41659, dtype: object
```

In [46]:
```
def listToString(s):
    str1 = " "
    return (str1.join(s))
```

In [47]:
```
df['genres'].apply(listToString)
```

Out[47]:
```
0         animation comedy family
1        adventure fantasy family
2                  romance comedy
3            comedy drama romance
4                          comedy
                   ...
41654             science fiction
41655        drama action romance
41656                drama family
41657                       drama
41658       action drama thriller
Name: genres, Length: 41659, dtype: object
```

In [48]:
```
X = df['cast'].apply(removepunc) + df['keywords'].apply(removepunc) + df['genres'].apply(li

count_matrix = CountVectorizer('english').fit_transform(X)

cosine_sim2 = cosine_similarity(count_matrix,count_matrix)
```

In [49]:
```
get_recommendations('Minions',cosine_sim2)
```

Out[49]:
```
40104                          Binky Nelson Unpacified
25610                          The Wind in the Willows
24511                                   Tactical Force
40487                                  Despicable Me 3
9190                   High Roller: The Stu Ungar Story
9102                                       Kung Phooey
15246                               Life During Wartime
22831                   A Good Job: Stories of the FDNY
29294    Michael Jackson Dangerous Tour - Bucharest - 1992
31477                          N: The Madness Of Reason
Name: title, dtype: object
```

In [50]:
```
get_recommendations('Toy Story', cosine_sim2)
```

Out[50]:
```
2916                          Toy Story 2
14977                         Toy Story 3
24332          Toy Story That Time Forgot
20895                Toy Story of Terror!
23205                    Hawaiian Vacation
23206                            Small Fry
24330                      Partysaurus Rex
2608                                   Big
6100      Gigantic (A Tale Of Two Johns)
1748                        Small Soldiers
Name: title, dtype: object
```

Using different columns to get recommendations did yield different results

Collaborative Filtering

movie recommendations by user history & plot similarity

Used user rating csv to find top movies of specific users and recommended movies based on that.

In [141]:
```
user = pd.read_csv('/Users/davidshi/Downloads/movie/ratings_small.csv')
```

In [142]:
```
user
```

Out[142]:

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205
...	...	...	...	...
99999	671	6268	2.5	1065579370
100000	671	6269	4.0	1065149201
100001	671	6365	4.0	1070940363
100002	671	6385	2.5	1070979663
100003	671	6565	3.5	1074784724

100004 rows × 4 columns

User data contains rows of user ratings. rating column (1-5).

In [143]:
```
links = pd.read_csv('/Users/davidshi/Downloads/movie/links.csv')
```

In [144]:
```
links
```

Out[144]:

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0
...	...	...	...
45838	176269	6209470	439050.0
45839	176271	2028550	111109.0
45840	176273	303758	67758.0
45841	176275	8536	227506.0
45842	176279	6980792	461257.0

45843 rows × 3 columns

links df have movieId and tmbdid equivalent. Need links df to get movie title for user df

In [145]:
```
user = user.merge(links[['movieId','tmdbId']],on='movieId',how='left')
```

In [146]:
```
user = user.rename(columns={'tmdbId':'id'})
user = user.drop(columns =['movieId'])
```

In [147]:
```
user
```

Out[147]:

	userId	rating	timestamp	id
0	1	2.5	1260759144	9909.0
1	1	3.0	1260759179	11360.0
2	1	3.0	1260759182	819.0
3	1	2.0	1260759185	1103.0
4	1	4.0	1260759205	11216.0
...	...	...	...	...
99999	671	2.5	1065579370	25461.0
100000	671	4.0	1065149201	51927.0
100001	671	4.0	1070940363	604.0
100002	671	2.5	1070979663	1088.0
100003	671	3.5	1074784724	4464.0

100004 rows × 4 columns

In [148]:
```
user = user.merge(movies[['id','title','average_vote']],on='id',how='left')
```

In [149]:
```
user
```
Out[149]:

	userId	rating	timestamp	id	title	average_vote
0	1	2.5	1260759144	9909.0	Dangerous Minds	6.4
1	1	3.0	1260759179	11360.0	Dumbo	6.8
2	1	3.0	1260759182	819.0	Sleepers	7.3
3	1	2.0	1260759185	1103.0	Escape from New York	6.9
4	1	4.0	1260759205	11216.0	Cinema Paradiso	8.2
...	...	...	...	...	...	...
100311	671	2.5	1065579370	25461.0	Raising Victor Vargas	7.8
100312	671	4.0	1065149201	51927.0	Stevie	6.7
100313	671	4.0	1070940363	604.0	The Matrix Reloaded	6.7
100314	671	2.5	1070979663	1088.0	Whale Rider	7.1
100315	671	3.5	1074784724	4464.0	Seabiscuit	6.8

100316 rows × 6 columns

In [150]:
```
user.isnull().sum()
```
Out[150]:
```
userId            0
rating            0
timestamp         0
id              106
title           194
average_vote    194
dtype: int64
```

In [151]:
```
user = user.dropna(subset = ['id','title'])
```

In [152]:
```
user
```
Out[152]:

	userId	rating	timestamp	id	title	average_vote
0	1	2.5	1260759144	9909.0	Dangerous Minds	6.4
1	1	3.0	1260759179	11360.0	Dumbo	6.8
2	1	3.0	1260759182	819.0	Sleepers	7.3
3	1	2.0	1260759185	1103.0	Escape from New York	6.9
4	1	4.0	1260759205	11216.0	Cinema Paradiso	8.2
...	...	...	...	...	...	...
100311	671	2.5	1065579370	25461.0	Raising Victor Vargas	7.8
100312	671	4.0	1065149201	51927.0	Stevie	6.7
100313	671	4.0	1070940363	604.0	The Matrix Reloaded	6.7
100314	671	2.5	1070979663	1088.0	Whale Rider	7.1
100315	671	3.5	1074784724	4464.0	Seabiscuit	6.8

100122 rows × 6 columns

In [153]:
```
user.userId.value_counts().min()
```
Out[153]:
```
19
```

Users rated atleast 19 movies

In [154]:
```
user = user.sort_values(by=['userId','rating','average_vote'],ascending=[True,False,False])
```

In [155]:
```
#get top 5 movies for user

