```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from ast import literal_eval
from sklearn.metrics.pairwise import linear_kernel,cosine_similarity

!pip install nltk

import nltk
nltk.download('stopwords')
nltk.download('wordnet')
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.6/dist-packages (3.2.5)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from nltk) (1.11.0)
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Unzipping corpora/wordnet.zip.
```

```
True
```

```
import nltk
from sklearn.feature_extraction.text import
TfidfVectorizer,CountVectorizer
from nltk.stem.snowball import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import wordnet, stopwords
import string
from requests import get

#Library for Collaborative filtering
!pip install surprise
from surprise import Reader,Dataset,SVD,evaluate
import warnings;warnings.simplefilter('ignore')
%matplotlib inline
```

```
Collecting surprise
  Downloading
https://files.pythonhosted.org/packages/61/de/e5cba8682201fcf9c3719a6f
dda95693468ed061945493dea2dd37c5618b/surprise-0.1-py2.py3-none-any.whl
Collecting scikit-surprise (from surprise)
ent already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-surprise->surprise) (0.13.2)
Requirement already satisfied: numpy>=1.11.2 in
/usr/local/lib/python3.6/dist-packages (from scikit-surprise->surprise) (1.14.6)
```

```
Requirement already satisfied: scipy>=1.0.0 in
/usr/local/lib/python3.6/dist-packages (from scikit-surprise-
>surprise) (1.1.0)
Requirement already satisfied: six>=1.10.0 in
/usr/local/lib/python3.6/dist-packages (from scikit-surprise-
>surprise) (1.11.0)
Building wheels for collected packages: scikit-surprise
  Building wheel for scikit-surprise (setup.py) ...
```

```
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

```
True
```

```
movies_metadata=pd.read_csv('movies_metadata.csv',error_bad_lines=Fals
e)
movies_metadata.head()
```

```
b'Skipping line 2562: expected 24 fields, saw 27\nSkipping line 3818:
expected 24 fields, saw 29\nSkipping line 7704: expected 24 fields,
saw 35\nSkipping line 8966: expected 24 fields, saw 31\nSkipping line
11543: expected 24 fields, saw 27\nSkipping line 12831: expected 24
fields, saw 25\nSkipping line 16729: expected 24 fields, saw 40\
nSkipping line 19352: expected 24 fields, saw 33\nSkipping line 20687:
expected 24 fields, saw 25\nSkipping line 21975: expected 24 fields,
saw 28\nSkipping line 26002: expected 24 fields, saw 38\nSkipping line
27334: expected 24 fields, saw 27\nSkipping line 28702: expected 24
fields, saw 36\nSkipping line 32776: expected 24 fields, saw 27\n'
b'Skipping line 35530: expected 24 fields, saw 32\nSkipping line
38289: expected 24 fields, saw 27\nSkipping line 39698: expected 24
fields, saw 29\nSkipping line 43901: expected 24 fields, saw 30\
nSkipping line 45361: expected 24 fields, saw 27\nSkipping line 48203:
expected 24 fields, saw 25\nSkipping line 49612: expected 24 fields,
saw 36\nSkipping line 51034: expected 24 fields, saw 26\nSkipping line
52476: expected 24 fields, saw 29\nSkipping line 55408: expected 24
fields, saw 35\nSkipping line 59748: expected 24 fields, saw 27\
nSkipping line 61170: expected 24 fields, saw 31\nSkipping line 62622:
expected 24 fields, saw 43\n'
b'Skipping line 65629: expected 24 fields, saw 30\nSkipping line
67033: expected 24 fields, saw 27\nSkipping line 68460: expected 24
fields, saw 33\nSkipping line 71375: expected 24 fields, saw 25\
nSkipping line 72827: expected 24 fields, saw 29\nSkipping line 74318:
expected 24 fields, saw 26\nSkipping line 75853: expected 24 fields,
saw 31\nSkipping line 77343: expected 24 fields, saw 28\nSkipping line
```

```
78770: expected 24 fields, saw 31\nSkipping line 80105: expected 24
fields, saw 28\n'

   adult                              belongs_to_collection    budget
\
0  False  {'id': 10194, 'name': 'Toy Story Collection', ...  30000000

1  False                                                NaN  65000000

2  False  {'id': 119050, 'name': 'Grumpy Old Men Collect...         0

3  False                                                NaN  16000000

4  False  {'id': 96871, 'name': 'Father of the Bride Col...         0


                                              genres  \
0  [{'id': 16, 'name': 'Animation'}, {'id': 35, '...
1  [{'id': 12, 'name': 'Adventure'}, {'id': 14, '...
2  [{'id': 10749, 'name': 'Romance'}, {'id': 35, ...
3  [{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...
4                     [{'id': 35, 'name': 'Comedy'}]

                               homepage     id    imdb_id
original_language  \
0  http://toystory.disney.com/toy-story    862  tt0114709
en
1                                   NaN   8844  tt0113497
en
2                                   NaN  15602  tt0113228
en
3                                   NaN  31357  tt0114885
en
4                                   NaN  11862  tt0113041
en

                original_title  \
0                    Toy Story
1                      Jumanji
2             Grumpier Old Men
3            Waiting to Exhale
4  Father of the Bride Part II

                                            overview    ...
release_date  \
0  Led by Woody, Andy's toys live happily in his ...    ...
1995-10-30
1  When siblings Judy and Peter discover an encha...    ...
1995-12-15
2  A family wedding reignites the ancient feud be...    ...
```

```
1995-12-22
3  Cheated on, mistreated and stepped on, the wom...    ...
1995-12-22
4  Just when George Banks has recovered from his ...    ...
1995-02-10

     revenue runtime
spoken_languages  \
0  373554033    81.0           [{'iso_639_1': 'en', 'name':
'English'}]
1  262797249   104.0  [{'iso_639_1': 'en', 'name': 'English'},
{'iso...
2          0   101.0           [{'iso_639_1': 'en', 'name':
'English'}]
3   81452156   127.0           [{'iso_639_1': 'en', 'name':
'English'}]
4   76578911   106.0           [{'iso_639_1': 'en', 'name':
'English'}]

     status                                            tagline  \
0  Released                                                NaN
1  Released          Roll the dice and unleash the excitement!
2  Released  Still Yelling. Still Fighting. Still Ready for...
3  Released  Friends are the people who let you be yourself...
4  Released  Just When His World Is Back To Normal... He's ...

                         title  video vote_average vote_count
0                    Toy Story  False          7.7     5415.0
1                      Jumanji  False          6.9     2413.0
2             Grumpier Old Men  False          6.5       92.0
3            Waiting to Exhale  False          6.1       34.0
4  Father of the Bride Part II  False          5.7      173.0

[5 rows x 24 columns]
```

```
movies_metadata.columns
```

```
Index(['adult', 'belongs_to_collection', 'budget', 'genres',
'homepage', 'id',
       'imdb_id', 'original_language', 'original_title', 'overview',
       'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title', 'video',
       'vote_average', 'vote_count'],
      dtype='object')
```

```
movies_metadata.info()
```

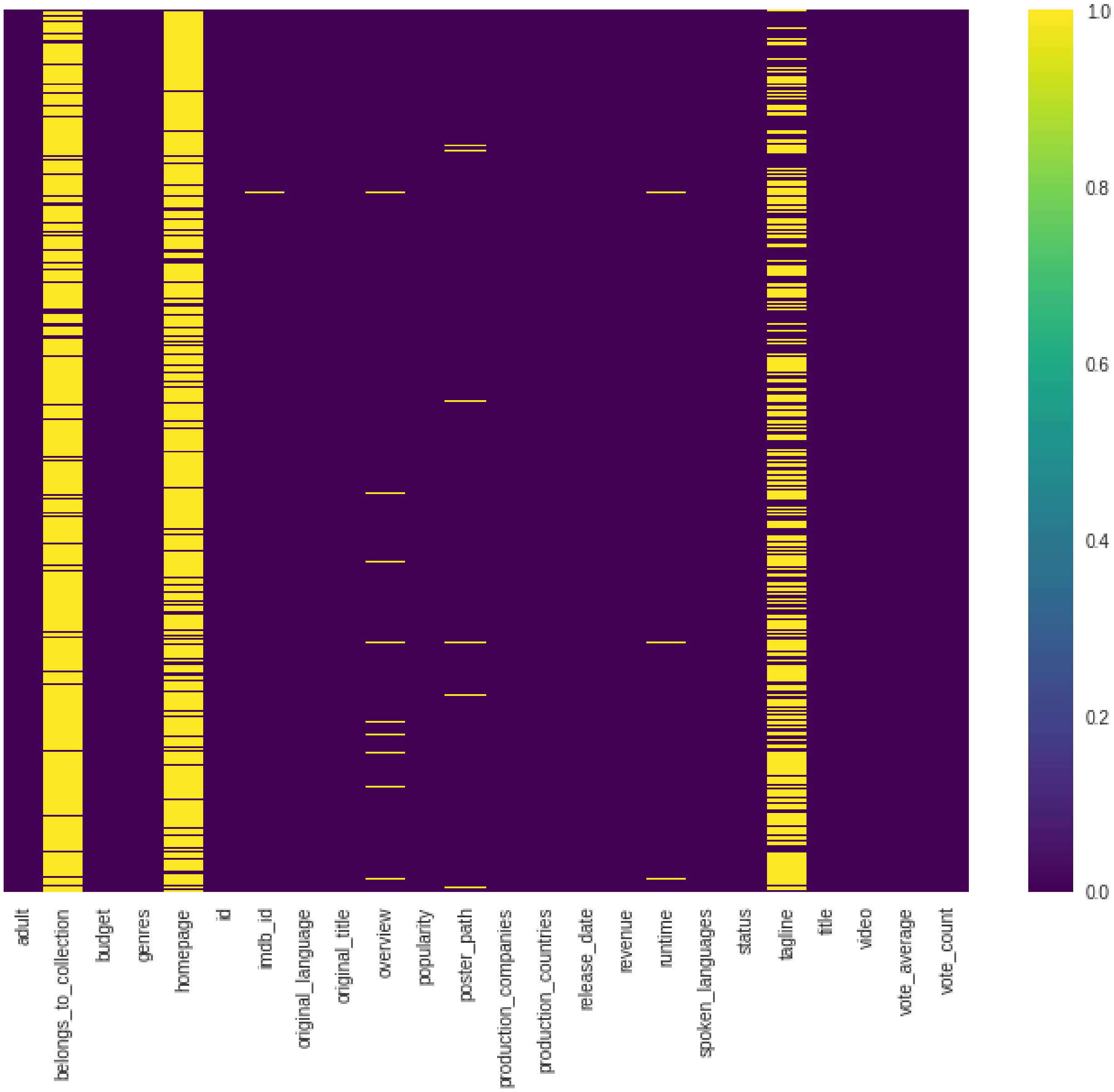
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85814 entries, 0 to 85813
Data columns (total 24 columns):
```

```
adult                        85814 non-null object
belongs_to_collection        8152 non-null object
budget                       85814 non-null object
genres                       85814 non-null object
homepage                     15240 non-null object
id                           85813 non-null object
imdb_id                      85780 non-null object
original_language            85792 non-null object
original_title               85814 non-null object
overview                     83927 non-null object
popularity                   85803 non-null object
poster_path                  85061 non-null object
production_companies         85806 non-null object
production_countries         85806 non-null object
release_date                 85643 non-null object
revenue                      85800 non-null object
runtime                      85288 non-null object
spoken_languages             85794 non-null object
status                       85637 non-null object
tagline                      36992 non-null object
title                        85793 non-null object
video                        85792 non-null object
vote_average                 85789 non-null float64
vote_count                   85788 non-null float64
dtypes: float64(2), object(22)
memory usage: 15.7+ MB
```

Lets explore the movies metadata

```
fig,ax=plt.subplots()
fig.set_size_inches(12,9)
sns.heatmap(movies_metadata.isnull(),yticklabels=False,cmap='viridis',
ax=ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd030b86b70>
```




```
#From the graph we can easily visualize how much daa is missing for
our dataset ,We have lots of data is missing in tagline ,belongs to
collection

#Reading the movie from our small movies data set
movies_small=pd.read_csv('movies.csv')
movies_small.head()

   movieId                                title  \
0        1                     Toy Story (1995)
1        2                       Jumanji (1995)
2        3              Grumpier Old Men (1995)
3        4             Waiting to Exhale (1995)
```

```
4        5  Father of the Bride Part II (1995)

                                        genres
0  Adventure|Animation|Children|Comedy|Fantasy
1                    Adventure|Children|Fantasy
2                                Comedy|Romance
3                          Comedy|Drama|Romance
4                                        Comedy
```

```
movies_small.info()
```

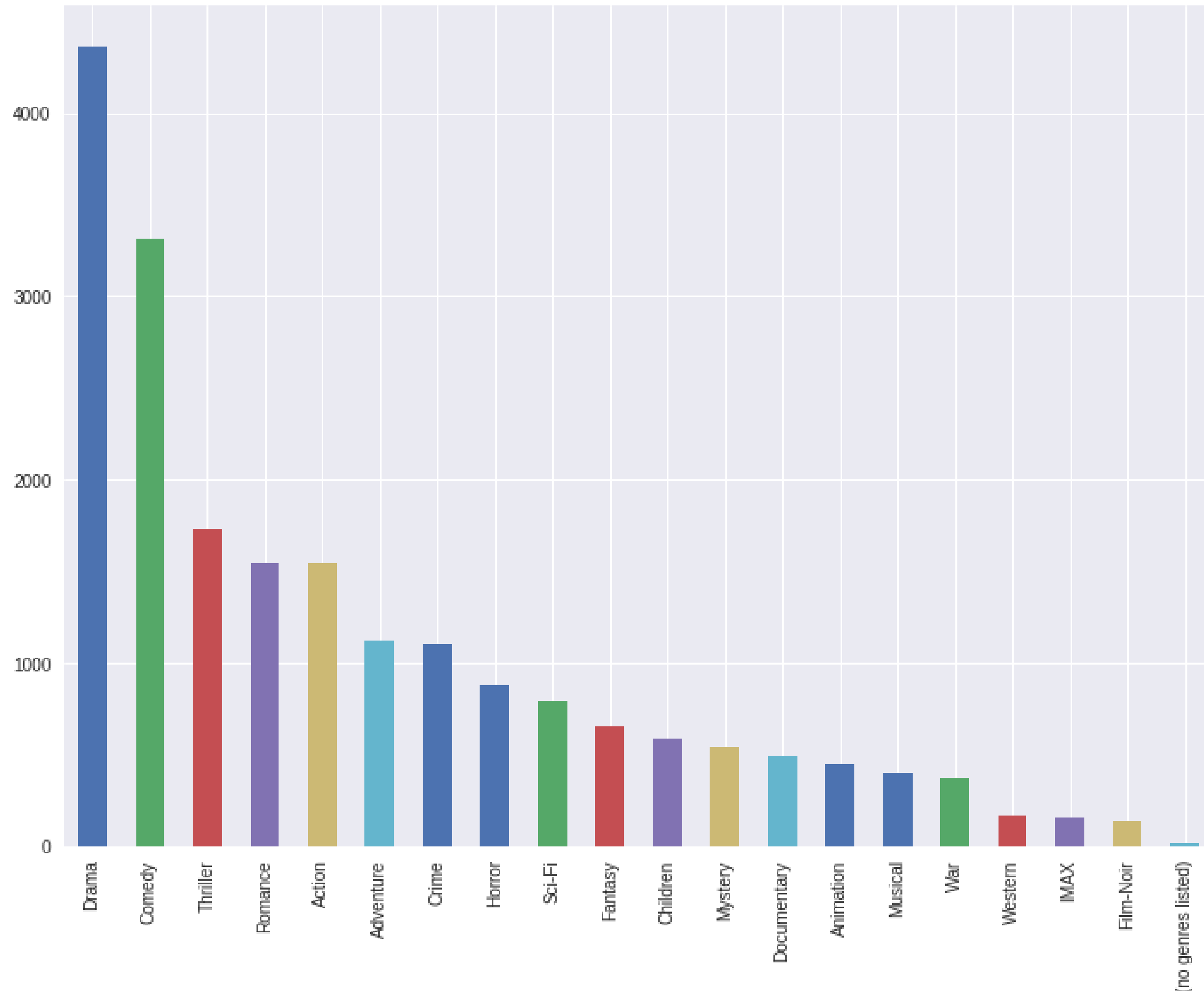
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9125 entries, 0 to 9124
Data columns (total 3 columns):
movieId    9125 non-null int64
title      9125 non-null object
genres     9125 non-null object
dtypes: int64(1), object(2)
memory usage: 213.9+ KB
```

```
#Cheking null values in dataset
movies_small.isnull().sum()
```

```
movieId    0
title      0
genres     0
dtype: int64
```

```
# Creating a plot for Genre Distribution
df1 = movies_small['genres'].apply(lambda genrelist :
str(genrelist).split("|"))
df1 = pd.Series(df1).apply(frozenset).to_frame(name='givengenres')
for givengenres in frozenset.union(*df1.givengenres):
    df1[givengenres] = df1.apply(lambda _: int(givengenres in
_.givengenres), axis=1)
df1.drop('givengenres',axis=1,inplace=True)
df1['movieId']=movies_small['movieId']
df1 = pd.merge(movies_small,df1,on='movieId')
df1.head()
genre_columns= ['Film-Noir',
       'Romance', 'Western', 'Documentary', 'Thriller', 'Action',
'Musical',
       'War', 'Drama', 'IMAX', 'Crime', 'Children', 'Adventure',
'Horror',
       'Fantasy', 'Animation', 'Comedy', 'Mystery', '(no genres
listed)',
       'Sci-Fi']
df1[genre_columns].sum().sort_values(ascending=False).plot(kind='bar',
figsize=(12,9))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd02d4ab3c8>
```



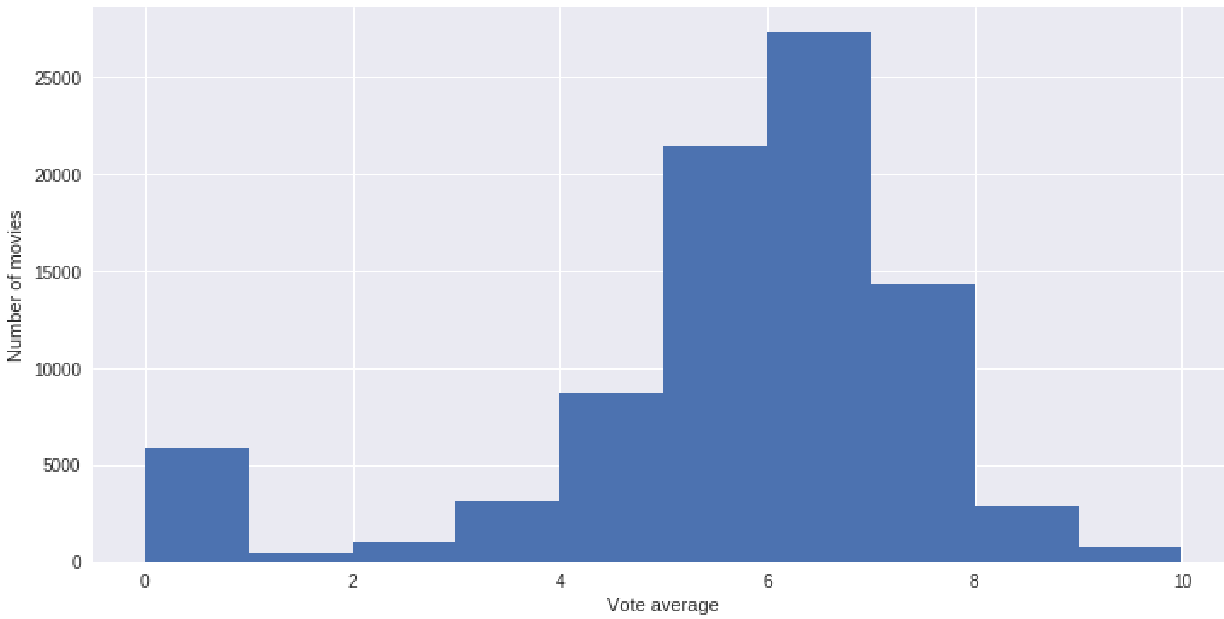
We can see from the above graph that majority of the movies are of Drama , comedy and thriller

Plotting the graph to see the distribution of votes across

```
#plt.figure(figsize=
```

most of the vote counts is between 0-5000

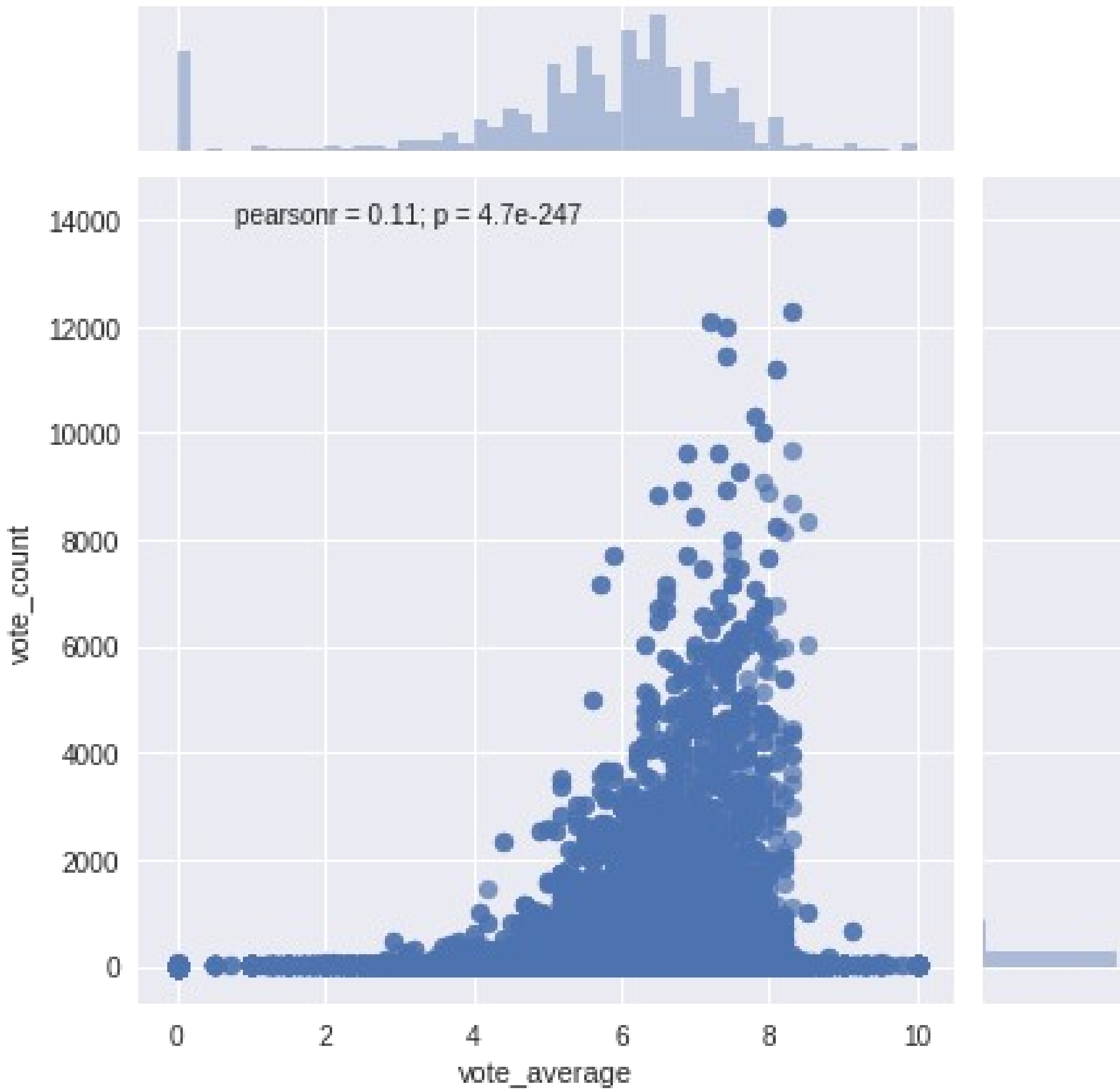
```
# Look into the distribution of vote average for out movies dataset
plt.figure(figsize=(12,6))
movies_metadata['vote_average'].plot(kind='hist')
plt.xlabel('Vote average')
plt.ylabel('Number of movies')
plt.show()
```



This is IMDB rating here we can visualize that most of the vote is between 5 to 7

```
#Let's create a join plot to see the voete counts and vote average
distribution
sns.jointplot(x='vote_average',y='vote_count',data=movies_metadata,alp
ha=0.7)

