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1. Abstract

1.1 Problem Statement:

The need for building a good recommendation system for movies cannot be undermined, especially considering the huge increase in viewership of on-demand movies. The goal of this project is – Given a movies attributes and user ratings, design a robust recommendation system using content based and collaborative filtering approaches.

1.2 Client:

The data is related with User Ratings, of Movie Lens Data institution. GroupLens Research has collected over various periods of time & made available on (www.movielens.org)

1.3 Dataset:

This dataset is collected from Grouplens Website.

No demographic information of the user is included. Each user is represented by an id, and no other information is provided.

The data are contained in six files.

rating that contains ratings of movies by users:

- `userId`
- `movieId`
- `rating`
- `timestamp`

movie that contains movie information:

- `movieId`
- `title`
- `genres`

link that contains identifiers that can be used to link to other sources:

- `movieId`
- `imdbId`
- `tmbdId`

2. Data Merging

pd.merge():

```
users_1 = pd.read_csv("data/u.user",sep='|',names=u_cols)
ratings_1 = pd.read_csv('data/u.data',sep='\t', names=r_cols)
movies_1 = pd.read_csv('data/u.item', sep='|', names=m_cols, encoding='latin-1')
movielens=pd.merge(users_1 , ratings_1)
movielens=pd.merge(movielens,movies_1)
movielens.head(3)
```

Interpretation: All individual dataframes are merged into a single dataframe based on the common columns.

This is the consolidated dataframe has the following columns

	0	1	2
movie_id	1	2	3
title	Toy Story (1995)	GoldenEye (1995)	Four Rooms (1995)
release_date	01-Jan-1995	01-Jan-1995	01-Jan-1995
video_release_date	NaN	NaN	NaN
imdb_url	http://us.imdb.com/M/title-exact?Toy%20Story%2...	http://us.imdb.com/M/title-exact?GoldenEye%20(...	http://us.imdb.com/M/title-exact?Four%20Rooms%...
unknown	0	0	0
Action	0	1	0
Adventure	0	1	0
Animation	1	0	0
Children's	1	0	0
Comedy	1	0	0
Crime	0	0	0
Documentary	0	0	0
Drama	0	0	0
Fantasy	0	0	0
Film-Noir	0	0	0
Horror	0	0	0
Musical	0	0	0
Mystery	0	0	0
Romance	0	0	0
Sci-Fi	0	0	0
Thriller	0	1	1
War	0	0	0
Western	0	0	0

3. Data Inspection

Check for Null values:

```
# Checking for null values in the dataframe
zz.isnull().values.any()
```

```
True
```

```
# Checking for null values in the columns
zz.isnull().any()
```

```
user_id               False
age                   False
sex                   False
occupation            False
zip_code              False
movie_id              False
rating                False
timestamp             False
title                 False
release_date           True
video_release_date     True
imdb_url               True
unknown               False
```

Interpretation: Null values are in `release_date`, `video_release_date`, `imdb_url`; the features which are not significant for this project.

4. Data Pre-Processing

movie['title']:

movie_id	1	2
title	Toy Story (1995)	GoldenEye (1995)
release_date	01-Jan-1995	01-Jan-1995

Interpretation: The movie title also has the year included.

Following code-snippet demonstrates the updated column names.

```
# Format 'title' i.e. remove 'year' from title
zz['title'] = zz['title'].astype(str).str[:-7]
```

```
zz.title.head()
```

```
0                    Kolya
1        Legends of the Fall
2    Hunt for Red October, The
3      Remains of the Day, The
4                Men in Black
Name: title, dtype: object
```

Interpretation: The attributes (column names) by default are self-explanatory. However, some of these are renamed to make it less confusing.

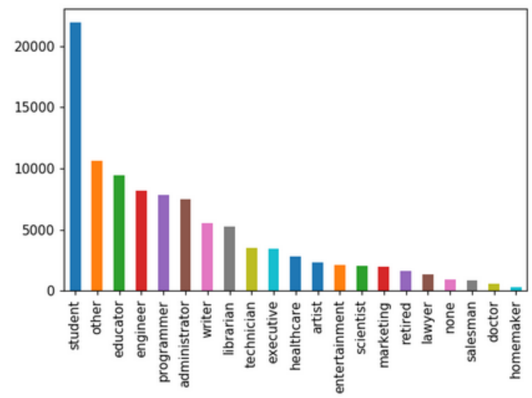
5 – Exploratory Data Analysis

5.1 Univariate Analysis

‘occupation’:

```
plt.gcf().subplots_adjust(bottom=0.25)
pd.value_counts(zz['occupation']).plot.bar()
```

```
<IPython.core.display.Javascript object>
```

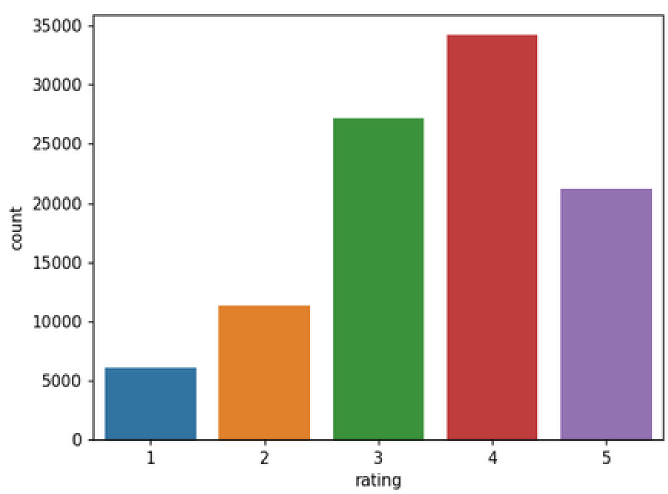


Interpretation: Highest number of users are students.

‘rating’:

```
# Ratings and their respective counts
sns.countplot(x = zz.rating, data = zz)
```

```
<IPython.core.display.Javascript object>
```



Interpretation: From the above plot, it is apparent that most of the user ratings were either 3 or 4.

‘top movies’:

```
top_movies = zz.groupby('title').size().sort_values(ascending = False)[:10]
```

```
top_movies
```

```
title
Star Wars                   583
Contact                     509
Fargo                       508
Return of the Jedi          507
Liar Liar                   485
English Patient, The        481
Scream                      478
Toy Story                   452
Air Force One               431
Independence Day (ID4)      429
dtype: int64
```

Interpretation: The above code displays the movies that are rated most.

5.2 Bivariate Analysis

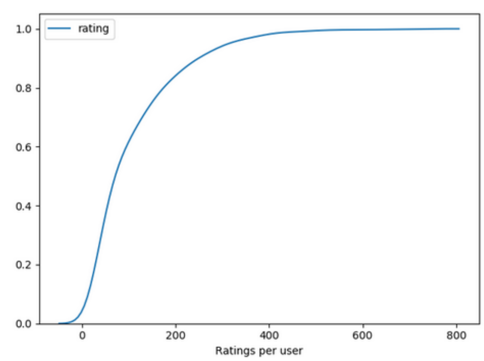
Ratings vs User - Cumulative Density Function

```
movies_per_user = zz.groupby(by='user_id')['rating'].count()
```

```
movies_per_user = movies_per_user.sort_values(ascending=False)
movies_per_user.head()
```

```
user_id
405    737
655    685
13     636
450    540
276    518
Name: rating, dtype: int64
```

```
# Cumulative Density Function
sns.kdeplot(movies_per_user, cumulative = True)
plt.xlabel('Ratings per user')
```



Interpretation: 82% of the users have made less than 200 ratings while 18% of the users have rated more than 200 of them.

Gender vs Rating vs Title

Gen dataframe has ‘sex’, ‘title’ and ‘rating’

```
gen = z[['sex', 'title', 'rating']]
```

We pivot the dataframe with title as index, sex as columns and fill values with rating.

```
new_gen = gen.pivot_table(index = 'title', columns = 'sex', values = 'rating')
```

```
new_gen.head()
```

sex	F	M
title		
'Til There Was You (1997)	2.200000	2.500000
1-900 (1994)	1.000000	3.000000
101 Dalmatians (1996)	3.116279	2.772727
12 Angry Men (1957)	4.269231	4.363636
187 (1997)	3.500000	2.870968

Now that we have a pivot table with average male and female ratings for each movie, we can go ahead and calculate their difference to find any interesting patterns in movie selection.

```
new_gen['diff'] = new_gen['M'] - new_gen['F']
```

```
new_gen.head()
```

sex	F	M	diff
title			
'Til There Was You (1997)	2.200000	2.500000	0.300000
1-900 (1994)	1.000000	3.000000	2.000000
101 Dalmatians (1996)	3.116279	2.772727	-0.343552
12 Angry Men (1957)	4.269231	4.363636	0.094406
187 (1997)	3.500000	2.870968	-0.629032

 # Top 10 movies highly rated by Females but not by Males

Negative values represent that females rated the movies higher than males on an average.

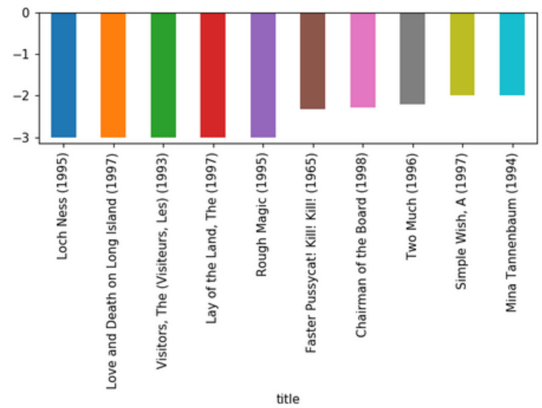
```
# Top 10 movies highly rated by Females but not by Males
new_gen.sort_values('diff').head(10)
```

sex	F	M	diff
title			
Loch Ness (1995)	4.0	1.000000	-3.000000
Love and Death on Long Island (1997)	4.0	1.000000	-3.000000
Visitors, The (Visiteurs, Les) (1993)	5.0	2.000000	-3.000000
Lay of the Land, The (1997)	4.0	1.000000	-3.000000
Rough Magic (1995)	4.0	1.000000	-3.000000
Faster Pussycat! Kill! Kill! (1965)	5.0	2.666667	-2.333333
Chairman of the Board (1998)	4.0	1.714286	-2.285714
Two Much (1996)	4.0	1.800000	-2.200000
Simple Wish, A (1997)	3.0	1.000000	-2.000000
Mina Tannenbaum (1994)	5.0	3.000000	-2.000000

Visual representation of movies:

```
new_gen.sort_values('diff').head(10)['diff'].plot(kind='bar')
```

<IPython.core.display.Javascript object>



Interpretation: We see that ‘Loch Ness’, ‘Love Death and Long Island’ are among the movies that have been rated highly by females than that of males.

 # Top 10 movies highly rated by Males but not by Females

Positive values represent that females rated the movies higher than males on an average.

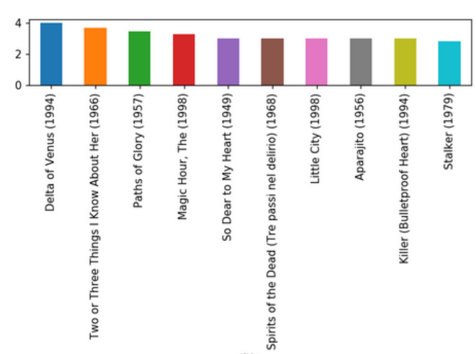
```
# Top 10 movies highly rated by Males but not by Females
new_gen.sort_values('diff', ascending=False).head(10)
```

sex	F	M	diff
title			
Delta of Venus (1994)	1.0	5.000000	4.000000
Two or Three Things I Know About Her (1966)	1.0	4.666667	3.666667
Paths of Glory (1957)	1.0	4.419355	3.419355
Magic Hour, The (1998)	1.0	4.250000	3.250000
So Dear to My Heart (1949)	1.0	4.000000	3.000000
Spirits of the Dead (Tre passi nel delirio) (1968)	1.0	4.000000	3.000000
Little City (1998)	2.0	5.000000	3.000000
Aparajito (1956)	1.0	4.000000	3.000000
Killer (Bulletproof Heart) (1994)	1.0	4.000000	3.000000
Stalker (1979)	1.0	3.800000	2.800000

Visual representation of movies:

```
new_gen.sort_values('diff', ascending=False).head(10)['diff'].plot(kind = 'bar')
```

<IPython.core.display.Javascript object>



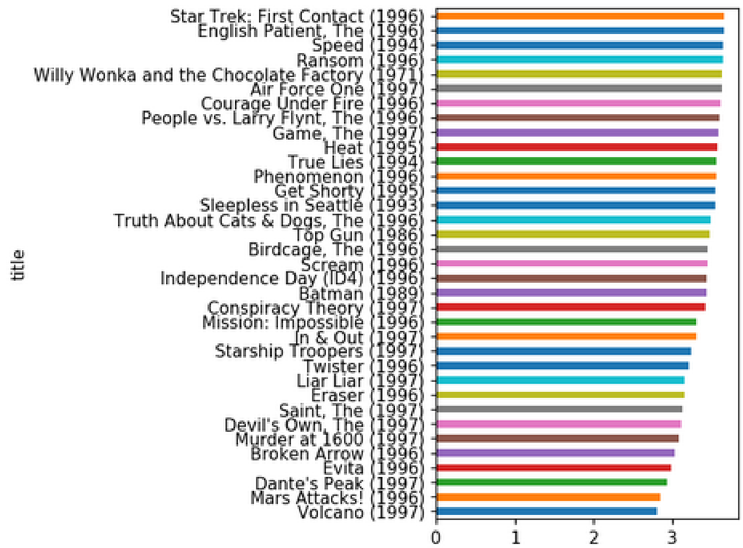
Interpretation: We see that ‘Loch Ness’, ‘Love Death and Long Island’ are among the movies that have been rated highly by females than that of males.

High rated movies (by rating)

Visual representation of highly rated movies.

```
dff_1[dff_1['rating']['size']> 200]['rating']['mean'].sort_values(ascending = True).he
ad(35).plot(kind = 'barh')
```

:IPython.core.display.Javascript object>



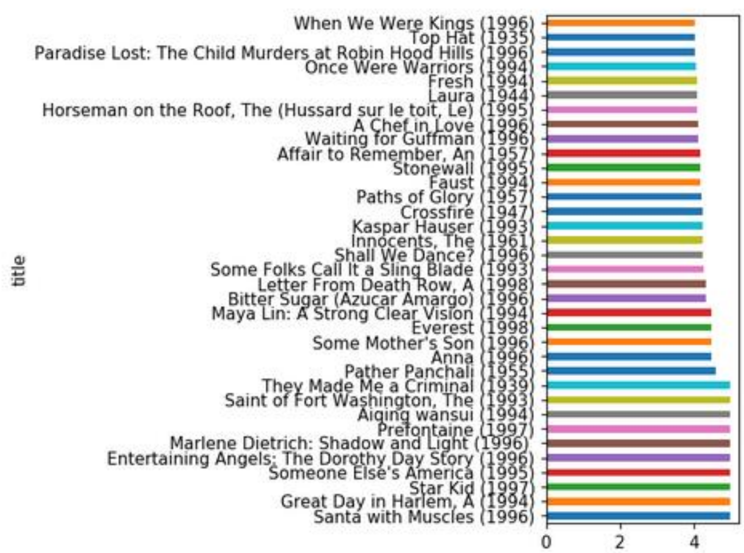
Low rated movies (by rating)

Visual representation of low rated movies.

5.2.6.2 Low rated movies (by rating)

```
dff_1[dff_1['rating']['size'] < 50]['rating']['mean'].sort_values(ascending = False).h
ead(35).plot(kind = 'barh')
```

<IPython.core.display.Javascript object>



6 – Transformations

Replacing occupation with categories:

Occupation is categorized based on the number of entries

```
# Function to categorize 'rating'
def transformation_3(df):
    df['occupation'].replace(['student', 'other', 'educator', 'engineer', 'programmer',
'administrator', 'writer', 'librarian', 'technician', 'executive', 'healthcare', 'artis
t', 'entertainment', 'scientist', 'marketing', 'retired', 'lawyer', 'none', 'salesman',
'doctor', 'homemaker'],
                             ['category_1', 'category_2', 'category_2', 'category_2', 'cate
gory_2', 'category_2', 'category_3', 'category_3', 'category_4', 'category_4', 'categor
y_4', 'category_4', 'category_4', 'category_4', 'category_5', 'category_5', 'category_5
', 'category_5', 'category_5', 'category_5', 'category_5'],
                             inplace = True)
```

```
transformation_3(zz)
```

```
zz['occupation'].head()
```

```
0    category_4
1    category_4
2    category_4
3    category_4
4    category_4
Name: occupation, dtype: object
```

Replacing ratings with below_avg, avg and above_avg:

Ratings 1, 2 are replaced by ‘below_average’, while 3 is replaced as ‘average’ and 4, 5 are categorized as ‘above_average’.

```
# Function to categorize 'rating'
def transformation_1(df):
    df['rating'].replace([1, 2, 3, 4, 5],
                         ['below_avg', 'below_avg', 'avg', 'above_avg', 'above_avg'],
                         inplace = True)
```

```
transformation_1(zz)
```

```
zz.rating.head(10)
```

```
0    above_avg
1    above_avg
2    above_avg
3    above_avg
4    above_avg
5    above_avg
6          avg
7    below_avg
8    above_avg
9          avg
Name: rating, dtype: object
```

6. Web Scraping

6.1 Beautiful Soup:

Using Python's Beautiful Soup to get data from IMDB's Top 150 movies

```
url = 'http://www.imdb.com/search/title?release_date=2017&sort=num_votes,desc&page=1'
```

```
response = get(url)
print(response.text[:500])
```

```
<!DOCTYPE html>
<html
    xmlns:og="http://ogp.me/ns#"
    xmlns:fb="http://www.facebook.com/2008/fbml">
    <head>

        <meta charset="utf-8">
        <meta http-equiv="X-UA-Compatible" content="IE=edge">

    <meta name="apple-itunes-app" content="app-id=342792525, app-argument=imdb:///?src=mdot">



        <script type="text/javascript">var IMDbTimer={starttime: new Date().getTime(),pt:'java'};</script>

<script>
    if (typeof uet == 'function') {
      uet("bb", "LoadTitle",
```

The above code snippet returns an unprettified html text.

```
html_soup = BeautifulSoup(response.text, 'html.parser')
type(html_soup)
```

```
bs4.BeautifulSoup
```

I use html parser to convert html text into beautiful soup object.

```
html_soup = BeautifulSoup(response.text, 'html.parser')
type(html_soup)
```

```
bs4.BeautifulSoup
```

```
movie_containers = html_soup.find_all('div', class_ = 'lister-item mode-advanced')
print(type(movie_containers))
print(len(movie_containers))
```

```
<class 'bs4.element.ResultSet'>
50
```

```
first_movie = movie_containers[0]
```

This returns a prettified version of html text.

movie title:

```
first_name = first_movie.h3.a.text
first_name
```

```
'Logan'
```

movie year:

```
first_year = first_movie.h3.find('span', class_ = 'lister-item-year text-muted unbold').text
first_year
```

```
'(2017)'
```

imdb rating:

```
first_imdb = float(first_movie.strong.text)
first_imdb
```

```
8.1
```

Cons: This approach seems tedious and computationally expensive. Also, this requires revisiting the IMDB website once for every request.

6.2 Tmdbsimple:

Importing ‘tmdbsimple' and key in the credentials

```
import tmdbsimple as tmdb
```

```
tmdb.API_KEY = 'f875e3c0cde708e575e3b72bea080a66'
```

```
movie = tmdb.Movies(603)
```

```
movie
```

```
<tmdbsimple.movies.Movies at 0x54451d0>
```

```
movie = movie.info()
```

```
movie
```


```
{'adult': False,
 'backdrop_path': '/7u3pxc0K1wx32IleAkLv78MKgrw.jpg',
 'belongs_to_collection': {'backdrop_path': '/bRm2DEgUiYciDw3myHuYFInD7la.jpg',
  'id': 2344,
  'name': 'The Matrix Collection',
  'poster_path': '/lh4aGpd3U9rm9B8Oqr6CUgQLtZL.jpg'},
 'budget': 63000000,
 'genres': [{'id': 28, 'name': 'Action'},
  {'id': 878, 'name': 'Science Fiction'}],
 'homepage': 'http://www.warnerbros.com/matrix',
 'id': 603,
 'imdb_id': 'tt0133093',
```

Extracting Movie Attributes:

```
movie['adult']
```

```
False
```

```
movie['title']
```

```
'The Matrix'
```

```
movie['budget']
```

```
63000000
```

```
movie['overview']
```

```
'Set in the 22nd century, The Matrix tells the story of a computer hacker who joins a group of underground
insurgents fighting the vast and powerful computers who now rule the earth.'
```

Another way of accessing movie data is by passing the movie name to the argument 'query'.

```
search = tmdb.Search()
response = search.movie(query='The Bourne')
```

```
for s in search.results:
    print(s['title'], s['id'], s['release_date'], s['popularity'])
```

```
The Bourne Identity 2501 2002-06-14 13.959
The Bourne Supremacy 2502 2004-07-23 13.047
The Bourne Legacy 49040 2012-08-08 12.672
The Bourne Ultimatum 2503 2007-08-03 12.482
Bette Bourne: It Goes with the Shoes 179304 2013-03-21 0.6
Jason Bourne 324668 2016-07-27 13.083
Untitled Jeremy Renner/Bourne Sequel 393640  0.806
```

Note: When we use tmdb.search() we do get the tmdb_id as well as the title. But using tmdb.Movies() yields much more information about the movie.

New Approach:

We can query TMDB API only using movie_ids and not by movie titles. (When queried, API throws a 404 Cleint Error) and also takes longer time to that of movie_id. However, Movie Lens dataset has its own movie_id which are quite different from that of TMDBs (tmdb_id)

Hence, we use the following approach:

- Get the movielens_id and title from movielens dataset
- Query TMDB API using movie title to get TMDB_IDs
- Use queried tmdb_id to get additional info about the movie

Based on this approach I web scrape using TMDB simple and get the metadata of the movie titles matching from movielens data.

7. Popularity Based Recommendation

7.1.1 Transformations

Transformation 1: Format title

Transformation 1: Format `title`

```
# Format 'title' i.e. remove 'year' from title
zz['title'] = zz['title'].astype(str).str[:-7]
```

```
# Format 'title' i.e. remove 'year' from title
movies['title'] = movies['title'].astype(str).str[:-7]
```

Transformation 2: Categorize rating

Transformation 2: Categorize `rating`

```
# Categorize 'rating'
zz['rating_cat'] = zz['rating']
```

```
# Function to categorize 'rating'
def transformation_1(df):
    df['rating_cat'].replace([1, 2, 3, 4, 5],
                            ['below_avg', 'below_avg', 'avg', 'above_avg', 'above_avg'],
                            inplace = True)
```

```
# Apply transformation_1
transformation_1(zz)
```

```
# Updated column
zz.rating_cat.value_counts()
```

```
above_avg    55375
avg          27145
below_avg    17480
Name: rating_cat, dtype: int64
```

Transformation 3: Categorize occupation

```
# Categorize 'occupation'
zz['occupation_cat'] = zz['occupation']
```

```
# Function to categorize 'occupation'
def transformation_3(df):
    df['occupation_cat'].replace(['student', 'other', 'educator', 'engineer', 'programm
er', 'administrator', 'writer', 'librarian', 'technician', 'executive', 'healthcare', '
artist', 'entertainment', 'scientist', 'marketing', 'retired', 'lawyer', 'none', 'sales
man', 'doctor', 'homemaker'],
                                 ['category_1', 'category_2', 'category_2', 'category_2', 'cate
gory_2', 'category_2', 'category_3', 'category_3', 'category_4', 'category_4', 'categor
y_4', 'category_4', 'category_4', 'category_4', 'category_5', 'category_5', 'category_5
', 'category_5', 'category_5', 'category_5', 'category_5'],
                            inplace = True)
```

```
# Apply transformation_3
transformation_3(zz)
```

```
# Updated column
zz.occupation_cat.value_counts()
```

```
category_2    43560
category_1    21957
category_4    16174
category_3    10809
category_5     7500
Name: occupation_cat, dtype: int64
```

7.1.2 Simple Recommendation System (Popularity based - Ratings)

Ratings matrix with movie_id as columns and user_id as rows and ratings as values

```
ratings_matrix = ratings.pivot_table(index = ['movie_id'], columns = ['user_id'], value
s = 'rating').reset_index(drop = True)

# Fill nans with 0
ratings_matrix.fillna(0, inplace = True)
ratings_matrix.head()
```

user_id	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
0	5.0	4.0	0.0	0.0	4.0	4.0	0.0	0.0	0.0	4.0	0.0	0.0	3.0	0.0	1.0	5.0	4.0	5.0	0.0	3.0	5.0	0.0	5.0	0.0	5.0	3.0
1	3.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0
2	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	[illegible]	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	3.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	4.0	0.0	5.0	5.0	0.0	0.0	5.0	0.0	3.0	4.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0
4	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0

The above matrix has:

Rows – Users
Columns – Movies
Values – Ratings

```
def pop_rec_system_new(user_input, metricc):

    if metricc == "cosine":
        movie_similarity = 1 - pairwise_distances(ratings_matrix.as_matrix(), metric = "cosine")
    elif metricc == "euclidean":
        movie_similarity = 1 - pairwise_distances(ratings_matrix.as_matrix(), metric = "euclidean")
    elif metricc == "manhattan":
        movie_similarity = 1 - pairwise_distances(ratings_matrix.as_matrix(), metric = "manhattan")
    elif metricc == "correlation":
        movie_similarity = 1 - pairwise_distances(ratings_matrix.as_matrix(), metric = "correlation")

    np.fill_diagonal(movie_similarity, 0)
    cosine_similarity_matrix = pd.DataFrame(movie_similarity)

    if (any(movies.title == user_input)):

            inp = movies[movies['title']==user_input].index.tolist() # Index of the user imput (movie)
            inp = inp[0]                                            # Index of the user imput (movie)

            similar_movies = movies[['movie_id', 'title']]          # similar Movies [dataframe with id,
title]
            # 'similarity' column contains cosine values of each movie with user input
            similar_movies['similarity'] = cosine_similarity_matrix.iloc[inp]
            similar_movies.columns = ['movie_id', 'title', 'similarity'] # rename columns

            # Reccommended Movies
            print("Reccommended movies")
            print("------------------")
            print(similar_movies.sort_values( ["similarity"], ascending = False )[1:10])

    # If movie is not in existing dataframe
    else:
        print("Movie doesn't exist in the database")
```

The above code calculates pairwise distances using various metrics to return movies.

Cosine Similarity:

Results for the movie ‘Golden Eye’ using cosine similarity as a metric.

```
pop_rec_system_new('GoldenEye', 'cosine')
```

```
Reccommended movies
------------------
     movie_id                         title  similarity
160       161                       Top Gun    0.623544
384       385                    True Lies    0.617274
402       403                        Batman    0.616143
61         62                      Stargate    0.604969
575       576                  Cliffhanger    0.601960
225       226                    Die Hard 2    0.597083
230       231               Batman Returns    0.595684
549       550  Die Hard: With a Vengeance    0.590124
95         96  Terminator 2: Judgment Day    0.584100
```

Euclidean Distance:

Results for the movie ‘Golden Eye’ using Euclidean distance as a metric.

```
pop_rec_system_new('GoldenEye', 'euclidean')
```

```
Reccommended movies
------------------
      movie_id                            title  similarity
575        576                      Cliffhanger  -30.543621
232        233                      Under Siege  -30.591138
28          29                   Batman Forever  -31.249031
577        578                   Demolition Man  -31.649655
1227      1228  Under Siege 2: Dark Territory  -31.741411
230        231                   Batman Returns  -31.756679
553        554                       Waterworld  -32.555923
61          62                         Stargate  -32.570821
801        802                      Hard Target  -32.882149
```