def getTopMov(uid) :
    return user[user['userId']==uid].title.values
```

In [156]:
```
#recommendation by finding 10 highest pair similartiy from list of movies

def get_recommendations2(title,cosine_sim):
    sim_scores=[]
    for i in title:
        # Get the index of movie
        idx = indices[i]

        # pair similarity scores
        sim_scores = sim_scores + list(enumerate(cosine_sim[idx]))

    # Sort the movies based on similarity scores
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)


    sim_scores = sim_scores[5:15]
    movie_indices = [i[0] for i in sim_scores]
    return df['title'].iloc[movie_indices]
```

In [157]:
```
getTopMov(10)
```

Out[157]:
```
array(['The Usual Suspects', 'The Matrix', 'Sling Blade',
       'My Own Private Idaho', 'Runaway Train'], dtype=object)
```

In [158]:
```
get_recommendations2(getTopMov(10), cosine_sim)
```

Out[158]:
```
10430                The White Countess
6441                    Day of the Dead
6567                Charlotte Sometimes
22669                        Camouflage
2470      Invasion of the Body Snatchers
5279                The Care Bears Movie
27134                   That Sugar Film
8297                King Solomon's Mines
4250                           Critters
11502                Meet the Robinsons
Name: title, dtype: object
```

In [159]:
```
#recommendation by finding 3 highest pair similartiy for each movie in list

def get_recommendations3(title,cosine_sim):
    sim_scores_final =[]
    for i in title:
        # Get the index of movie
        idx = indices[i]

        # pair similarity scores
        sim_scores = list(enumerate(cosine_sim[idx]))

    # Sort the movies based on similarity scores
        sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
        sim_scores_final = sim_scores_final + sim_scores[1:4]


    movie_indices = [i[0] for i in sim_scores_final]

    return df['title'].iloc[movie_indices]
```

In [160]:
```
getTopMov(10)
```

Out[160]:
```
array(['The Usual Suspects', 'The Matrix', 'Sling Blade',
       'My Own Private Idaho', 'Runaway Train'], dtype=object)
```

In [161]:
```
get_recommendations3(getTopMov(10),cosine_sim)
```

Out[161]:
```
8914                              Gummo
32264                         Pestonjee
27965                         The Hands
6567                Charlotte Sometimes
22669                        Camouflage
27134                   That Sugar Film
10430                 The White Countess
6441                    Day of the Dead
2470     Invasion of the Body Snatchers
4896                          The Arena
6315                        Big Trouble
18695               Under African Skies
26883                             Nymph
12310                   Are You Scared?
31721                     OceanWorld 3D
Name: title, dtype: object
```

In [ ]:

In [ ]:

In [ ]: