CS582 Machine Learning - Project 2

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Project Colab URL:

https://colab.research.google.com/drive/1B8HxIE6tlmFq5gLVam4pnLkSSZRThzD0

Dataset:

https://www.kaggle.com/rounakbanik/the-movies-dataset

Ref:

https://www.kaggle.com/ibtesama/getting-started-with-a-movie-recommendation-system

https://www.ijert.org/research/recommender-systems-types-of-filtering-techniques-IJERTV3IS110197.pdf

https://www.kaggle.com/fabiendaniel/film-recommendation-engine

https://github.com/NicolasHug/Surprise

Part 1: Recommend top trending movies

What are top trending movies?

Recently popular, most watched or widely discussed online, especially on social media websites such as IMDB.

Data Resource

Movie metadata from imdb dataset

What is Demographic Filtering?

RS based on Demographic filtering (DF) classify users according to their demographic information and recommend services accordingly

Solution

By applying the Demographic Filtering technique on imdb dataset we can find the most trending movies which allows finding a score for ranking movies.

Take a look at the dataset we have voting information from the imdb users who watched the movie and shared their opinion. There are 2 values we can use: **vote_average** - average ratings the movie received **vote_count** - the count of votes received We can use IMDB's weighted rating (wr) formula to generate the appropriate way to set the score:

$$Weighted\ Rating\ (WR) = \left(\frac{v}{v+m} \times R\right) + \left(\frac{m}{v+m} \times C\right)$$

- v is the number of votes for the movie - vote_count
- m is the minimum votes required to be listed in the chart
- R is the average rating of the movie - vote_average
- C is the mean vote across the whole report

Load all libs

```
from random import randrange
import numpy as np
import seaborn as sns
import pandas as pd
import pandas.util.testing as tm
import matplotlib.pyplot as plt
from ast import literal_eval
import warnings
warnings.filterwarnings('ignore')
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

Dataset - Movie Metadata

```
df_movies_metadata = pd.read_csv('movies_metadata.csv')
df_movies_metadata.sample(3)
```

	adult	belongs_to_collection	budget	genres	homepage	id	imdb_id	original_language	original_title	overview	popularity	poster_path	production_compan
37186	False	NaN	0	[{'id': 878, 'name': 'Science Fiction'}, {'id'...	NaN	48128	tt0976216	el	Straight Story	This film is about an upside down world, where...	0.258855	/wwPdXFx2H8Fs3N3o9fpq8StBJPm.jpg	
3052	False	NaN	0	[{'id': 53, 'name': 'Thriller'}, {'id': 18, 'n...	NaN	26578	tt0087231	en	The Falcon and the Snowman	The true story of a disillusioned military con...	4.69085	/9bEjyzGYqtUfnKt7DSRac3U48km.jpg	[{'name': 'O Pictures', 'id': {'nam
41510	False	NaN	11178	[{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam...	NaN	121173	tt2244376	en	Bwakaw	Bwakaw is a drama-comedy about growing old, an...	0.079287	/nWaHRhz9RPQA82KQy7pqLKhorkf.jpg	[{'name': ' Entertainment', 8355},

```
df_date = df_movies_metadata[['release_date']]
df_date = df_date.sort_values(by='release_date',ascending=False)
df_date.head()
```

	release_date
35586	22
26558	2020-12-16
38884	2018-12-31
30401	2018-11-07
38129	2018-04-25

There is one movie hasn't release comparing to current date. So let's say the dataset for 2018. There is a release date is 22, we may assume the movie will be released in 2022

```
df_movies_metadata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45465 entries, 0 to 45464
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   adult                  45465 non-null  object
 1   belongs_to_collection  4493 non-null   object
 2   budget                 45465 non-null  object
 3   genres                 45465 non-null  object
 4   homepage               7781 non-null   object
 5   id                     45465 non-null  object
 6   imdb_id                45448 non-null  object
 7   original_language      45454 non-null  object
 8   original_title         45465 non-null  object
 9   overview               44511 non-null  object
 10  popularity             45462 non-null  object
 11  poster_path            45080 non-null  object
 12  production_companies   45463 non-null  object
 13  production_countries   45463 non-null  object
 14  release_date           45379 non-null  object
 15  revenue                45461 non-null  float64
 16  runtime                45204 non-null  float64
 17  spoken_languages       45461 non-null  object
 18  status                 45380 non-null  object
 19  tagline                20412 non-null  object
 20  title                  45461 non-null  object
 21  video                  45461 non-null  object
 22  vote_average           45461 non-null  float64
 23  vote_count             45461 non-null  float64
dtypes: float64(4), object(20)
memory usage: 8.3+ MB
```

We have data size of **45465 x 24**

Clean movies metadata

```
print(df_movies_metadata.adult.unique())
```

```
['False' 'True'
 ' Rune Balot goes to a casino connected to the October corporation to try to wrap up her case once and for all.'
 ' Avalanche Sharks tells the story of a bikini contest that turns into a horrifying affair when it is hit by a shark avalanche.']
```

There are some invalid data here, let's clean it up

```
df_movies_metadata.drop(df_movies_metadata[(df_movies_metadata['adult'] != 'False')
                    & (df_movies_metadata['adult'] != 'True')].index, inplace=True)
```

```
print(df_movies_metadata.adult.unique())
```

```
['False' 'True']
```

Handle Null Data

```
def unique_nullcount(df):
  rows = []
  for (i, j) in df.iteritems():
      rows.append([i, df[i].nunique(), df[i].isna().sum()])
  df_null_ct = pd.DataFrame(rows,
                            columns=["Feature",
                                   "Unique value",
                                   "Count null"]).sort_values(["Unique value",
                                                               "Count null"],
                                                              ascending = (True,True))
  pd.set_option('display.max_rows', df_null_ct.shape[0]+1)
  return df_null_ct

def unique_value_list(df,df_train, feature, ct):
  features = df[df[feature] < ct]['Feature']
  for i in features:
      print(i, df_train[i].unique())
```

```
df = unique_nullcount(df_movies_metadata.select_dtypes(include=[np.number]))
print(df[df['Count null']>0])
```

```
          Feature  Unique value  Count null
2  vote_average            92           2
1       runtime           353         259
3    vote_count          1820           2
0       revenue          6863           2
```

```
df_movies_metadata[df_movies_metadata['vote_count'].isna()]
```

These values are the second half of above invalid records. We can manually fix the error or drop they off the dataset.

```
df_movies_metadata.drop(df_movies_metadata[df_movies_metadata['vote_count'].isna()].index,
                        inplace=True)
```

Demographic Filtering

We already have **v(vote_count)** and **R (vote_average)**

We will calculate **C** and **m**

```
movie_watched = df_movies_metadata[['vote_average','vote_count']]
movie_watched.describe()
```

	vote_average	vote_count
count	45461.000000	45461.000000
mean	5.618216	109.894943
...	...	...
75%	6.800000	34.000000
max	10.000000	14075.000000

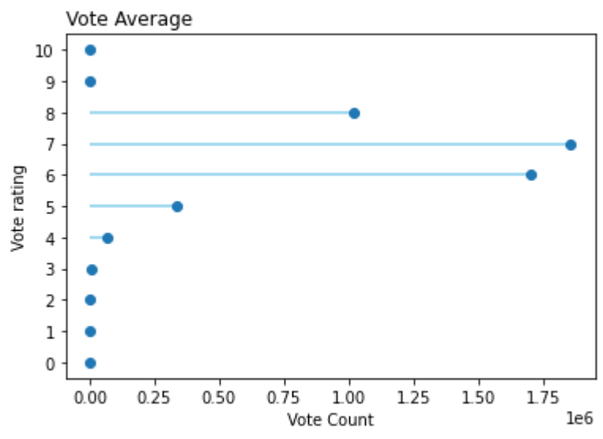
8 rows × 2 columns

Take a look at the distribution of vote average

```
def show_lolipop_graph(values,value_name,labels,label_name,colr,title):
  import seaborn as sns
  my_range=range(1,len(labels)+1)
  plt.hlines(y=my_range, xmin=0, xmax=values, color='skyblue')
  plt.plot(values, my_range, "o")
  # Add titles and axis names
  plt.yticks(my_range, labels)
  plt.title(title, loc='left')
  plt.xlabel(value_name)
  plt.ylabel(label_name)
```

```
df = movie_watched
import math
df.vote_average = df.vote_average.apply(round)
df.vote_average.unique()
# Reorder it following the values:
df = df.groupby(by='vote_average', as_index=False).agg({'vote_count': sum})
```

```
ordered_df = df.sort_values(by='vote_average')

show_lolipop_graph(ordered_df.vote_count, 'Vote Count', ordered_df.vote_average,
                   'Vote rating', 'skyblue', 'Vote Average')
```



We can see the higher number of voting have higher distribution from 4 - 8.

It is understandable because the people who didn't like the movie tend to ignore rating while the people who really love or hate the movie are most likely to give the feedback. So the data is valid and we can perform calculation C and m on this dataset

Let's calculate **C - Mean of vote_average**

```
C= df_movies_metadata['vote_average'].mean()
C
```

```
5.618215613382605
```

The mean rating for all the movies is about 5.5 on a scale of 10.

The next step is to determine an appropriate value for **m**, the **minimum votes** required to be listed in the chart. We will use 90th percentile as our cutoff. In other words, for a movie to feature in the charts, it must have more votes than at least **90%** of the movies in the list.

```
m= df_movies_metadata['vote_count'].quantile(0.98)
m
```

```
1236.7999999999956
```

```
q_movies = df_movies_metadata.copy().loc[df_movies_metadata['vote_count'] >= m]
q_movies.shape
```

```
(910, 24)
```

```
def weighted_rating(x, m=m, C=C):
    v = x['vote_count']
    R = x['vote_average']
    # Calculation based on the IMDB formula
    return (v/(v+m) * R) + (m/(m+v) * C)
```

```
q_movies['score'] = q_movies.apply(weighted_rating, axis=1)
```

```
#Sort movies based on score calculated above
q_movies = q_movies.sort_values('score', ascending=False)
pd.set_option('display.max_rows', 20)
#Print the top 15 movies
q_movies[['title', 'release_date', 'vote_count',
          'vote_average', 'score']].head(10)
```

	title	release_date	vote_count	vote_average	score
314	The Shawshank Redemption	1994-09-23	8358.0	8.5	8.128529
12481	The Dark Knight	2008-07-16	12269.0	8.3	8.054414
834	The Godfather	1972-03-14	6024.0	8.5	8.009119
2843	Fight Club	1999-10-15	9678.0	8.3	7.996116
292	Pulp Fiction	1994-09-10	8670.0	8.3	7.965197
15480	Inception	2010-07-14	14075.0	8.1	7.899536
351	Forrest Gump	1994-07-06	8147.0	8.2	7.859717
22878	Interstellar	2014-11-05	11187.0	8.1	7.852936
7000	The Lord of the Rings: The Return of the King	2003-12-01	8226.0	8.1	7.775628
1154	The Empire Strikes Back	1980-05-17	5998.0	8.2	7.758640

From the result it makes sense because the movie having high review and more watched times will make to top 10. But let's take a look at the release_date. It looks like the older movies have higher chance to be in this list.

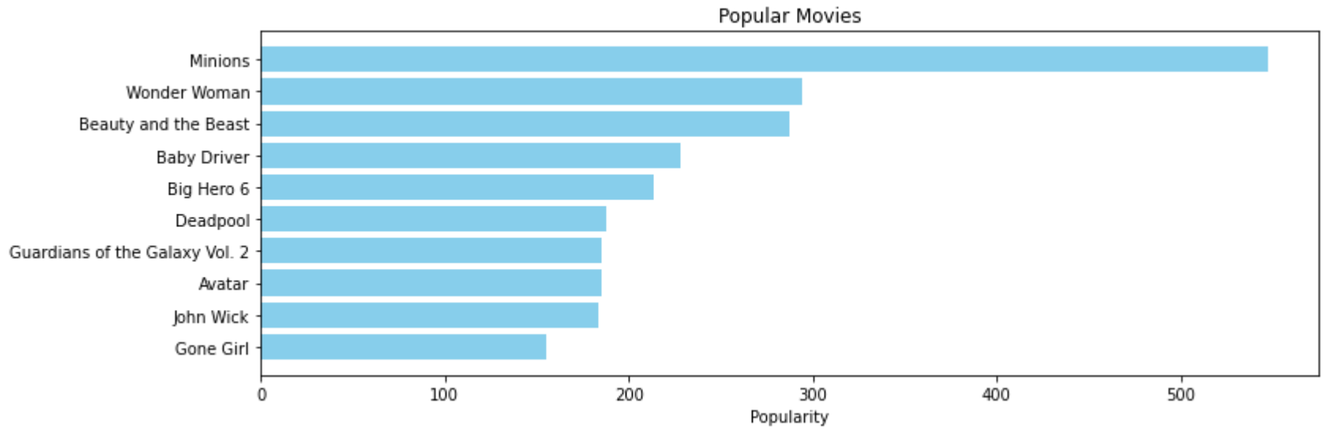
The most popular movies

In the dataset we can find the **popularity** - A numeric quantity specifying the movie popularity. Let's see what are the most popular movies based on this value

```
df_movies_metadata.popularity = df_movies_metadata.popularity.apply(float)
pop= df_movies_metadata.sort_values('popularity', ascending=False)
import matplotlib.pyplot as plt
plt.figure(figsize=(12,4))

plt.barh(pop['title'].head(10),pop['popularity'].head(10), align='center'
```

```
plt.barh(pop['title'].head(10),pop['popularity'].head(10), align='center',
        color='skyblue')
plt.gca().invert_yaxis()
plt.xlabel("Popularity")
plt.title("Popular Movies")
```

```
Text(0.5, 1.0, 'Popular Movies')
```




```
pop[['title', 'release_date', 'vote_count', 'vote_average','popularity']].head(10)
```

	title	release_date	vote_count	vote_average	popularity
30699	Minions	2015-06-17	4729.0	6.4	547.488298
33355	Wonder Woman	2017-05-30	5025.0	7.2	294.337037
42221	Beauty and the Beast	2017-03-16	5530.0	6.8	287.253654
43643	Baby Driver	2017-06-28	2083.0	7.2	228.032744
24454	Big Hero 6	2014-10-24	6289.0	7.8	213.849907
26563	Deadpool	2016-02-09	11444.0	7.4	187.860492
26565	Guardians of the Galaxy Vol. 2	2017-04-19	4858.0	7.6	185.330992
14551	Avatar	2009-12-10	12114.0	7.2	185.070892
24350	John Wick	2014-10-22	5499.0	7.0	183.870374
23674	Gone Girl	2014-10-01	6023.0	7.9	154.801009

If we look at this, the date show that these movies are more recent and it has high number of vote_count and vote_average too (higher than mean). **So question is the Demographic Filtering is good enough?**

Part 2: Recommend similar movies

What are similar movies?

The movies have the similar attributes such as: genres, directors, production companies, the main characters, ..etc and especially the contents

Data Resource

Movie metadata from imdb dataset Credits dataset

What is Content-based Filtering?

Content-based filtering (CBF) is an outgrowth and continuation of information filtering research. The objects of interest are defined by their associated features in a CBF system. For instance, like the newsgroup filtering system, a text recommendation system, uses the words of their texts as features. Based on the features present in objects that the user has rated, a content-based recommender learns a profile of the user"s interests which is called as “item-to-item correlation” and it derives the type of user profile depending on the learning method employed.

Solution

We are going to apply the technique Content-based filtering on different features of the system

Movies' description - Plot description based Recommender

Let's find the similar movie based on their description/overview

```
df_movies_metadata['overview'].head(5)
```

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

We are going to perform text processing by converting the word vector of each overview - computing TF-IDT vectors

TF-IDF (term frequency-inverse document frequency) is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. This is done by multiplying two metrics:

- How many times a word appears in a document
- The inverse document frequency of the word across a set of documents.

```
#Import TfIdfVectorizer from scikit-learn
from sklearn.feature_extraction.text import TfidfVectorizer

#Define a TF-IDF Vectorizer Object. Remove all english stop words such as 'the', 'a'
tfidf = TfidfVectorizer(stop_words='english')

#Replace NaN with an empty string
df_movies_metadata['overview'] = df_movies_metadata['overview'].fillna('')

#Construct the required TF-IDF matrix by fitting and transforming the data
```

```
tfidf_matrix = tfidf.fit_transform(df_movies_metadata['overview'])

#Output the shape of tfidf_matrix
tfidf_matrix.shape
```

```
(45461, 75828)
```

Cosine Similarity

We see that there are also **76,000** different words were used to describe more than **45000** movies in our dataset.

We will be using the **cosine similarity** to calculate a numeric quantity that denotes the similarity between two movies. We use the cosine similarity score since it is independent of magnitude and is relatively easy and fast to calculate. Mathematically, it is defined as follows:

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

```
from sklearn.metrics.pairwise import linear_kernel

# Compute the cosine similarity matrix
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

We are going to define a function that takes in a movie title as an input and outputs a list of the 10 most similar movies.

Firstly, for this, we need a reverse mapping of movie titles and DataFrame indices. In other words, we need a mechanism to identify the index of a movie in our metadata DataFrame, given its title.

```
#Construct a reverse map of indices and movie titles
indices = pd.Series(df_movies_metadata.index, index=df_movies_metadata['title']).drop_duplicates()
```

We are now in a good position to define our recommendation function. These are the following steps we'll follow :-

Get the index of the movie given its title. Get the list of cosine similarity scores for that particular movie with all movies. Convert it into a list of tuples where the first element is its position and the second is the similarity score. Sort the aforementioned list of tuples based on the similarity scores; that is, the second element. Get the top 10 elements of this list. Ignore the first element as it refers to self (the movie most similar to a particular movie is the movie itself). Return the titles corresponding to the indices of the top elements.

```
# Function that takes in movie title as input and outputs most similar movies
def get_recommendations(title, cosine_sim=cosine_sim):
    # Get the index of the movie that matches the title
    idx = indices[title]

    # Get the pairwsie similarity scores of all movies with that movie
    sim_scores = list(enumerate(cosine_sim[idx]))

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

    # Get the scores of the 10 most similar movies
    sim_scores = sim_scores[1:11]

    # Get the movie indices
    movie_indices = [i[0] for i in sim_scores]

    # Return the top 10 most similar movies
    return df_movies_metadata['title'].iloc[movie_indices]
```

```
get_recommendations('Skyfall')
```

```
7333         Never Say Never Again
44631                Atomic Blonde
2441        Children of the Damned
43273                   London Spy
36257                      Grimsby
7415     Tinker Tailor Soldier Spy
2833                        Dr. No
18395                      Haywire
30760                      Spectre
34071                The Diplomat
Name: title, dtype: object
```

The results show all James Bond movies that makes the function quite impressive. But we should have gotten some similar movie that has Daniel Craig in it also. Let's try to add more features into the recommend system.

Credits, Genres and Keywords Based Recommender

Let's add more features to see if the result of the similar movies will be better or not

```
df_credit = pd.read_csv("credits.csv")
df_keyword = pd.read_csv("keywords.csv")
df_movie = df_movies_metadata
df_movie['id'] = df_movie['id'].astype('int')
df_movie = df_movie.merge(df_credit, on='id')
df_movie = df_movie.merge(df_keyword, on='id')
df_movie.head(3)
```

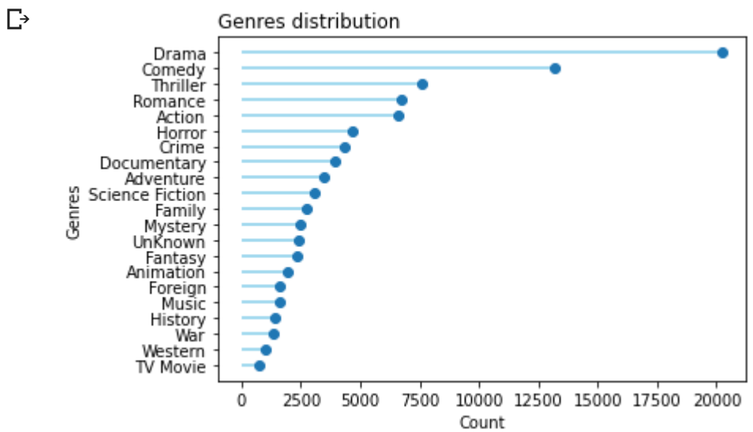
	adult	belongs_to_collection	budget	genres	homepage	id	imdb_id	original_language	original_title	overview	popularity	poster_path	produ
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	http://toystory.disney.com/toy-story	862	tt0114709	en	Toy Story	Led by Woody, Andy's toys live happily in his ...	21.946943	/rhIRbceoE9lR4veEXuwCC2wARtG.jpg	Anim
1	False	NaN	65000000	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	NaN	8844	tt0113497	en	Jumanji	When siblings Judy and Peter discover an encha...	17.015539	/vzmL6fP7aPKNKPRTFnZmiUfciyV.jpg	
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[{'id': 10749, 'name': 'Romance'}, {'id': 35, ...	NaN	15602	tt0113228	en	Grumpier Old Men	A family wedding reignites the ancient feud be...	11.712900	/6ksm1sjKMFLbO7UY2i6G1ju9SML.jpg	[{'nam 'ic

Genres

```
def get_name(g_jason):
  return str(g_jason['name'])

def breaking_value(df, feature):
  from ast import literal_eval
  df[feature] = df[feature].apply(literal_eval)
  df = df.explode(feature)
  df[feature] = df[feature].apply(get_name)
  return df

df_genres = df_movie[['id','title','genres']]
unknown_genres = "[{'id': 0, 'name': 'UnKnown'}]"
df_genres.loc[(df_genres.genres == '[]'),'genres'] = unknown_genres
df_genres = breaking_value(df_genres, 'genres').sort_values(by='genres')
df_genres.head(5)
```

	id	title	genres
40137	102961	Seven	Action
18114	85365	Tony Arzenta	Action
18122	58878	Three Outlaw Samurai	Action
18125	39254	Real Steel	Action
18151	133123	The Last Days of Pompeii	Action

```
df = df_genres
df = df.groupby(by='genres', as_index=False).agg({'id': pd.Series.nunique})
# Reorder it following the values:
ordered_df = df.sort_values(by='id')

show_lolipop_graph(ordered_df.id, 'Count', ordered_df.genres, 'Genres',
                   'skyblue', 'Genres distribution')
```



We can see that the drama movie has the most watched count

Credits and Keywords

From credits we going the break the **cast**, **keywords** and **crew** data

General Methods

```
for key in ['cast', 'crew', 'keywords', 'genres']:
    df_movie[key] = df_movie[key].apply(literal_eval)
```

```
def get_director(x):
    for i in x:
        if i['job'] == 'Director':
            return i['name']
    return ''

def get_list(x):
    if isinstance(x, list):
        names = [i['name'] for i in x]
        if len(names) > 3: names = names[:3]
        return names
    return []

df_movie['director'] = df_movie['crew'].apply(get_director)
for col in ['cast', 'keywords', 'genres']:
    df_movie[col] = df_movie[col].apply(get_list)
```

```
def word_set(df,ref_col):
  w_set = set()
  for i, row in df.iterrows():
    keys = df[ref_col][i]
    for key in keys:
        w_set.add(key)
  return w_set

def count_word(df, ref_col):
    w_set = word_set(df,ref_col)
    keyword_count = dict()
    for s in w_set: keyword_count[s] = 0
    for i,row in df.iterrows():
      keys = df[ref_col][i]
      for key in keys:
            keyword_count[key] += 1
    #_____________________________________________________________________
    # convert the dictionary in a list to sort the keywords by frequency
    keyword_occurences = []
    for k,v in keyword_count.items():
        keyword_occurences.append([k,v])
    keyword_occurences.sort(key = lambda x:x[1], reverse = True)
    return keyword_occurences
```

```
def random_color_func(word=None, font_size=None, position=None,
                      orientation=None, font_path=None, random_state=None):
    h = int(360.0 * tone / 255.0)
    s = int(100.0 * 255.0 / 255.0)
    l = int(100.0 * float(random_state.randint(70, 120)) / 255.0)
    return "hsl({}, {}%, {}%)".format(h, s, l)
def show_population(keyword_occurences, type_pt):
  words = dict()
  trunc_occurences = keyword_occurences[0:50]
  for s in trunc_occurences:
```

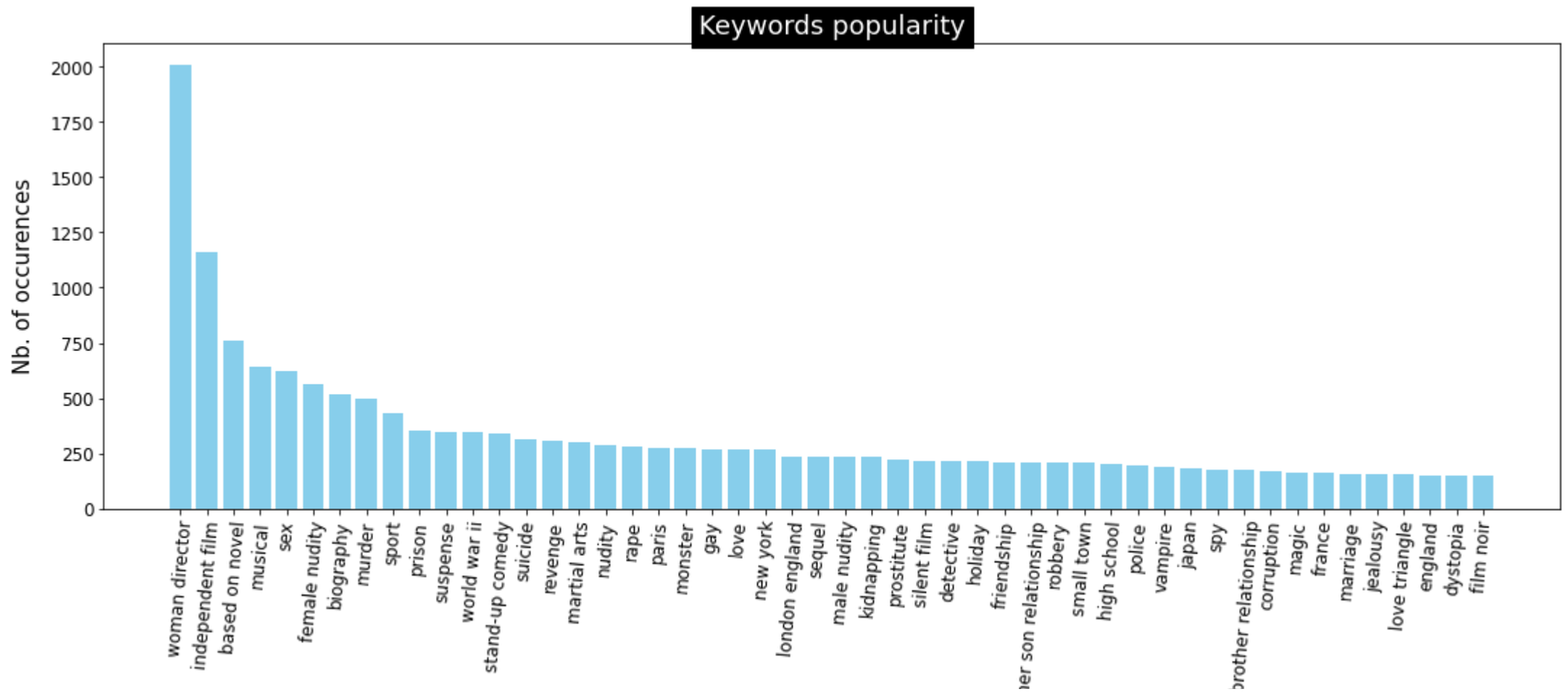
```
    words[s[0]] = s[1]
tone = 55.0 # define the color of the words
#WORDCLOUD
if type_pt == 'WC':
  fig = plt.figure(1, figsize=(18,13))
  ax1 = fig.add_subplot(2,1,1)
  from wordcloud import WordCloud, STOPWORDS
  wordcloud = WordCloud(width=1000,height=300, background_color='black',
                        max_words=1628,relative_scaling=1,
                        # color_func = random_color_func,
                        colormap="Blues",
                        normalize_plurals=False)
  wordcloud.generate_from_frequencies(words)
  ax1.imshow(wordcloud, interpolation="bilinear")
  ax1.axis('off')
if type_pt == 'HG':
  #HISTOGRAMS
  fig = plt.figure(1, figsize=(18,13))
  ax2 = fig.add_subplot(2,1,2)
  y_axis = [i[1] for i in trunc_occurences]
  x_axis = [k for k,i in enumerate(trunc_occurences)]
  x_label = [i[0] for i in trunc_occurences]
  plt.xticks(rotation=85, fontsize = 12)
  plt.yticks(fontsize = 12)
  plt.xticks(x_axis, x_label)
  plt.ylabel("Nb. of occurences", fontsize = 15, labelpad = 10)
  ax2.bar(x_axis, y_axis, align = 'center', color='skyblue')
  #_________________________
  plt.title("Keywords popularity",bbox={'facecolor':'k', 'pad':5},
            color='w',fontsize = 18)
  plt.show()
```

```
keywords = count_word(df_movie, 'keywords')
```

Ploting some graphs

```
show_population(keywords, 'WC')
```

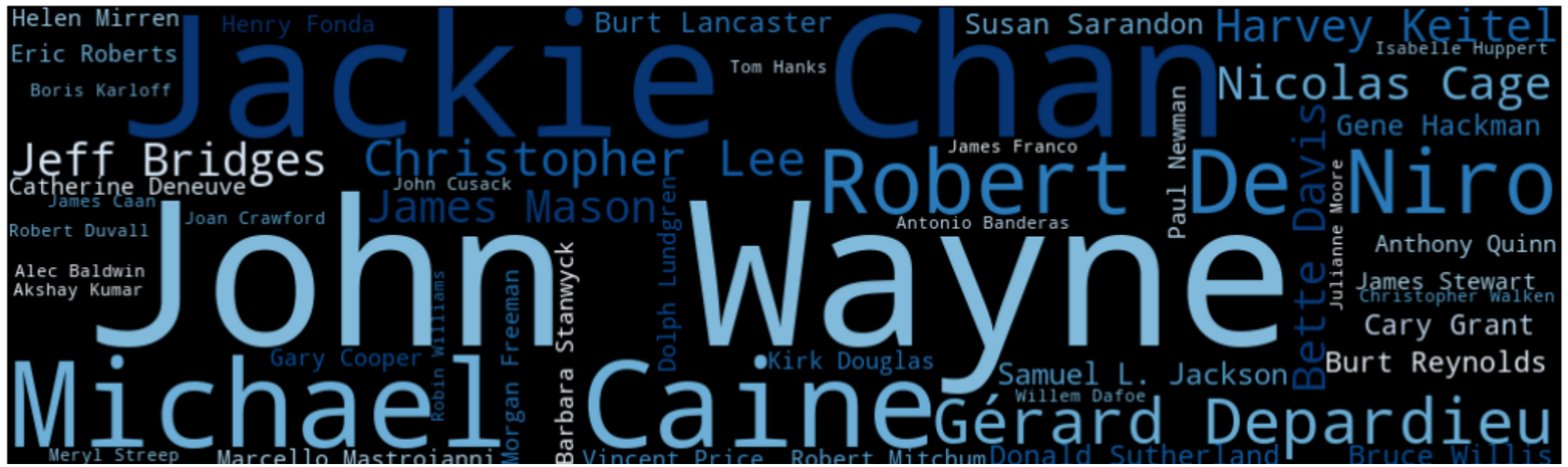

```
show_population(keywords, 'HG')
```




```
cast[:5]
```

```
[['John Wayne', 106],
 ['Jackie Chan', 89],
 ['Michael Caine', 86],
 ['Robert De Niro', 86],
 ['Gérard Depardieu', 84]]
```

```
cast = count_word(df_movie, 'cast')
show_population(cast, 'WC')
```



We can see that John Wayne has higher population than Christopher even though in record Christopher Lee participate in more movie than John Wayne. This happens because we only get top 3 main characters from a movies for the model.

Clean Data

```
df_movie[['title', 'cast', 'director', 'keywords', 'genres']]
```

	title	cast	director	keywords	genres
0	Toy Story	[Tom Hanks, Tim Allen, Don Rickles]	John Lasseter	[jealousy, toy, boy]	[Animation, Comedy, Family]
1	Jumanji	[Robin Williams, Jonathan Hyde, Kirsten Dunst]	Joe Johnston	[board game, disappearance, based on children'...	[Adventure, Fantasy, Family]
2	Grumpier Old Men	[Walter Matthau, Jack Lemmon, Ann-Margret]	Howard Deutch	[fishing, best friend, duringcreditsstinger]	[Romance, Comedy]
3	Waiting to Exhale	[Whitney Houston, Angela Bassett, Loretta Devine]	Forest Whitaker	[based on novel, interracial relationship, sin...	[Comedy, Drama, Romance]
4	Father of the Bride Part II	[Steve Martin, Diane Keaton, Martin Short]	Charles Shyer	[baby, midlife crisis, confidence]	[Comedy]
...	...	...	...	...	...
46620	Subdue	[Leila Hatami, Kourosh Tahami, Elham Korda]	Hamid Nematollah	[tragic love]	[Drama, Family]
46621	Century of Birthing	[Angel Aquino, Perry Dizon, Hazel Orencio]	Lav Diaz	[artist, play, pinoy]	[Drama]
46622	Betrayal	[Erika Eleniak, Adam Baldwin, Julie du Page]	Mark L. Lester	[]	[Action, Drama, Thriller]
46623	Satan Triumphant	[Iwan Mosschuchin, Nathalie Lissenko, Pavel Pa...	Yakov Protazanov	[]	[]
46624	Queerama	[]	Daisy Asquith	[]	[]

46625 rows × 5 columns

We are going to remove all space, lowercase all characters

```
def clean_data(x):
    if isinstance(x, list):
        return [str.lower(i.replace(" ", "")) for i in x]
    return str.lower(x.replace(" ", ""))

for col in ['cast', 'keywords', 'director', 'genres']:
    df_movie[col] = df_movie[col].apply(clean_data)
```

Create "metadata soup", which is a string that contains all the metadata that we want to feed to our vectorizer (namely actors, director and keywords).

The next steps are the same as what we did with our plot description based recommender. One important difference is that we use the CountVectorizer() to convert a collection of text documents to a matrix of token counts instead of TF-IDF.

This is because we do not want to down-weight the presence of an actor/director if he or she has acted or directed in relatively more movies. It

```
def create_soup(x):
    soup = ""
    if len(x['keywords']) > 0:
      soup += ' '.join(x['keywords']) + ' '
    if len(x['cast']) > 0:
      soup += ' '.join(x['cast']) + ' '
    soup += x['director'] + ' '
    if len(x['genres']) > 0:
      soup += ' '.join(x['genres'])
    return soup
# Import CountVectorizer and create the count matrix
from sklearn.feature_extraction.text import CountVectorizer

df_movie['soup'] = df_movie.apply(create_soup, axis=1)
count_matrix = CountVectorizer(stop_words='english').fit_transform(df_movie['soup'])
count_matrix.shape
```

```
(46625, 73879)
```

Get similar movies

Because of the memory capicity, we are going to compute the Cosine Similarity for a movie by getting the movie vector and calculate cosine against other movies

```
df_movie = df_movie.reset_index()
indices = pd.Series(df_movie.index, index=df_movie['title'])
```

```
from sklearn.metrics.pairwise import cosine_similarity
def _top_similar_movie(m_name, df, sim_matrix):
    idx = df[df.title == m_name].index[0]
    sim_scores = cosine_similarity(sim_matrix[idx], sim_matrix)[0]
    movie_indices = sorted(range(len(sim_scores)), key=lambda i: sim_scores[i],
                           reverse=True)[:11]
    if idx not in movie_indices:
        movie_indices.append(idx)
    top10 = df.iloc[movie_indices]
    for index, row in top10.iterrows():
        print(row.title)
    return top10
def get_top10_similar_movies(m_name):
  _top_similar_movie(m_name, df_movie, sim_matrix=count_matrix)
```

```
get_top10_similar_movies('Skyfall')
```

```
Skyfall
Spectre
Quantum of Solace
Behind Enemy Lines
Evil Behind You
The Venetian Affair
Triple Cross
Arabesque
Mission: Impossible
Tomorrow Never Dies
Never Say Never Again
```

We see that our recommender has been successful in capturing more information due to more metadata and has given us (arguably) better recommendations.

It is more likely that Action movie fans will like the movies of the same production house. Therefore, to our features above we can add production_company . We can also increase the weight of the director , by adding the feature multiple times in the soup.

Part 3: Recommendation movies for an user

What movies which an user will like?

The movies have the similar attributes to the movie the user watched and liked before The movies that someone like who has similar movie ratings record to the user

Data Resource

Rating dataset: contains 100,000 ratings from 700 users on 9,000 movies

What is Collaborative Filtering?