Manhattan Distance:

Results for the movie ‘Golden Eye’ using Euclidean distance as a metric.

```
pop_rec_system_new('GoldenEye', 'manhattan')
```

```
Reccommended movies
------------------
      movie_id                            title  similarity
232        233                      Under Siege      -315.0
575        576                      Cliffhanger      -326.0
577        578                   Demolition Man      -333.0
1227      1228  Under Siege 2: Dark Territory      -341.0
801        802                      Hard Target      -353.0
28          29                   Batman Forever      -353.0
230        231                   Batman Returns      -362.0
778        779                        Drop Zone      -362.0
61          62                         Stargate      -362.0
```

Correlation:

Results for the movie 'Golden Eye' using Euclidean distance as a metric.

```
pop_rec_system_new('GoldenEye', 'correlation')
```

```
Reccommended movies
------------------
     movie_id            title  similarity
575       576      Cliffhanger    0.555861
160       161          Top Gun    0.553483
61         62         Stargate    0.548701
384       385        True Lies    0.547434
402       403           Batman    0.546641
230       231   Batman Returns    0.535239
577       578   Demolition Man    0.531821
225       226       Die Hard 2    0.530296
28         29   Batman Forever    0.526570
```

Note: This recommendation system is solely based on popularity. The movies returned with cosine, euclidean and manhattan distance are quite similar to each other. However, they are not so much when the recommendation system uses pearson correlation.

Limitation: This recommendation system suggests movies IRRSPECTIVE OF USER PREFERENCES.

8 – Content Based Recommendation

8.1 Description Based Recommendation:

We use three columns for our description-based recommendation:

- overview
- tagline
- description (overview + tagline)

Python code for Recommendation Engine:

```
# Recommendation Engine
def recommendations(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:10]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

Step 1 – Extract the indices of the title passed as argument to recommendations (title)

Step 2 – Calculate cosine similarities with respect to the movie index.

Step 3 – Sorts similarity scores.

Step 4 – Returns the titles of the indices with highest similarity scores.

Creation of the series ‘titles’ and ‘indices’ is show in the below sections. Above steps are revisited using different approaches in the following three subsections.

8.1.1 Recommendation Engine using ‘overview’:

First recommendation engine considers only the ‘overview’ of the movie. ‘Overview’ stands for the descriptive text that is outlined for a movie in ‘IMDB’ official site.

```
zz_metadata = metadata[metadata['id'].isin(zz['movie_id'])]
```

```
# tf-idf vectorizer
tf = TfidfVectorizer(analyzer = 'word', ngram_range = (1, 2), min_df = 0, stop_words = 'english')
tfidf_matrix = tf.fit_transform(zz_metadata['overview'])                    # Fit Transform 'ov
erview'
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)                      # Cosine Similarity
 of td-idf matrix

zz_metadata_1 = zz_metadata.reset_index()                                   # Reset Index
titles = zz_metadata_1['title']                                             # Titles
indices = pd.Series(zz_metadata_1.index, index = zz_metadata_1['title'])    # Indices
```

The above code snippets demonstrates:

Step 1 – Instantiate a Tf-Idf Vectorizer object

Step 2 – Fit-Transform the tf-idf object to metadata[‘overview’]

Step 3 – Calculate the consine similarities using linear kernel.

Step 4 – Reset Index

Step 5 – Create a series of titles

Step 6 – Create a series of indices.

```
# Recommendation Engine
def recommendations_overview(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:10]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

```
recommendations_overview('The Dark Knight')
```

```
21                    Batman Forever
233                   Batman Returns
71                            Batman
427                              JFK
843                    Batman Begins
248                   Batman & Robin
324                  A Few Good Men
435     Teenage Mutant Ninja Turtles
261               Tomorrow Never Dies
Name: title, dtype: object
```

Interpretation: This model provides robust recommendations using metadata ['overview'].

Limitation: But there are few not-so meaningful recommendations. Example: (Teenage Mutant Ninja Turtles, Tomorrow Never Dies)

8.1.2 Recommendation Engine using ‘tagline’:

Second recommendation engine considers only the ‘tagline’ of a movie. ‘Tagline’ stands for the extended movie title which certain movies have.

Example: ‘Die Hard 3: With a Vengeance’

Title of the movie is ‘Die Hard 3’ while the tagline is ‘With a Vengeance’.

```
# Dropping null values using index
zz_metadata = zz_metadata.drop(list(zz_metadata[zz_metadata['tagline'].isnull()]['id'].index))
```

```
# tf-idf vectorizer
tf = TfidfVectorizer(analyzer = 'word', ngram_range = (1, 2), min_df = 0, stop_words = 'english')
tfidf_matrix = tf.fit_transform(zz_metadata['tagline'])                                  # Fit Transform 'over
view'
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)                                   # Cosine Similarity o
f td-idf matrix

zz_metadata_1 = zz_metadata.reset_index()                                                # Reset Index
titles = zz_metadata_1['title']                                                          # Titles
indices = pd.Series(zz_metadata_1.index, index=zz_metadata_1['title'])                   # Indices
```

```
# Recommendation Engine
def recommendations_tagline(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:10]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

```
recommendations_tagline('The Dark Knight')
```

```
1                    GoldenEye
2              Cutthroat Island
3                       Casino
4                   Four Rooms
5             Leaving Las Vegas
6     The City of Lost Children
7                Twelve Monkeys
8                   To Die For
9                        Se7en
Name: title, dtype: object
```

Interpretation: The model built with respect to 'tagline' is not as robust as the previous model. It is apparent that the first model (using metadata ['overview']) provides highly similar movies than the model using 'taglines'.

8.1.3 Recommendation Engine using metadata ['overview'] + metadata ['tagline']:

Final recommendation engine using description considers both the 'overview' and the 'tagline' of a movie. These two columns are concatenated to form a new column 'description'.

```
# Filling nans with empty strings
zz_metadata['tagline'] = zz_metadata['tagline'].fillna('')

# Create a new column 'description' = 'overview' + 'tagline'
zz_metadata['description'] = zz_metadata['overview'] + zz_metadata['tagline']

# Filling nans with empty strings
zz_metadata['description'] = zz_metadata['description'].fillna('')
```

```
# tf-idf vectorizer
tf = TfidfVectorizer(analyzer = 'word', ngram_range = (1, 2), min_df = 0, stop_words = 'english')
tfidf_matrix = tf.fit_transform(zz_metadata['description'])                     # Fit Transform
 'overview'
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)                          # Cosine Simila
rity of td-idf matrix

zz_metadata_1 = zz_metadata.reset_index()                                       # Reset Index
titles = zz_metadata_1['title']                                                 # Titles
indices = pd.Series(zz_metadata_1.index, index=zz_metadata_1['title'])          # Indices
```

```
# Recommendation Engine
def recommendations_description(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:10]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

```
recommendations_description('The Dark Knight')
```

```
19                    Batman Forever
210                   Batman Returns
61                            Batman
392                              JFK
697                    Batman Begins
223                   Batman & Robin
399    Teenage Mutant Ninja Turtles
236              Tomorrow Never Dies
506                          48 Hrs.
Name: title, dtype: object
```

Interpretation: This model provides similar recommendations to that of the initial model (using metadata ['overview']). We can infer that 'tagline' is not the best feature to consider building a recommendation system.

8.2 Metadata Based Recommendation System

After scraping data from the web for the movie ids in the merged dataframe ('movielens'), we can now use the metadata to build the recommendation system.

```
# Sample version of the full dataset
links_small = pd.read_csv('data_full/links_small.csv')
```

```
links_small.head(1)
```

	movieId	imdbId	tmdbId
0	1	114709	862.0

Movie lens data has a file 'links' that consists of 'movie id', 'imdb id' and 'tmdb id' using which the data was scraped from the web.

Missing Values:

```
# Null values in tmdbId
links_small.tmdbId.isnull().sum()
```

```
13
```

```
# Removing null records in 'tmdbid'
links_small = links_small[links_small['tmdbId'].notnull()]
```

The metadata has column values in dictionary. This can be trickier can handle. Instead of using the dictionary to operate on, I convert the dictionary to a list.

```
# Converting genre dictionary to list
def dict_to_list(x):
    ls = []
    for i in literal_eval(x):
        ls.append(i['name'])
    return ls
```

```
# Apply 'dict_to_list' method
for col in ['cast', 'crew', 'keywords']:
    metadata_full[col] = metadata_full[col].apply(dict_to_list)
```

Updated columns after merging movie titles and metadata:

```
links_small_new.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', 'cast', 'crew', 'keywords', 'director'],
      dtype='object')
```

Checking for null values in ‘tagline’ and ‘overview’:

```
# Null values in tagline = 2137
print(links_small_new['tagline'].isnull().sum())

# Null values in tagline = 12
print(links_small_new['overview'].isnull().sum())
```

```
2137
12
```

Note: Since there are null values in 'tagline' and 'overview', we cannot simply join them together to create a new column ('description').

Solution: Strip off the white spaces.

```
# Strip off white spaces from 'tagline'
links_small_new['tagline'] = links_small_new['tagline'].fillna('')

# Create new column 'description' = 'overview' + 'tagline'
links_small_new['description'] = links_small_new['overview'] + links_small_new['tagline']

# Strip off white spaces from 'description', if any
links_small_new['description'] = links_small_new['description'].fillna('')
```

Note: So far, `links_small_new` has cast, crew, credits and genres. But we do not need all the data in them. To efficiently use them, I clean each column further.

Creating new columns ‘cast_size’ and ‘crew_size’:

```
# Creating new features 'cast_size' and 'crew size'
links_small_new['cast_size'] = links_small_new['cast'].apply(lambda x: len(x))
links_small_new['crew_size'] = links_small_new['crew'].apply(lambda x: len(x))
```

```
# Cast of a movie
links_small_new['cast'][0]
```

```
['Tom Hanks',
 'Tim Allen',
 'Don Rickles',
 'Jim Varney',
 'Wallace Shawn',
 'John Ratzenberger',
 'Annie Potts',
 'John Morris',
 'Erik von Detten',
 'Laurie Metcalf',
 'R. Lee Ermey',
 'Sarah Freeman',
 'Penn Jillette']
```

Note: Cast can include actors and actress that are both famous and infamous. However, famous artists are most likely to play a significant role in affecting the user’s opinion than others.

Solution: Select 4 artists [lead actor 1, lead actor 2, supporting actor 1, supporting actor 2] rather than considering all.

These are steps I follow in the preparation of genres and credits data:

1. **Strip Spaces and Convert to Lowercase** from all our features. This way, engine will not confuse between **Johnny Depp** and **Johnny Galecki.**
2. **Mention Director 2 times** to give it more weight relative to the entire cast.

```
# Strip spaces from 'cast' and convert to lowercase
links_small_new['cast'] = links_small_new['cast'].apply(lambda x: [str.lower(i.replace(" ", "")) for i in
x])
```

```
# Strip spaces from 'director'
links_small_new['director'] = links_small_new['director'].astype('str').apply(lambda x: str.lower(x.replac
e(" ", "")))

# Adding weight to 'director'
links_small_new['director'] = links_small_new['director'].apply(lambda x: [x,x])
```

Keywords:

We will do a small amount of pre-processing of our keywords before putting them to any use. As a first step, we calculate the frequency counts of every keyword that appears in the dataset.

```
links_small_new['keywords'][:3]
```

```
0    [jealousy, toy, boy, friendship, friends, riva...
1    [board game, disappearance, based on children'...
2    [fishing, best friend, duringcreditsstinger, o...
Name: keywords, dtype: object
```

Not all words could prove significant.

```
# Stacking all words from 'keywords'
w = links_small_new.apply(lambda x: pd.Series(x['keywords']), axis = 1).stack().reset_index(level = 1, dro
p = True)
w.name = 'keyword'
```

```
# Value counts
w = w.value_counts()
w[:5]
```

```
independent film        610
woman director          550
murder                  399
duringcreditsstinger    327
based on novel          318
Name: keyword, dtype: int64
```

Note: Keywords occur in frequencies ranging from 1 to 610. We do not have any use for keywords that occur only once.
Interpretation: Keywords that occur just once.

```
w = w[w > 1]
```

Stemming:

Words like 'play', 'played' and 'playing' can be stemmed to the word 'play'. This process is called stemming.

Code to perform stemming.

```
# Initialize stemmer object
stemmer = SnowballStemmer('english')
```

```
# Function to filter keywords
def filter_keywords(x):
    words = []
    for i in x:                        # For each word in input
        if i in w:                     # If that word in keywords
            words.append(i)            # append i to words
    return words
```

Preprocess 'keywords' column:

Step 1 – Apply filter words function

1 – Loop for each word in the input
2 – If the word in keywords
3 – Add to the temporary list words
4 – Returns temporary list

Step 2 – Stem all words

Step 3 – Remove blank spaces

```
# Apply filter_keywords to 'keywords'
links_small_new['keywords'] = links_small_new['keywords'].apply(filter_keywords)

# Stem keywords
links_small_new['keywords'] = links_small_new['keywords'].apply(lambda x: [stemmer.stem(i) for i in x])

# Convert string to lower case and strip spaces
links_small_new['keywords'] = links_small_new['keywords'].apply(lambda x: [str.lower(i.replace(" ", "")) f
or i in x])
```

Updated 'keywords' column:

```
links_small_new['keywords'][1]
```

```
['boardgam',
 'disappear',
 "basedonchildren'sbook",
 'newhom',
 'reclus',
 'giantinsect']
```

Soup:

Soup is the metadata of genres, director, cast and keywords.

```
# Soup = 'keywords' + 'cast' + 'director' + 'genres'
links_small_new['soup'] = links_small_new['keywords'] + links_small_new['cast'] + links_small_new['directo
r'] + links_small_new['genres']
```

Soup contains genres, director, cast and keywords.

```
links_small_new['soup'][1]
```

```
['boardgam',
 'disappear',
 "basedonchildren'sbook",
 'newhom',
 'reclus',
 'giantinsect',
 'robinwilliams',
 'jonathanhyde',
 'kirstendunst',
 'bradleypierce',
 'joejohnston',
 'joejohnston',
 'Adventure',
 'Fantasy',
 'Family']
```