<seaborn.axisgrid.JointGrid at 0x7fd02d5e77b8>
```



From here we can refer one thing that movie whcih have higher rating has higher vote count means more people watch and rate popular movies

```
links=pd.read_csv('links.csv')
links.head()
```

	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

```
links.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9125 entries, 0 to 9124
Data columns (total 3 columns):
movieId    9125 non-null int64
imdbId     9125 non-null int64
tmdbId     9112 non-null float64
dtypes: float64(1), int64(2)
memory usage: 213.9 KB
```

```
#Checking Null values
links.isnull().sum()
```

```
movieId     0
imdbId      0
tmdbId     13
dtype: int64
```

```
movies_metadata.id.isnull().sum()
```

```
1
```

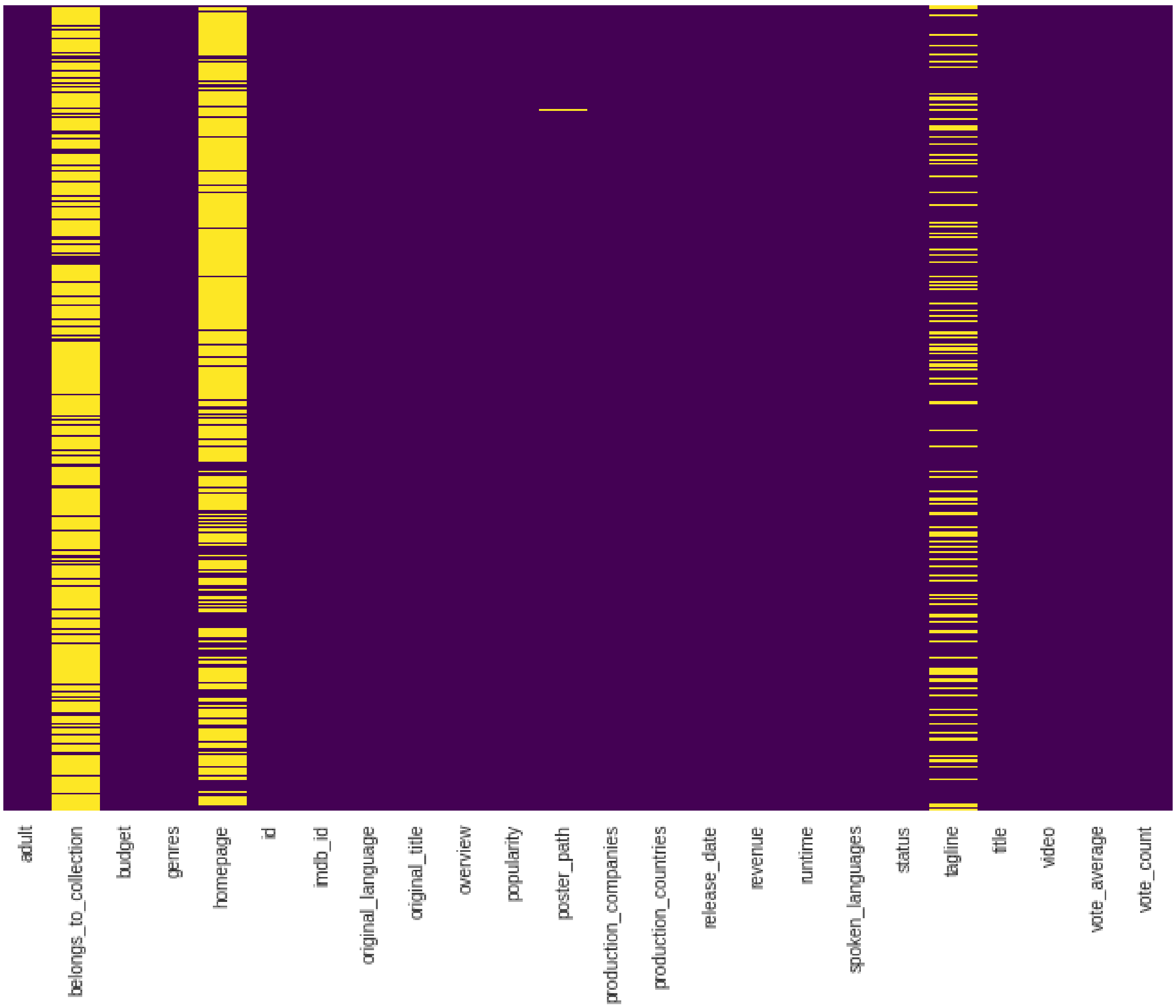
```
links.tmdbId.isnull().sum()
```

```
13
```

```
#Since we are using movies small dataset, we will only keep values in
movies_metadata for movies in movies_small
movies_metadata =
movies_metadata[movies_metadata.id.isin(links['tmdbId'].astype(str).ap
ply(lambda x:x[:-2]).tolist())]
```

```
#Lets look at the null values after we have created this smaller
version of movies_metadata
fig, ax = plt.subplots()
# the size of A4 paper
fig.set_size_inches(11.7, 8.27)
sns.heatmap(movies_metadata.isnull(),yticklabels=False,cbar=False,cmap
='viridis',ax=ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd02d275be0>
```




```
movies_metadata['genres'] =
movies_metadata['genres'].fillna('[]').apply(literal_eval).apply(lambd
a x: [i['name'] for i in x] if isinstance(x, list) else [])
```

We also need to add movie id to our movies metadata, we can do it through links.csv

```
def convert_int(x):
    try:
        return int(x)
    except:
        return 0

links['tmdbId'] = links['tmdbId'].apply(convert_int)

movies_metadata['id'] = movies_metadata['id'].apply(convert_int)

def return_movieId(tmdbId):
    return links[links['tmdbId']==tmdbId]['movieId'].iloc[0]
```

```
#Get movie Id to the movies_metadata
movies_metadata['movieId'] =
movies_metadata['id'].apply(return_movieId)
movies_metadata.head()

   adult                              belongs_to_collection    budget
\
0  False  {'id': 10194, 'name': 'Toy Story Collection', ...  30000000

1  False                                                NaN  65000000

2  False  {'id': 119050, 'name': 'Grumpy Old Men Collect...         0

3  False                                                NaN  16000000

4  False  {'id': 96871, 'name': 'Father of the Bride Col...         0


                         genres                              homepage
id  \
0   [Animation, Comedy, Family]  http://toystory.disney.com/toy-story
862
1  [Adventure, Fantasy, Family]                                   NaN
8844
2             [Romance, Comedy]                                   NaN
15602
3      [Comedy, Drama, Romance]                                   NaN
31357
4                      [Comedy]                                   NaN
11862

     imdb_id original_language               original_title  \
0  tt0114709                en                    Toy Story
1  tt0113497                en                      Jumanji
2  tt0113228                en             Grumpier Old Men
3  tt0114885                en            Waiting to Exhale
4  tt0113041                en  Father of the Bride Part II

                                            overview   ...
revenue  \
0  Led by Woody, Andy's toys live happily in his ...   ...
373554033
1  When siblings Judy and Peter discover an encha...   ...
262797249
2  A family wedding reignites the ancient feud be...   ...
0
3  Cheated on, mistreated and stepped on, the wom...   ...
81452156
4  Just when George Banks has recovered from his ...   ...
76578911
```

```
  runtime                                    spoken_languages    status  \
0    81.0           [{'iso_639_1': 'en', 'name': 'English'}]  Released

1   104.0  [{'iso_639_1': 'en', 'name': 'English'}, {'iso...  Released

2   101.0           [{'iso_639_1': 'en', 'name': 'English'}]  Released

3   127.0           [{'iso_639_1': 'en', 'name': 'English'}]  Released

4   106.0           [{'iso_639_1': 'en', 'name': 'English'}]  Released


                                             tagline  \
0                                                NaN
1          Roll the dice and unleash the excitement!
2  Still Yelling. Still Fighting. Still Ready for...
3  Friends are the people who let you be yourself...
4  Just When His World Is Back To Normal... He's ...