Collaborative filtering (CF) systems and computer-based recommendation are often related with the origin of the system called Tapestry. In Tapestry, with arbitrary text comments users were able to annotate documents and other users based on the comments of other users could then query. One of the main attributes of this system is that it allowed recommendations to be generated based on a combination of ideas of the input from many other users. Rather than

Solution

User based filtering- These systems recommend products to a user that similar users have liked. For measuring the similarity between two users we can either use pearson correlation or cosine similarity.

Item Based Collaborative Filtering - Instead of measuring the similarity between users, the item-based CF recommends items based on their similarity with the items that the target user rated. Likewise, the similarity can be computed with Pearson Correlation or Cosine Similarity. The major difference is that, with item-based collaborative filtering, we fill in the blank vertically, as oppose to the horizontal manner that user-based CF does. This method faces an issue of scalability when there are large number of users and items

Single Value Decomposition One way to handle the scalability and sparsity issue created by CF is to leverage a latent factor model to capture the similarity between users and items. Essentially, we want to turn the recommendation problem into an optimization problem. We can view it

as how good we are in predicting the rating for items given a user. One common metric is Root Mean Square Error (RMSE). The lower the RMSE, the better the performance.

```
#!pip install scikit-surprise
```

Load data

```
from surprise import Reader, Dataset, SVD
reader = Reader()
df_ratings = pd.read_csv('ratings_small.csv')
df_ratings.head(5)
```

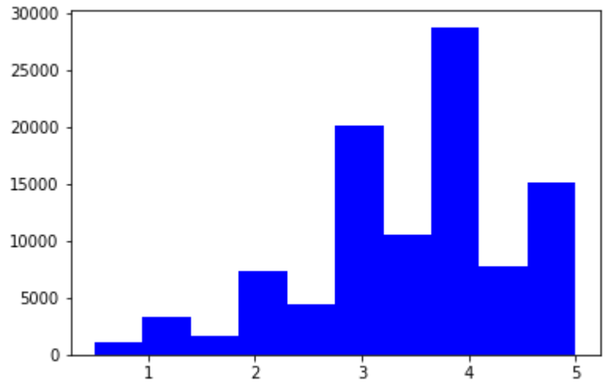
	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

```
df_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100004 entries, 0 to 100003
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   userId     100004 non-null  int64  
 1   movieId    100004 non-null  int64  
 2   rating     100004 non-null  float64
 3   timestamp  100004 non-null  int64  
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
```

There is no null data in this dataset. Let's take a look at the distribution.

```
ax = plt.hist(df_ratings.rating, color='blue')
```



Double-click (or enter) to edit

SVD training model

Here are the average RMSE, MAE and total execution time of various algorithms (with their default parameters) on a 5-fold cross-validation procedure. The datasets are the Movielens 100k and 1M datasets. The folds are the same for all the algorithms. All experiments are run on a notebook with Intel Core i5 7th gen (2.5 GHz) and 8G. The code for generating these tables can be found in the benchmark example.

Movielens 100k	RMSE	MAE	Time
SVD	0.934	0.737	0:00:11
SVD++	0.92	0.722	0:09:03
NMF	0.963	0.758	0:00:15
Slope One	0.946	0.743	0:00:08
k-NN	0.98	0.774	0:00:10
Centered k-NN	0.951	0.749	0:00:10
k-NN Baseline	0.931	0.733	0:00:12
Co-Clustering	0.963	0.753	0:00:03
Baseline	0.944	0.748	0:00:01
Random	1.514	1.215	0:00:01

So we choose SVD for our API

```
from surprise.model_selection import cross_validate
data = Dataset.load_from_df(df_ratings[['userId', 'movieId', 'rating']], reader)
svd = SVD()
cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
trainset = data.build_full_trainset()
svd.fit(trainset)
```

```
testset = trainset.build_anti_testset()
predictions = svd.test(testset)
```

```
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8987  0.8939  0.9001  0.9005  0.8910  0.8969  0.0038
MAE (testset)     0.6881  0.6903  0.6921  0.6919  0.6882  0.6901  0.0017
Fit time          4.88    4.94    4.95    4.95    4.93    4.93    0.03
Test time         0.75    0.15    0.15    0.15    0.15    0.27    0.24
```

Generate the top 10 recommendation movies for an user

```
from collections import defaultdict
def get_top_n(predictions, n=20):
    top_n = defaultdict(list)
    for uid, iid, true_r, est, _ in predictions:
        top_n[uid].append((iid, est))

    # Then sort the predictions for each user and retrieve the k highest ones.
    for uid, user_ratings in top_n.items():
        user_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[uid] = user_ratings[:n]

    return top_n

top10_svd = get_top_n(predictions)

def _top10_recommend(user_id, df):
    movie_indices = []
    ids = df.id.unique()
    for movie_id, rating in top10_svd[user_id]:
        # print(movie_id, rating)
        if movie_id in ids:
            movie_indices.append(df[df.id == movie_id].index[0])
    return df.iloc[movie_indices]

def top10_recommend(user_id):
    top10 = _top10_recommend(user_id, df_movie)
    return top10
```

Pick an user for example

```
#userID = 1
df=top10_recommend(1)
columns=['id', 'title']
```

```
dt[columns]
```

	id	title
952	260	The 39 Steps
534	858	Sleepless in Seattle
4047	318	The Million Dollar Hotel
11590	1259	Notes on a Scandal
2674	745	The Sixth Sense
286	527	Once Were Warriors
8399	905	Pandora's Box
34127	3578	The Tunnel
22544	5995	Miffo
3409	593	Solaris
2085	4011	Beetlejuice
3085	926	Galaxy Quest

Part 4: API and UI webapp

Recommendation System API:

VM - EC2 instance - 4cpu and 16 GB

Dockerfile:

```
FROM python:3.7

COPY ./requirements.txt /app/requirements.txt
WORKDIR /app
RUN pip install -r requirements.txt
ENTRYPOINT [ "python" ]
CMD [ "app/main.py" ]
```

http://ec2-18-222-249-229.us-east-2.compute.amazonaws.com:5000/

UI Webapp:

Dockerfile:

```
# base image
FROM node:12.2.0-alpine
```

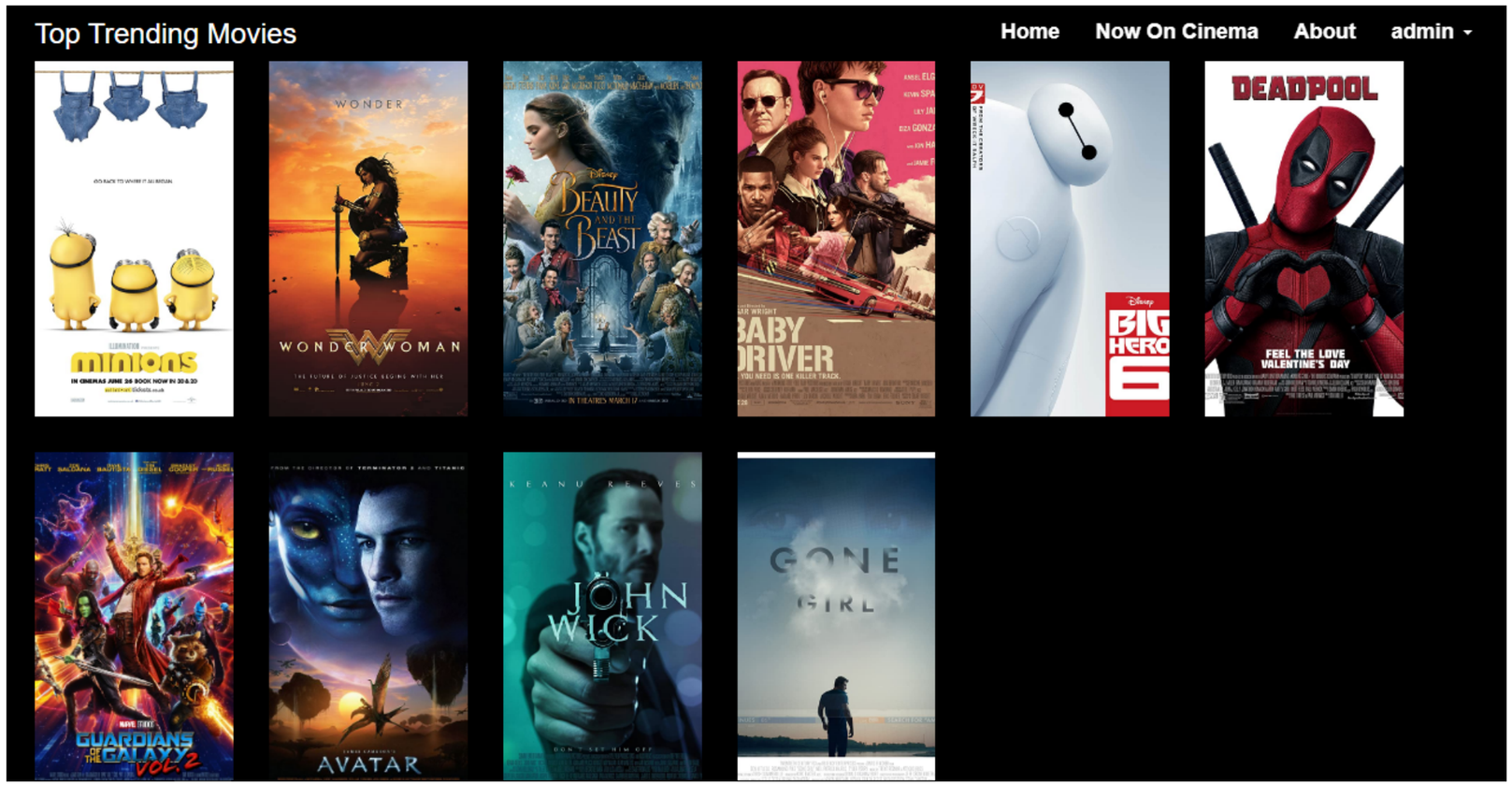
```
# set working directory
WORKDIR /app

# add `/app/node_modules/.bin` to $PATH
ENV PATH /app/node_modules/.bin:$PATH

# install and cache app dependencies
COPY package.json /app/package.json
RUN npm install
RUN npm install @vue/cli@3.7.0 -g

# start app
CMD ["npm", "run", "serve"]
```

http://ec2-18-222-249-229.us-east-2.compute.amazonaws.com:8081/

Code:

https://github.com/votamvan/Movie-Recommendation

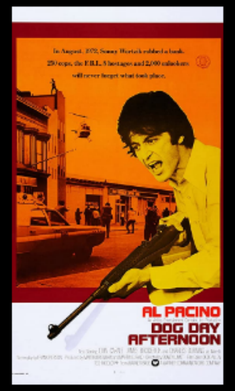
- Top Trending Movies - based on popularity



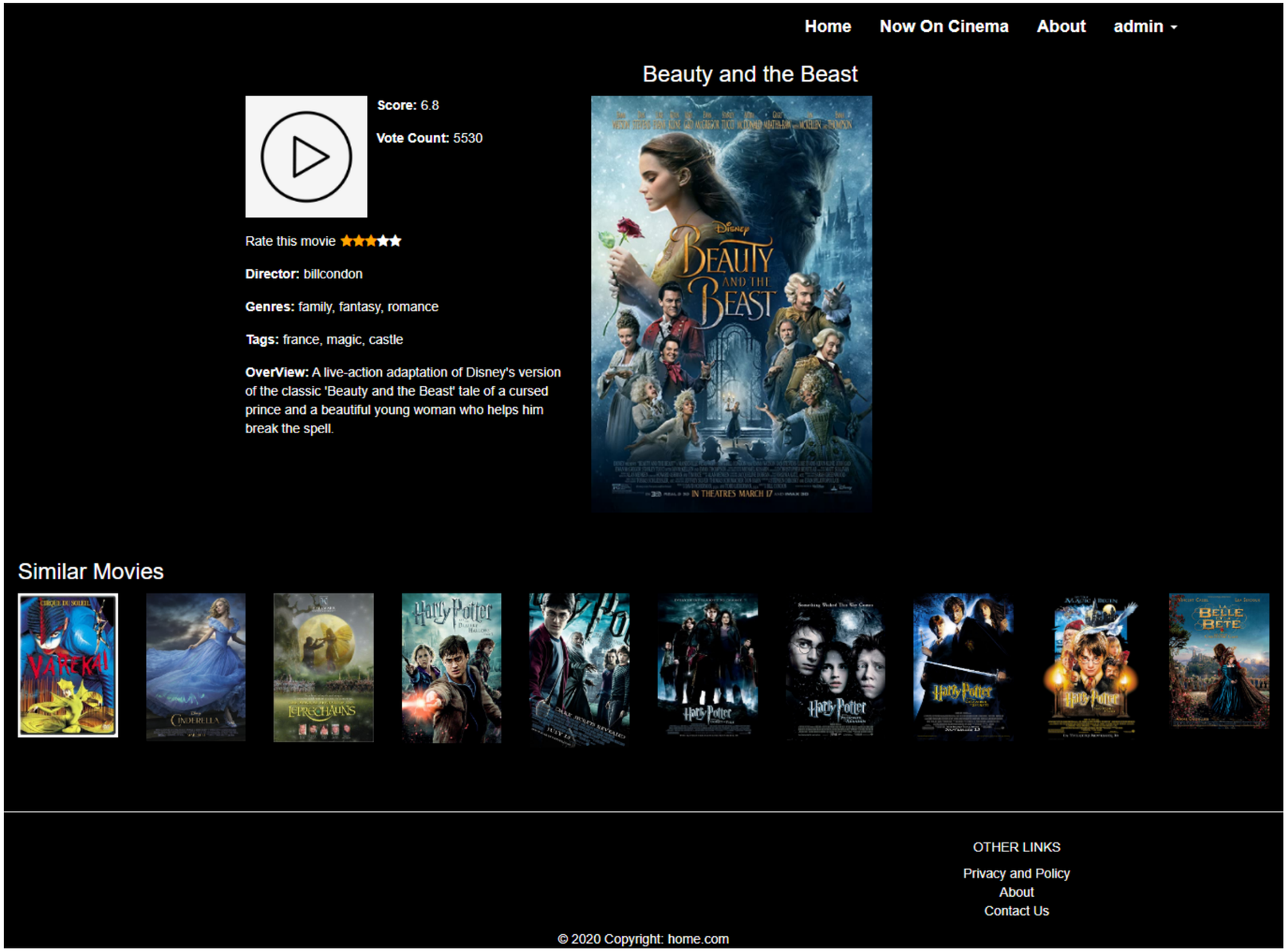
- Top recommendations for an user - ID **44**