Removing quotations and commas:

```
# Remove quotations ('') and commas (,) from soup
links_small_new['soup'] = links_small_new['soup'].apply(lambda x: ' '.join(x))
```

```
links_small_new['soup'][1]
```

```
"boardgam disappear basedonchildren'sbook newhom reclus giantinsect robinwilliams jonathanhyde kirstenduns
t bradleypierce joejohnston joejohnston Adventure Fantasy Family"
```

Count Vectorizer:

Create a count matrix and calculate the cosine similarities to find movies that are most similar.

```
# Count Vectorizer
count = CountVectorizer(analyzer = 'word', ngram_range = (1, 2), min_df = 0, stop_words = 'english')

# Build a count matrix by fitting and transforming 'soup'
count_matrix = count.fit_transform(links_small_new['soup'])
```

```
# Calculating cosine similarity of count matrix
cosine_sim = cosine_similarity(count_matrix, count_matrix)
```

```
# Reset Index
links_small_new = links_small_new.reset_index()

# Titles
titles = links_small_new['title']

# Indices
indices = pd.Series(links_small_new.index, index = links_small_new['title'])
```

Python code for recommendation engine

```
# Recommendation Engine
def recommendations(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:10]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

Recommendations:

```
recommendations('The Dark Knight').head(10)
```

```
8031         The Dark Knight Rises
6218                 Batman Begins
7659    Batman: Under the Red Hood
6623                  The Prestige
1134                Batman Returns
5943                      Thursday
8927       Kidnapping Mr. Heineken
1260                Batman & Robin
2085                     Following
Name: title, dtype: object
```

Limitation: This recommendation system returns only the movies based on soup. It does not consider popularity.

Solution: We use the results returned from our Count Vectorizer (indices) and return the movies that are popular based on the IMDB's weighted average. Additionally, I use three different criteria to cut-off the movies (75% percentile, Mean and No Cut-Off criteria)

Weighted Average:

IMDB's *weighted rating* formula:

[Weighted Rating](#) (WR) =

where,

- *v* - number of ratings for the movie
- *m* - number of ratings needed to qualify (usually mean)
- *R* - average rating of the movie
- *C* - mean rating of the population (whole dataset)

Before we could use the above weighted average formula, m and C should be determined.

Calculate c:

```
# Claculation of c
vote_counts = metadata[metadata['vote_count'].notnull()]['vote_count'].astype('int')
vote_averages = metadata[metadata['vote_average'].notnull()]['vote_average'].astype('int')
C = vote_averages.mean()
C
```

Calculate m:

```
## Claculation of m
m = vote_counts.quantile(0.95)
m
```

```
434.0
```

Function to calculate weighted average:

```
# Function to calculate 'weighted_rating'
def weighted_rating(x):
    v = x['vote_count']
    R = x['vote_average']
    return (v/(v+m) * R) + (m/(m+v) * C)
```

I try three different cutoff criteria:

1. 95th percentile
2. Mean
3. No cut-off

```
# Apply weighted rating method to qualified_perc, qualified_mean, new_qualified, sm_df, metadata
for df in [qualified_perc, qualified_mean, new_qualified, sm_df, metadata, metadata_full]:
    df['weighted_rating'] = df.apply(weighted_rating, axis=1)
```

```
# Columns for qualified movies
col_list = ['title', 'release_date', 'vote_count', 'vote_average', 'popularity', 'genres']

# qualification criteria
qualified_perc = metadata[(metadata_full['vote_count'] >= m)
                 & (metadata_full['vote_count'].notnull())
                 & (metadata_full['vote_average'].notnull())][col_list]

# converting vote_count and vote_average colums to integer
qualified_perc['vote_count'] = qualified['vote_count'].astype('int')
qualified_perc['vote_average'] = qualified['vote_average'].astype('int')

qualified_perc.shape
```

(i) Getting qualified movies (cutoff: 95%)

Code for recommendation system with movies cutoff 95%

```
# Better recommendation engine
def better_recommendations_percentile_popularity(title):
    idx = indices[title]                              # Considers indices of the previous recommedat
ion system
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:51]
    movie_indices = [i[0] for i in sim_scores]

    improved_movies = links_small_new.iloc[movie_indices][['title', 'vote_count', 'vote_average']]
    vote_counts = improved_movies[improved_movies['vote_count'].notnull()]['vote_count'].astype('int')
    vote_averages = improved_movies[improved_movies['vote_average'].notnull()]['vote_average'].astype('in
t')

    C = vote_averages.mean()
    m = vote_counts.quantile(0.75)

    qualified = improved_movies[(improved_movies['vote_count'] >= m) & (improved_movies['vote_count'].notn
ull()) & (improved_movies['vote_average'].notnull())]
    qualified['vote_count'] = qualified['vote_count'].astype('int')
    qualified['vote_average'] = qualified['vote_average'].astype('int')
    qualified['wr'] = qualified.apply(weighted_rating, axis=1)
    qualified = qualified.sort_values('wr', ascending=False).head(10)
    return qualified
```

We see that the movies recommended by the engine highly emphasized on the crew (director).

```
# Better recommendations
better_recommendations_percentile_popularity('The Dark Knight')
```

	title	vote_count	vote_average	wr
7648	Inception	14075	8	7.917588
6623	The Prestige	4510	8	7.758148
8031	The Dark Knight Rises	9263	7	6.921448
6218	Batman Begins	7511	7	6.904127
7583	Kick-Ass	4747	7	6.852979
1134	Batman Returns	1706	6	5.846862
4145	Insomnia	1181	6	5.797081
8970	Hitman: Agent 47	1183	5	5.065730
132	Batman Forever	1529	5	5.054144
9162	London Has Fallen	1656	5	5.050854

(ii) Getting qualified movies (cutoff: mean)

Code for recommendation system with mean cutoff for movies.

```
# Better recommendation engine
def better_recommendations_mean_popularity(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:51]
    movie_indices = [i[0] for i in sim_scores]

    improved_movies = links_small_new.iloc[movie_indices][['title', 'vote_count', 'vote_average']]
    vote_counts = improved_movies[improved_movies['vote_count'].notnull()]['vote_count'].astype('int')
    vote_averages = improved_movies[improved_movies['vote_average'].notnull()]['vote_average'].astype('in
t')

    C = vote_averages.mean()
    m = vote_counts.mean()

    qualified = improved_movies[(improved_movies['vote_count'] >= m) & (improved_movies['vote_count'].notn
ull()) & (improved_movies['vote_average'].notnull())]
    qualified['vote_count'] = qualified['vote_count'].astype('int')
    qualified['vote_average'] = qualified['vote_average'].astype('int')
    qualified['wr'] = qualified.apply(weighted_rating, axis=1)
    qualified = qualified.sort_values('wr', ascending=False).head(10)
    return qualified
```

We see that the movies recommended by the new engine includes.