                         title  video vote_average vote_count movieId

0                    Toy Story  False          7.7     5415.0       1

1                      Jumanji  False          6.9     2413.0       2

2             Grumpier Old Men  False          6.5       92.0       3

3            Waiting to Exhale  False          6.1       34.0       4

4  Father of the Bride Part II  False          5.7      173.0       5


[5 rows x 25 columns]
```

```
movies_metadata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 14196 entries, 0 to 85613
Data columns (total 25 columns):
adult                        14196 non-null object
belongs_to_collection    2562 non-null object
budget                       14196 non-null object
genres                       14196 non-null object
homepage                     3663 non-null object
id                           14196 non-null int64
imdb_id                      14196 non-null object
original_language            14196 non-null object
original_title               14196 non-null object
overview                     14177 non-null object
```

```
popularity                 14196 non-null object
poster_path                14192 non-null object
production_companies       14196 non-null object
production_countries       14196 non-null object
release_date               14196 non-null object
revenue                    14195 non-null object
runtime                    14195 non-null object
spoken_languages           14194 non-null object
status                     14192 non-null object
tagline                    10810 non-null object
title                      14194 non-null object
video                      14194 non-null object
vote_average               14193 non-null float64
vote_count                 14193 non-null float64
movieId                    14196 non-null int64
dtypes: float64(2), int64(2), object(21)
memory usage: 2.8+ MB
```

Since some movies may have low vote average but more number of votes, while other movies may have high vote average and less vote counts, We need a common medium to sort the movies to create top movies chart. For this, let's use IMDB's weighted rating formula to construct top movies chart. Mathematically, it is represented as follows:

Weighted Rating (WR) = (v/(v+m)) R+(m/(v+m)) C

Where, R = average for the movie (mean) = (Rating) v = number of votes for the movie = (votes) m = minimum votes required to be listed in the C = the mean vote across the whole report

The next step is to determine an appropriate value for m, the minimum votes required to be listed in the chart. We will use 95th percentile as our cutoff. In other words, for a movie to feature in the charts, it must have more votes than at least 95% of the movies in the list.

I will build our overall Top 100 Chart and will define a function to build charts for a particular genre. Let's begin!

<<<<< enter link for IMDB weighted rating here

```
no_of_votes = movies_metadata[movies_metadata['vote_count'].notnull()]
['vote_count'].astype('int')
vote_mean = movies_metadata[movies_metadata['vote_average'].notnull()]
['vote_average'].astype('int')
C = vote_mean.mean()
C

5.933065595716198

m = no_of_votes.quantile(0.95)
m

2313.3999999999996
```

```
# Adding year column based on movies release date
movies_metadata['year'] =
pd.to_datetime(movies_metadata['release_date'],
errors='coerce').apply(lambda x: str(x).split('-')[0] if x != np.nan
else np.nan)

movies_metadata['year'] =
pd.to_datetime(movies_metadata['release_date'],
errors='coerce').apply(lambda x: str(x).split('-')[0] if x != np.nan
else np.nan)
top_movies = movies_metadata[(movies_metadata['vote_count'] >= m) &
(movies_metadata['vote_count'].notnull()) &
(movies_metadata['vote_average'].notnull())][['title', 'year',
'vote_count', 'vote_average', 'popularity', 'genres']]
top_movies['vote_count'] = top_movies['vote_count'].astype('int')
top_movies['vote_average'] = top_movies['vote_average'].astype('int')
top_movies.shape
```

```
(710, 6)
```

Therefore, to qualify to be considered for the chart, a movie has to have at least 2079 votes on TMDB. We also see that the average rating for a movie on TMDB is 5.916 on a scale of 10. 455 Movies qualify to be on our chart.

```
def weighted_rating(x):
  V=x['vote_count']
  R=x['vote_average']
  return (V/(V+m)*R)+(m/(m+V)*C)

top_movies['wr']=top_movies.apply(weighted_rating,axis=1)

top_movies = top_movies.sort_values('wr', ascending=False).head(100)

top_movies.head(15)
```

```
                                                    title  year  \
vote_count  \
29996                                           Inception  2010
14075
20651                                           Inception  2010
14075
24256                                     The Dark Knight  2008
12269
15057                                     The Dark Knight  2008
12269
45852                                        Interstellar  2014
11187
36025                                        Interstellar  2014
11187
5424                                           Fight Club  1999
```

```
9678
8750   The Lord of the Rings: The Fellowship of the Ring  2001
8892
292                                         Pulp Fiction  1994
8670
314                             The Shawshank Redemption  1994
8358
13462      The Lord of the Rings: The Return of the King  2003
8226
4453       The Lord of the Rings: The Return of the King  2003
8226
351                                         Forrest Gump  1994
8147
2013               The Lord of the Rings: The Two Towers  2002
7641
10990              The Lord of the Rings: The Two Towers  2002
7641

       vote_average  popularity  \
29996             8   29.108149
20651             8   29.108149
24256             8  123.167259
15057             8  123.167259
45852             8   32.213481
36025             8   32.213481
5424              8   63.869599
8750              8   32.070725
292               8  140.950236
314               8   51.645403
13462             8   29.324358
4453              8   29.324358
351               8   48.307194
2013              8   29.423537
10990             8   29.423537

                                                  genres        wr
29996  [Action, Thriller, Science Fiction, Mystery, A...  7.708230
20651  [Action, Thriller, Science Fiction, Mystery, A...  7.708230
24256                 [Drama, Action, Crime, Thriller]  7.672095
15057                 [Drama, Action, Crime, Thriller]  7.672095
45852              [Adventure, Drama, Science Fiction]  7.645814
36025              [Adventure, Drama, Science Fiction]  7.645814
5424                                           [Drama]  7.601244
8750                    [Adventure, Fantasy, Action]  7.573273
292                                [Thriller, Crime]  7.564648
314                                   [Drama, Crime]  7.551920
13462                   [Adventure, Fantasy, Action]  7.546308
4453                    [Adventure, Fantasy, Action]  7.546308
351                         [Comedy, Drama, Romance]  7.542881
```

```
2013                              [Adventure, Fantasy, Action]  7.519645
10990                             [Adventure, Fantasy, Action]  7.519645
```

```
top_movies.columns
```

```
Index(['title', 'year', 'vote_count', 'vote_average', 'popularity',
'genres',
       'wr'],
      dtype='object')
```

```
y = movies_metadata.apply(lambda x:
pd.Series(x['genres']),axis=1).stack().reset_index(level=1, drop=True)
y.name = 'genre'
gen_data = movies_metadata.drop('genres', axis=1).join(y)
```

Let us now construct our function that builds charts for particular genres. For this, we will use relax our default conditions to the 85th percentile instead of 95.

```
def top_movies_genre(genre, percentile=0.85):
    df = gen_data[gen_data['genre'] == genre]
    no_of_votes = df[df['vote_count'].notnull()]
['vote_count'].astype('int')
    vote_mean = df[df['vote_average'].notnull()]
['vote_average'].astype('int')
    C = vote_mean.mean()
    m = no_of_votes.quantile(percentile)

    top_movies = df[(df['vote_count'] >= m) &
(df['vote_count'].notnull()) & (df['vote_average'].notnull())]
[['title', 'year', 'vote_count', 'vote_average', 'popularity']]
    top_movies['vote_count'] = top_movies['vote_count'].astype('int')
    top_movies['vote_average'] =
top_movies['vote_average'].astype('int')

    top_movies['wr'] = top_movies.apply(lambda x:
(x['vote_count']/(x['vote_count']+m) * x['vote_average']) +
(m/(m+x['vote_count']) * C), axis=1)
    top_movies = top_movies.sort_values('wr',
ascending=False).head(100)

    return top_movies
```

```
top_movies_genre('Animation').head(10)
```

```
                      title  year  vote_count  vote_average popularity
\
359           The Lion King  1994        5520             8  21.605761

1680         Spirited Away  2001        3968             8  41.048867
```

```
10657         Spirited Away  2001        3968              8  41.048867

18786  Howl's Moving Castle  2004        2049              8  16.136048

9693   Howl's Moving Castle  2004        2049              8  16.136048

5465      Princess Mononoke  1997        2041              8  17.166725

26875                    Up  2009        7048              7  19.330884

17606                    Up  2009        7048              7  19.330884

50384            Inside Out  2015        6737              7  23.985587

60516            Inside Out  2015        6737              7  23.985587


             wr
359    7.583768
1680   7.471422
10657  7.471422
18786  7.206649
9693   7.206649
5465   7.204989
26875  6.857607
17606  6.857607
50384  6.852409
60516  6.852409
```

Content Based Recommender

The simple recommender that we just built provides just the top results for the genre, and it shows the the same results for every user looking for that genre.

It also dosen't account for fan following towards particular director or Actors, which accounts for people also watching the movies that are less popular but from famous actors and directors.

For personalized recommendations, We will create a recommendation system that computes similarity between movies based on certain features and recommend movies that are similar to user's taste. As we are using movie's metadata (or content) for creating this system, it is also referred as Content Based Filtering.

We will build four Content Based Recommenders based on:

- Movie overview's that particular user has liked and use latent semantic similarity for comparing similar movies
- Adding Taglines and Movie Overviews and compare using pairwise cosine similarity
- Movie Cast, Crew, Keywords and Genre

Movie Description Based Recommender

Let us first try to build a recommender using movie descriptions and taglines. We do not have a quantitative metric to judge our machine's performance so this will have to be done qualitatively.