Top Recommendations For You

Home Now On Cinema About admin



Recommend similar movies



Calling to API through Notebook

```
import requests

BASE_URL = "http://ec2-18-222-249-229.us-east-2.compute.amazonaws.com:5000/api/v0/"
TOP_TREND_URL = BASE_URL + "toptrending/us"
```

```
r = requests.post(TOP_TREND_URL)
r.json()
```

```
{'data': [{'director': 'kylebalda',
   'genres': ['family', 'animation', 'adventure'],
   'imdb_id': 'tt2293640',
   'keywords': ['assistant', 'aftercreditsstinger', 'duringcreditsstinger'],
   'movieId': 211672,
   'overview': 'Minions Stuart, Kevin and Bob are recruited by Scarlet Overkill, a super-villain who, alongside her inventor husband Herb, hatches a plot to take over the world.',
   'score': 6.4,
   'title': 'Minions',
   'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt2293640.jpg',
   'vote_average': 6.4,
   'vote_count': 4729.0},
  {'director': 'pattyjenkins',
   'genres': ['action', 'adventure', 'fantasy'],
   'imdb_id': 'tt0451279',
   'keywords': ['dccomics', 'hero', 'greekmythology'],
   'movieId': 297762,
   'overview': 'An Amazon princess comes to the world of Man to become the greatest of the female superheroes.',
   'score': 7.2,
   'title': 'Wonder Woman',
   'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt0451279.jpg',
   'vote_average': 7.2,
   'vote_count': 5025.0},
  {'director': 'billcondon',
   'genres': ['family', 'fantasy', 'romance'],
   'imdb_id': 'tt2771200',
   'keywords': ['france', 'magic', 'castle'],
   'movieId': 321612,
   'overview': "A live-action adaptation of Disney's version of the classic 'Beauty and the Beast' tale of a cursed prince and a beautiful young woman who helps him break the spell.",
   'score': 6.8,
   'title': 'Beauty and the Beast',
   'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt2771200.jpg',
   'vote_average': 6.8,
   'vote_count': 5530.0},
  {'director': 'edgarwright',
   'genres': ['action', 'crime'],
   'imdb_id': 'tt3890160',
   'keywords': ['robbery', 'atlanta', 'music'],
   'movieId': 339403,
   'overview': 'After being coerced into working for a crime boss, a young getaway driver finds himself taking part in a heist doomed to fail.',
   'score': 7.1,
   'title': 'Baby Driver',
   'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt3890160.jpg',
   'vote_average': 7.2,
   'vote_count': 2083.0},
  {'director': 'chriswilliams',
   'genres': ['adventure', 'family', 'animation'],
   'imdb_id': 'tt2245084',
   'keywords': ['brotherbrotherrelationship', 'hero', 'talent'],
   'movieId': 177572,
   'overview': 'The special bond that develops between plus-sized inflatable robot Baymax, and prodigy Hiro Hamada, who team up with a group of friends to form a band of high-tech heroes.',
   'score': 7.7,
   'title': 'Big Hero 6',
   'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt2245084.jpg',
   'vote_average': 7.8,
   'vote_count': 6289.0},
  {'director': 'timmiller',
   'genres': ['action', 'adventure', 'comedy'],
```

```
 'imdb_id': 'tt1431045',
 'keywords': ['antihero', 'mercenary', 'marvelcomic'],
 'movieId': 293660,
 'overview': 'Deadpool tells the origin story of former Special Forces operative turned mercenary Wade Wilson, who after being subjected to a rogue experiment that leaves him with accelerated
 'score': 7.4,
 'title': 'Deadpool',
 'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt1431045.jpg',
 'vote_average': 7.4,
 'vote_count': 11444.0},
{'director': 'jamesgunn',
 'genres': ['action', 'adventure', 'comedy'],
 'imdb_id': 'tt3896198',
 'keywords': ['sequel', 'superhero', 'basedoncomic'],
 'movieId': 283995,
 'overview': "The Guardians must fight to keep their newfound family together as they unravel the mysteries of Peter Quill's true parentage.",
 'score': 7.5,
 'title': 'Guardians of the Galaxy Vol. 2',
 'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt3896198.jpg',
 'vote_average': 7.6,
 'vote_count': 4858.0},
{'director': 'jamescameron',
 'genres': ['action', 'adventure', 'fantasy'],
 'imdb_id': 'tt0499549',
 'keywords': ['cultureclash', 'future', 'spacewar'],
 'movieId': 19995,
 'overview': 'In the 22nd century, a paraplegic Marine is dispatched to the moon Pandora on a unique mission, but becomes torn between following orders and protecting an alien civilization.',
 'score': 7.2,
 'title': 'Avatar',
 'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt0499549.jpg',
 'vote_average': 7.2,
 'vote_count': 12114.0},
{'director': 'chadstahelski',
 'genres': ['action', 'thriller'],
 'imdb_id': 'tt2911666',
 'keywords': ['hitman', 'russianmafia', 'revenge'],
 'movieId': 245891,
 'overview': 'Ex-lunatic John Wick comes off his meds to track down the bounders that killed his dog and made off with his self-respect',
 'score': 7.0,
 'title': 'John Wick',
 'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt2911666.jpg',
 'vote_average': 7.0,
 'vote_count': 5499.0},
{'director': 'davidfincher',
 'genres': ['mystery', 'thriller', 'drama'],
 'imdb_id': 'tt2267998',
 'keywords': ['basedonnovel', 'marriagecrisis', 'disappearance'],
 'movieId': 210577,
 'overview': "With his wife's disappearance having become the focus of an intense media circus, a man sees the spotlight turned on him when it's suspected that he may not be innocent.",
 'score': 7.8,
 'title': 'Gone Girl',
 'url': 'https://raw.githubusercontent.com/votamvan/Movie-Recommendation/master/movie-posters/tt2267998.jpg',
 'vote_average': 7.9,
 'vote_count': 6023.0}],
'status': 'success'}
```

Part 5: AUTOML (NCF)

Research:

https://towardsdatascience.com/neural-collaborative-filtering-96cef1009401

Tried running demo:

https://github.com/hexiangnan/neural_collaborative_filtering

Experiment with MovieLens 1M Dataset, it tooks 4-5 hours to train on local CPU machine. If we have GPU machine, the training time may be reduced.

Although, the accuracy of NCF model is a little bit better than SVD algorithm. However, we choose SVD to be implemented as our API recommendation engine.

We have to trade off between fast API responses and the movie prediction performance. SVD is the best selection for industry business.

Output log file:

https://github.com/votamvan/Movie-Recommendation/blob/master/auto-ncf-log.txt

```
GMF arguments: Namespace(batch_size=256, dataset='ml-1m', epochs=20, learner='adam', lr=0.001, num_factors=8, num_neg=4, out=1, path='Data/', regs
Load data done [28.0 s]. #user=6040, #item=3706, #train=994169, #test=6040
Init: HR = 0.0962, NDCG = 0.0434     [12.4 s]
.
.
.
End. Best Iteration 16:  HR = 0.6361, NDCG = 0.3647.

MLP arguments: Namespace(batch_size=256, dataset='ml-1m', epochs=20, layers='[64,32,16,8]', learner='adam', lr=0.001, num_neg=4, out=1, path='Data
Load data done [30.3 s]. #user=6040, #item=3706, #train=994169, #test=6040
Init: HR = 0.0964, NDCG = 0.0442 [17.1]
.
.
.
End. Best Iteration 14:  HR = 0.6752, NDCG = 0.3995.

NeuMF arguments: Namespace(batch_size=256, dataset='ml-1m', epochs=20, layers='[64,32,16,8]', learner='adam', lr=0.001, mf_pretrain='Pretrain/ml-1
Load data done [27.4 s]. #user=6040, #item=3706, #train=994169, #test=6040
Load pretrained GMF (Pretrain/ml-1m_GMF_8_1501651698.h5) and MLP (Pretrain/ml-1m_MLP_[64,32,16,8]_1501652038.h5) models done.
Init: HR = 0.6710, NDCG = 0.3969
.
.
.
End. Best Iteration 2:  HR = 0.6823, NDCG = 0.4034.
```