```
# Better recommendations
better_recommendations_mean_popularity('The Dark Knight')
```

	title	vote_count	vote_average	wr
7648	Inception	14075	8	7.917588
6623	The Prestige	4510	8	7.758148
8031	The Dark Knight Rises	9263	7	6.921448
6218	Batman Begins	7511	7	6.904127
7583	Kick-Ass	4747	7	6.852979
1134	Batman Returns	1706	6	5.846862
132	Batman Forever	1529	5	5.054144
9162	London Has Fallen	1656	5	5.050854
9163	London Has Fallen	1656	5	5.050854
9024	Batman v Superman: Dawn of Justice	7189	5	5.013943

(iii) Getting qualified movies (cutoff: none)

Code for recommendation system with no cutoff for movies.

```
# Better recommendation engine
def better_recommendations_no_cutoff(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:51]
    movie_indices = [i[0] for i in sim_scores]

    improved_movies = links_small_new.iloc[movie_indices][['title', 'vote_count', 'vote_average']]
    vote_counts = improved_movies[improved_movies['vote_count'].notnull()]['vote_count'].astype('int')
    vote_averages = improved_movies[improved_movies['vote_average'].notnull()]['vote_average'].astype('in
t')

    C = vote_averages.mean()
    m = vote_counts.quantile(0.60)

    qualified = improved_movies[(improved_movies['vote_count'].notnull()) & (improved_movies['vote_averag
e'].notnull())]
    qualified['vote_count'] = qualified['vote_count'].astype('int')
    qualified['vote_average'] = qualified['vote_average'].astype('int')
    qualified['wr'] = qualified.apply(weighted_rating, axis=1)
    qualified = qualified.sort_values('wr', ascending=False).head(10)
    return qualified
```

It is evident that the top 5 movies returned by the recommendation system are the same across all three criteria.

```
# Better recommendations
better_recommendations_no_cutoff('The Dark Knight')
```

	title	vote_count	vote_average	wr
7648	Inception	14075	8	7.917588
6623	The Prestige	4510	8	7.758148
8031	The Dark Knight Rises	9263	7	6.921448
6218	Batman Begins	7511	7	6.904127
7583	Kick-Ass	4747	7	6.852979
7659	Batman: Under the Red Hood	459	7	6.147016
2085	Following	363	7	6.044272
8001	Batman: Year One	255	7	5.894463
2952	Magnum Force	251	7	5.888007
1134	Batman Returns	1706	6	5.846862

9 – Collaborative Filtering

9.1 Collaborative Filtering:

```
# Read 'ratings' data
# ratings = pd.read_csv('data_full/ratings.csv')
ratings_small = pd.read_csv('data_full/ratings_small.csv')
```

Note: Python throws 'Memory' Error when I use the full dataset. Hence, I pick 25% of the dataset and perform collborative filtering on it.

I pick only 25% of the data.

```
# Randomly sample 25% of the ratings dataset
small_data = ratings_small.sample(frac=0.25)
```

Dividing the data into train and test set:

```
train_data, test_data = train_test_split(small_data, test_size=0.2)
```

```
# Test and Train data matrix
train_data_matrix = train_data.as_matrix(columns = ['user_id', 'movie_id', 'rating'])
test_data_matrix = test_data.as_matrix(columns = ['user_id', 'movie_id', 'rating'])
```

The train and test dataframes are converted to arrays using .as_matrix()

Below are the dataframe and matrix versions of train dataset.

```
train_data.head()
```

	user_id	movie_id	rating
85067	571	34338	4.5
11050	73	6338	3.0
25459	187	586	3.5
18462	120	4306	2.5
20890	144	253	3.0

```
train_data_matrix[:4]
```

```
array([[5.7100e+02, 3.4338e+04, 4.5000e+00],
       [7.3000e+01, 6.3380e+03, 3.0000e+00],
       [1.8700e+02, 5.8600e+02, 3.5000e+00],
       [1.2000e+02, 4.3060e+03, 2.5000e+00]])
```

Idea behind user and item similarity:

User similarity can be calculated by measuring 'pairwise distances' between ratings datset.

However, if you have to calculate the 'item similarity', we have to transpose the 'ratings' data and then calculate the pairwise distances.

User Similarity Matrix:

```
# User Similarity Matrix
user_correlation = 1 - pairwise_distances(train_data, metric = 'correlation')
user_correlation[np.isnan(user_correlation)] = 0
print(user_correlation[:4, :4])
```

```
[[1.         0.99998855 0.95570253 0.9999543 ]
 [0.99998855 1.         0.9542832  0.9998971 ]
 [0.95570253 0.9542832  1.         0.9584729 ]
 [0.9999543  0.9998971  0.9584729  1.        ]]
```

Item Similarity Matrix:

```
# Item Similarity Matrix (Train_data_matrix.Transpose)
item_correlation = 1 - pairwise_distances(train_data_matrix.T, metric = 'correlation')
item_correlation[np.isnan(item_correlation)] = 0
print(item_correlation[:4, :4])
```

```
[[ 1.          0.00139149  0.00804213]
 [ 0.00139149  1.         -0.02296115]
 [ 0.00804213 -0.02296115  1.        ]]
```

User Correlation and Item Correlation:

```
user_correlation[:1]
```

```
array([[1.        , 0.99998855, 0.95570253, ..., 0.99972598, 0.99651712,
        0.97092856]])
```

```
item_correlation[:1]
```

```
array([[1.        , 0.00139149, 0.00804213]])
```

Function to predict ratings

```
# Function to predict ratings
def predict(ratings, similarity, type='user'):

    if type == 'user':
        mean_user_rating = ratings.mean(axis=1)                    # Calculate mean of ratings
        ratings_diff = (ratings - mean_user_rating[:, np.newaxis])  # Use np.newaxis so that mean_user_
rating has same format as ratings
        pred = mean_user_rating[:, np.newaxis] + similarity.dot(ratings_diff) / np.array([np.abs(simila
rity).sum(axis=1)]).T

    elif type == 'item':
        pred = ratings.dot(similarity) / np.array([np.abs(similarity).sum(axis=1)])

    return pred
```

Calling predict function:

```
# Predict ratings on the training data with both similarity score
user_prediction = predict(train_data_matrix, user_correlation, type = 'user')
item_prediction = predict(train_data_matrix, item_correlation, type = 'item')
```

Calculate Root Mean Squared Error:

```
# Function to calculate RMSE
def rmse(pred, actual):
    # Ignore nonzero terms.
    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()
    return sqrt(mean_squared_error(pred, actual))
```

Calling RMSE() to calculate error on user based and item based predictions:

```
# RMSE on the test data
print('User-based CF RMSE: ' + str(rmse(user_prediction, test_data_matrix)))
print('Item-based CF RMSE: ' + str(rmse(item_prediction, test_data_matrix)))
```

```
User-based CF RMSE: 17677.833472568193
Item-based CF RMSE: 21050.47348294261
```

10. Potential Next Steps:

Suggestions for Content-Based filtering from other data scientists I met during the meet-up:

1. Use weighted average on each movie:
   - How about multiplying rating count and average rating.
   - For a linear column, there can be huge variance. [Try normalize and standardize]
2. Use metadata td-idf matrix (cosine similarity) rather than just the movies.
   - Use 'word2vec'
3. For collaborative filtering - try 'movie-movie' similarity and 'user-user' similarity (Computationally Expensive)
4. Try to build a Hybrid Recommender