```
movies_metadata.head()
```

```
   adult                              belongs_to_collection    budget
\
0  False  {'id': 10194, 'name': 'Toy Story Collection', ...  30000000

1  False                                                NaN  65000000

2  False  {'id': 119050, 'name': 'Grumpy Old Men Collect...         0

3  False                                                NaN  16000000

4  False  {'id': 96871, 'name': 'Father of the Bride Col...         0


                         genres                              homepage
id  \
0   [Animation, Comedy, Family]  http://toystory.disney.com/toy-story
862
1  [Adventure, Fantasy, Family]                                   NaN
8844
2             [Romance, Comedy]                                   NaN
15602
3      [Comedy, Drama, Romance]                                   NaN
31357
4                      [Comedy]                                   NaN
11862

     imdb_id original_language               original_title  \
0  tt0114709                en                    Toy Story
1  tt0113497                en                      Jumanji
2  tt0113228                en             Grumpier Old Men
3  tt0114885                en            Waiting to Exhale
4  tt0113041                en  Father of the Bride Part II

                                            overview  ...  runtime  \
0  Led by Woody, Andy's toys live happily in his ...  ...     81.0
1  When siblings Judy and Peter discover an encha...  ...    104.0
2  A family wedding reignites the ancient feud be...  ...    101.0
3  Cheated on, mistreated and stepped on, the wom...  ...    127.0
4  Just when George Banks has recovered from his ...  ...    106.0

                                    spoken_languages    status  \
0           [{'iso_639_1': 'en', 'name': 'English'}]  Released
1  [{'iso_639_1': 'en', 'name': 'English'}, {'iso...  Released
```

```
2           [{'iso_639_1': 'en', 'name': 'English'}]  Released
3           [{'iso_639_1': 'en', 'name': 'English'}]  Released
4           [{'iso_639_1': 'en', 'name': 'English'}]  Released

                                             tagline  \
0                                                NaN
1          Roll the dice and unleash the excitement!
2  Still Yelling. Still Fighting. Still Ready for...
3  Friends are the people who let you be yourself...
4  Just When His World Is Back To Normal... He's ...

                         title  video vote_average vote_count movieId
year
0                    Toy Story  False          7.7     5415.0       1
1995
1                      Jumanji  False          6.9     2413.0       2
1995
2             Grumpier Old Men  False          6.5       92.0       3
1995
3            Waiting to Exhale  False          6.1       34.0       4
1995
4  Father of the Bride Part II  False          5.7      173.0       5
1995

[5 rows x 26 columns]
```

For our first attempt in building Description based recommendation system,

- We will first take list of movies which a user has watched
- Process the description of the movie using NLP techniques like removing stopwords and punctuations, applying Tokenization, lemmatization and stemming, and return a clean list of words
- Using similar techniques, we will process the description/overview of movie in our movies_metadata for the top 80 percentile of movies
- In the next step, we will calculate the similarity between the combined overview of the movies user has watched and the overview of the movies user hasn't watched
- To get this similarity, we will use UMBC's API service to provide latent semantic similarity between 2 scentences. The link to which can be found here

Lets get the top movies that a user has rated more than average

```
ratings=pd.read_csv('ratings.csv')
ratings.head()

   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
```

```
#Get movieId for above average ratings for userId 1
ratings[(ratings['userId']==1) & (ratings['rating']>2.5)]
['movieId'].tolist()
```

```
[1029, 1061, 1172, 1339, 1953, 2105, 2150, 3671]
```

```
def text_process(mess):
    """
    1. remove punc
    2. remove stop words
    3. apply lemmatization
    4. apply stemmization
    5. return list clean overview

    """
    #Remove Stopwords and punctuations
    nopunc = [char for char in mess if char not in string.punctuation]
    stopwords = nltk.corpus.stopwords.words('english')
    nopunc = ''.join(nopunc)

    #Apply tokenization
    tokenized_list = []
    tokenized_list =  [word for word in nopunc.split() if word.lower()
not in stopwords]


    wordnet_lemmatizer = WordNetLemmatizer()
    snowball_stemmer = SnowballStemmer('english')

    #Applying Lemmatization

    lemmatized_words = []
    for word in tokenized_list:
        lemmatized_words.append(wordnet_lemmatizer.lemmatize(word))

   #Applying Stemmization

    cleaned_list  = []
    for word in lemmatized_words:
        cleaned_list.append(snowball_stemmer.stem(word))
    return ' '.join(cleaned_list)


movies_metadata['overview'] = movies_metadata['overview'].astype(str)

# Pre-processing the overviews for all the movies
movies_metadata['pro_overview'] =
movies_metadata['overview'].apply(text_process)
```

```
percentile = 0.90
no_of_votes = movies_metadata[movies_metadata['vote_count'].notnull()]
['vote_count'].astype('int')
vote_mean = movies_metadata[movies_metadata['vote_average'].notnull()]
['vote_average'].astype('int')
C = vote_mean.mean()
m = no_of_votes.quantile(percentile)

top_movies = movies_metadata[(movies_metadata['vote_count'] >= m) &
(movies_metadata['vote_count'].notnull()) &
(movies_metadata['vote_average'].notnull())][['movieId','title',
'year', 'vote_count', 'vote_average', 'popularity','pro_overview']]
top_movies['vote_count'] = top_movies['vote_count'].astype('int')
top_movies['vote_average'] = top_movies['vote_average'].astype('int')

top_movies.sort_values(by='vote_count',ascending=False).head()
```

```
       movieId            title  year  vote_count  vote_average
popularity  \
29996    79132        Inception  2010       14075             8
29.108149
20651    79132        Inception  2010       14075             8
29.108149
15057    58559  The Dark Knight  2008       12269             8
123.167259
24256    58559  The Dark Knight  2008       12269             8
123.167259
19722    72998           Avatar  2009       12114             7
185.070892

                                            pro_overview
29996  cobb skill thief commit corpor espionag infilt...
20651  cobb skill thief commit corpor espionag infilt...
15057  batman rais stake war crime help lt jim gordon...
24256  batman rais stake war crime help lt jim gordon...
19722  22nd centuri parapleg marin dispatch moon pand...
```

```
# Using UMBC's API service to get latent sematic similarity score
sss_url = "http://swoogle.umbc.edu/SimService/GetSimilarity"

def sss(s1, s2, type='relation', corpus='webbase'):
    try:
        response = get(sss_url,
params={'operation':'api','phrase1':s1,'phrase2':s2,'type':type,'corpu
s':corpus})
        return float(response.text.strip())
    except:
        #print ('Error in getting similarity for %s: %s' % ((s1,s2),
response))
        return 0.0
```

```
user_1_movies=[]
for movieId in ratings[(ratings['userId']==1) &
(ratings['rating']>2.5)]['movieId'].tolist():

user_1_movies.append(movies_metadata[movies_metadata['movieId']==movie
Id]['pro_overview'].iloc[0])
user_1_movies = ' '.join(user_1_movies)

user_1_movies
```

```
'dumbo babi eleph born overs ear suprem lack confid thank even diminut
buddi timothi mous pintsiz pachyderm learn surmount obstacl two
gangster seek reveng state jail worker stay youth prison sexual abus
sensat court hear take place charg crime move drama director barri
levinson filmmak recal childhood fell love movi villag theater form
deep friendship theater projectionist dracula leaf captiv jonathan
harker transylvania london search mina harker spit imag dracula
longdead wife elisabeta obsess vampir hunter dr van hels set end mad
tough narcot detect popey doyl hot pursuit suav french drug dealer may
key huge heroinsmuggl oper kevin flynn search proof invent hit video
game digit laser find insid grid program suffer tyrann rule master
control program help tron secur program flynn seek free grid mcp
miseri brought small group sho kalahari desert form cola bottl quest
throw evil object edg earth xixo encount western civil haphazard
doctor tyran despot town – everyon seem name johnson – way railroad
order grab land hedley lemar polit connect nasti person send henchman
make town unliv sheriff kill town demand new sheriff governor hedley
convinc send town first black sheriff west'
```

```
%%time
top_movies['similarity'] = top_movies['pro_overview'].apply(lambda
x:sss(user_1_movies,x))
```

```
---------------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-1-378b2f75ea3a> in <module>()
----> 1 get_ipython().run_cell_magic('time', '',
"top_movies['similarity'] = top_movies['pro_overview'].apply(lambda
x:sss(user_1_movies,x))")

/usr/local/lib/python3.6/dist-packages/IPython/core/interactiveshell.p
y in run_cell_magic(self, magic_name, line, cell)
   2115             magic_arg_s = self.var_expand(line, stack_depth)
   2116             with self.builtin_trap:
-> 2117                 result = fn(magic_arg_s, cell)
   2118             return result
   2119
```

```
</usr/local/lib/python3.6/dist-packages/decorator.py:decorator-gen-60>
in time(self, line, cell, local_ns)

/usr/local/lib/python3.6/dist-packages/IPython/core/magic.py in
<lambda>(f, *a, **k)
    186     # but it's overkill for just that one bit of state.
    187     def magic_deco(arg):
--> 188         call = lambda f, *a, **k: f(*a, **k)
    189
    190         if callable(arg):

/usr/local/lib/python3.6/dist-packages/IPython/core/magics/execution.p
y in time(self, line, cell, local_ns)
   1191         else:
   1192             st = clock2()
-> 1193             exec(code, glob, local_ns)
   1194             end = clock2()
   1195             out = None

<timed exec> in <module>()

NameError: name 'top_movies' is not defined
```

```
top_movies.head()
```

```
top_movies[top_movies.movieId.isin(ratings[ratings['userId']!=1]
['movieId'].tolist())]
[['title','similarity','vote_count','vote_average']].sort_values(by='s
imilarity',ascending=False).head(10)
```

```
#Let's create a recommender based on the above method
def user_taste_recommender(userId,percentile = 0.90):
    no_of_votes =
movies_metadata[movies_metadata['vote_count'].notnull()]
['vote_count'].astype('int')
    vote_mean =
movies_metadata[movies_metadata['vote_average'].notnull()]
['vote_average'].astype('int')
    C = vote_mean.mean()
    m = no_of_votes.quantile(percentile)

    top_movies = movies_metadata[(movies_metadata['vote_count'] >= m)
& (movies_metadata['vote_count'].notnull()) &
(movies_metadata['vote_average'].notnull())][['movieId','title',
'year', 'vote_count', 'vote_average', 'popularity','pro_overview']]
    top_movies['vote_count'] = top_movies['vote_count'].astype('int')
    top_movies['vote_average'] =
top_movies['vote_average'].astype('int')

    user_movies=[]
    for movieId in ratings[(ratings['userId']==userId) &
```

```
(ratings['rating']>2.5)]['movieId'].tolist():

user_movies.append(movies_metadata[movies_metadata['movieId']==movieId
]['pro_overview'].iloc[0])
    user_movies = ' '.join(user_movies)

    top_movies['similarity'] = top_movies['pro_overview'].apply(lambda
x:sss(user_movies,x))
    top_movies =
top_movies[top_movies.movieId.isin(ratings[ratings['userId']!=userId]
['movieId'].tolist())]
[['title','similarity','vote_count','vote_average']].sort_values(by='s
imilarity',ascending=False).head(10)

    return top_movies

%%time
user_taste_recommender(100)
```

Just getting recommendation based on movie's synopsis dosent provide eye catching results, and is not reliable enough as Latent Semantic Similarity here takes into account movies from all the genre and most importantly, takes lot of time to calculate through the UMBC's API for soo many movies, So we will try Consine similarity from sklearn's linear kernel which is much faster to calculate

Also, lets add tagline to the description and check if we get better recommendations

```
movies_metadata['tagline'] = movies_metadata['tagline'].fillna('')
movies_metadata['description'] = movies_metadata['pro_overview'] +
movies_metadata['tagline']
movies_metadata['description'] =
movies_metadata['description'].fillna('')

movies_metadata['description'].head()

tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0,
stop_words='english')
tfidf_matrix = tf.fit_transform(movies_metadata['description'])

tfidf_matrix.shape
```

Cosine Similarity

I will be using the Cosine Similarity to calculate a numeric quantity that denotes the similarity between two movies. Mathematically, it is defined as follows:

cosine(x,y)=x.y⊺||x||.||y|| Since we have used the TF-IDF Vectorizer, calculating the Dot Product will directly give us the Cosine Similarity Score. Therefore, we will use sklearn's linear_kernel instead of cosine_similarities since it is much faster.

```
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)

cosine_sim[0]

We now have a pairwise cosine similarity matrix for all the movies in
our dataset. The next step is to write a function that returns the 30
most similar movies based on the cosine similarity score.

movies_metadata = movies_metadata.reset_index()
titles = movies_metadata['title']
indexes = pd.Series(movies_metadata.index,
index=movies_metadata['title'])

#To get pairwise similarity score for movie with index 0
similarity =  list(enumerate(cosine_sim[0]))
print(similarity[:10])

def desc_based_recommendation(title):
    idx = indexes[title]
    sim = list(enumerate(cosine_sim[idx]))
    #Sorting the list by descending order of similarity
    sim = sorted(sim, key=lambda x: x[1], reverse=True)
    #Taking top 30 similar movies
    sim = sim[1:31]
    rec_movies_indexes = [i[0] for i in sim]
    return titles.iloc[rec_movies_indexes]
```

Let's check recommendatio for start war

```
desc_based_recommendation('Star Wars').head(10)
```

We get Return of Jedi and Star Wars: The Force Awakens as a recommendation for star wars which is goodl!

Metadata Based Recommender

Lets add more details like cast, crew , directors, keywords etc to get better similarity score for movies with similar content. To do the same we need to prepare this data as our first step.

```
#loading data from credits.csv for cast and crew, and Keywords.csv for
keywords related to movies
credits = pd.read_csv('credits.csv')
keywords = pd.read_csv('keywords.csv')

#Converting id's to int
keywords['id'] = keywords['id'].astype('int')
credits['id'] = credits['id'].astype('int')
movies_metadata['id'] = movies_metadata['id'].astype('int')
```

```
# Add Cast and Crew column to our movies dataset
movies_metadata = movies_metadata.merge(credits, on='id')
#Add Keywords to the dataset
movies_metadata = movies_metadata.merge(keywords, on='id')

movies_metadata.head()
```

After getting the data in a single dataframe, we can get the following from the data: Crew: Since director is the most important person in the crew of the movie, we will take it as our feature from the crew Cast: We will take the first 3 actors from the Cast

```
#Checking for Python literal structures: strings, bytes, numbers,
tuples, lists, dicts, sets, booleans, and None.
movies_metadata['cast'] = movies_metadata['cast'].apply(literal_eval)
movies_metadata['crew'] = movies_metadata['crew'].apply(literal_eval)
movies_metadata['keywords'] =
movies_metadata['keywords'].apply(literal_eval)
#Get the cast and crew size
movies_metadata['cast_size'] = movies_metadata['cast'].apply(lambda x:
len(x))
movies_metadata['crew_size'] = movies_metadata['crew'].apply(lambda x:
len(x))

# function to get director from the dict of crew
def get_director(d):
    for i in d:
        if i['job'] == 'Director':
            return i['name']
    return np.nan

movies_metadata['director'] =
movies_metadata['crew'].apply(get_director)

movies_metadata['cast'] = movies_metadata['cast'].apply(lambda x:
[i['name'] for i in x] if isinstance(x, list) else [])
movies_metadata['cast'] = movies_metadata['cast'].apply(lambda x:
x[:3] if len(x) >=3 else x)

movies_metadata['keywords'] = movies_metadata['keywords'].apply(lambda
x: [i['name'] for i in x] if isinstance(x, list) else [])
```

We will add genre, keywords, director and main actors and create count matrix using count vectorizer as we did in Description based recommender and follow similar steps to calculate cosine similarities to get most similar movies.

- Remove Spaces between names
- Convert all features to lower case
- This will help to distinguish between Christopher Nolen and Christopher Columbus

- To get movies with same director more often, we will add director 3 times and provide additional weight to this feature

```
#Remove spaces between names
movies_metadata['cast'] = movies_metadata['cast'].apply(lambda x:
[str.lower(i.replace(" ", "")) for i in x])

#Remove spaces between names
movies_metadata['director'] =
movies_metadata['director'].astype('str').apply(lambda x:
str.lower(x.replace(" ", "")))
#Add more weight to director
movies_metadata['director'] = movies_metadata['director'].apply(lambda
x: [x,x, x])
```

Keywords: We only require keywords that occur more than once, having keywords that occur just once will increase complexity and reduce similarity score. So let's count the keywords and keep only those occuring more than once

```
k = movies_metadata.apply(lambda x:
pd.Series(x['keywords']),axis=1).stack().reset_index(level=1,
drop=True)
k.name = 'keyword'

k = k.value_counts()
k[:5]

#Removing keyword occuring just once
k = k[k > 1]
```

Using Snowball Stemmer, lets take the word back to its root form. This helps to reduce same features like forest and forests

```
stemmer = SnowballStemmer('english')
stemmer.stem('forests')

def filter_keywords(x):
    words = []
    for i in x:
        if i in k:
            words.append(i)
    return words

movies_metadata['keywords'] =
movies_metadata['keywords'].apply(filter_keywords)
movies_metadata['keywords'] = movies_metadata['keywords'].apply(lambda
x: [stemmer.stem(i) for i in x])
movies_metadata['keywords'] = movies_metadata['keywords'].apply(lambda
x: [str.lower(i.replace(" ", "")) for i in x])
```

```
movies_metadata['analyzer'] = movies_metadata['keywords'] +
movies_metadata['cast'] + movies_metadata['director'] +
movies_metadata['genres']
movies_metadata['analyzer'] = movies_metadata['analyzer'].apply(lambda
x: ' '.join(x))

count = CountVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0,
stop_words='english')
count_matrix = count.fit_transform(movies_metadata['analyzer'])

# Get pairwise cosine similarity
cosine_sim = cosine_similarity(count_matrix, count_matrix)

movies_metadata = movies_metadata.reset_index()
titles = movies_metadata['title']
indexes = pd.Series(movies_metadata.index,
index=movies_metadata['title'])

desc_based_recommendation('Star Wars').head(10)
```

We get much better results this time, most of the star war related movies are covered. Let's try for another movie 'Inception'

```
desc_based_recommendation('Inception').head(10)
```

This proves that adding weight to the director definetly works, as most of the movies in Top 10 is of Christopher Nolan

```

```

Popularity Based Recommendation

Since our current recommender dosen't take popularity and ratings into account, it shows movies like 'Sky Captain and the World of Tomorrow' over many other popular movies.

We will improve our recommendation system by returning only popular movies with more number of ratings

let's take top 25 movies based on similarity scores and calculate the vote of the 70th percentile movie. Then, using this as the value of m , we will calculate the weighted rating of each movie using IMDB's formula like we did in the Simple Recommender section.

```
def popularity_based_recommendations(title,percentile=0.70):
    idx = indexes[title]
    sim = list(enumerate(cosine_sim[idx]))
    sim = sorted(sim, key=lambda x: x[1], reverse=True)
    sim = sim[1:26]
    req_index = [i[0] for i in sim]

    movies = movies_metadata.iloc[req_index][['title', 'vote_count',
```

```
'vote_average', 'year']]
    no_of_votes = movies[movies['vote_count'].notnull()]
['vote_count'].astype('int')
    vote_mean = movies[movies['vote_average'].notnull()]
['vote_average'].astype('int')
    m = no_of_votes.quantile(percentile)
    C = vote_mean.mean()
    top_movies = movies[(movies['vote_count'] >= m) &
(movies['vote_count'].notnull()) & (movies['vote_average'].notnull())]
    top_movies['vote_count'] = top_movies['vote_count'].astype('int')
    top_movies['vote_average'] =
top_movies['vote_average'].astype('int')
    top_movies['wr'] = top_movies.apply(weighted_rating, axis=1)
    top_movies = top_movies.sort_values('wr',
ascending=False).head(25)
    return top_movies

popularity_based_recommendations('Star Wars')
```

We get even better recommendation using popularity based recommender, as we get X-Men and Iron Man 2 in the list , which are my favourites

Collaborative Filtering*

The Results from our popularity based recommender are impressive, we get most of the similar movies when querying for a movie. While content based are good when we have good amount of content for the movie like the name of actors, movie synopsis, director's information etc. we always don't have all the information required for making relevant recommendations. Also, while we tried to derive user's taste by using movies overview and taglines as input to our model, the recommendations provided by a collaborative filtering model are way better than a content based model. Another advantage of using a collaborative filtering model over Content based model is that it doesn't require any data related to movies content. We have built a CF model using Scikit learn's Surprise library which provides a simple data ingestion for making recommendations through CF. It also provides powerful algorithms like Singular Value Decomposition(SVD) to minimize RMSE and provide great recommendations.

*The code for Collaborative filtering is referred from Rounak Banik's Github Repository which can be accessed here

```
reader = Reader()

ratings = pd.read_csv('ratings.csv')
ratings.head()
```

```
data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']],
reader)
data.split(n_folds=5)

svd = SVD()
evaluate(svd, data, measures=['RMSE', 'MAE'])
```

We get a mean Root Mean Sqaure Error of 0.8951 which is more than good enough for our case. Let us now train on our dataset and arrive at predictions.

```
trainset = data.build_full_trainset()
svd.train(trainset)

#Provide userId, movieId and True Rating
svd.predict(1, 302, 3)
```

For movie with ID 302, we get an estimated prediction in range of 2.5-3.0. One startling feature of this recommender system is that it doesn't care what the movie is (or what it contains). It works purely on the basis of an assigned movie ID and tries to predict ratings based on how the other users have predicted the movie.

```

```

Hybrid Recommender*

Hybrid Recommender leverages the best of both Content based and collaborative filtering techniques.

Input: User ID and the Title of a Movie Output: Similar movies sorted on the basis of expected ratings by that particular user.

*Part of code for Hybrid Recommendation is referred from Rounak Banik's Github Repository which can be accessed from here

```
links.drop('imdbId',axis=1,inplace=True)
links.columns=['movieId', 'id']
id_map = links.merge(movies_metadata[['title', 'id']],
on='id').set_index('title'

indices_map = id_map.set_index('id')

def hybrid(userId, title):
    idx = indexes[title]
    tmdbId = id_map.loc[title]['id']
    #print(idx)
    movie_id = id_map.loc[title]['movieId']

    sim_scores = list(enumerate(cosine_sim[int(idx)]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:26]
```

```
    movie_indices = [i[0] for i in sim_scores]

    movies = movies_metadata.iloc[movie_indices][['title',
'vote_count','year', 'id']]
    movies['est rating'] = movies['id'].apply(lambda x:
svd.predict(userId, indices_map.loc[x]['movieId']).est)
    movies = movies.sort_values('est rating', ascending=False)
    return movies.head(10)

hybrid(1, 'Avatar')

hybrid(500, 'Avatar')
```

We see that for our hybrid recommender, we get different recommendations for different users although the movie is the same. Hence, our recommendations are more personalized and tailored towards particular users

Conclusion

- We created Top Movies Charts based on Genre and utilized IMDB's Weighted Rating System to calculate ratings which was used to then sort and return top movies.
- First we gathered movie's overviews which a user has already seen and rated above average, then we used latent semantic similarity to get the similarity score and created a recommender that provides most similar story to user's liking.
- On our second approach on creating taste based recommendation by using NLP techniques used for above, and added tagline to the description as an input
- Next we considered metadata such as cast, crew, genre and keywords as input features to our Recommendation Engine, We also added weights features like director to get more similar results
- We then improved our prediction by adding a popularity and ratings filter so that recommendations are given on popular movies
- We used the powerful Surprise Library to build a collaborative filter based on single value decomposition(SVD). The RMSE obtained was less than 1 and the engine gave estimated ratings for a given user and movie.
- Using ideas from Content based engine and Collaborative filtering based engine, we created a Hybrid recommender system which provided more personalized recommendations for users

How to use this dataset while running the google colab

- upload the datset in files parallel to sample_data(all ready presented in colab)