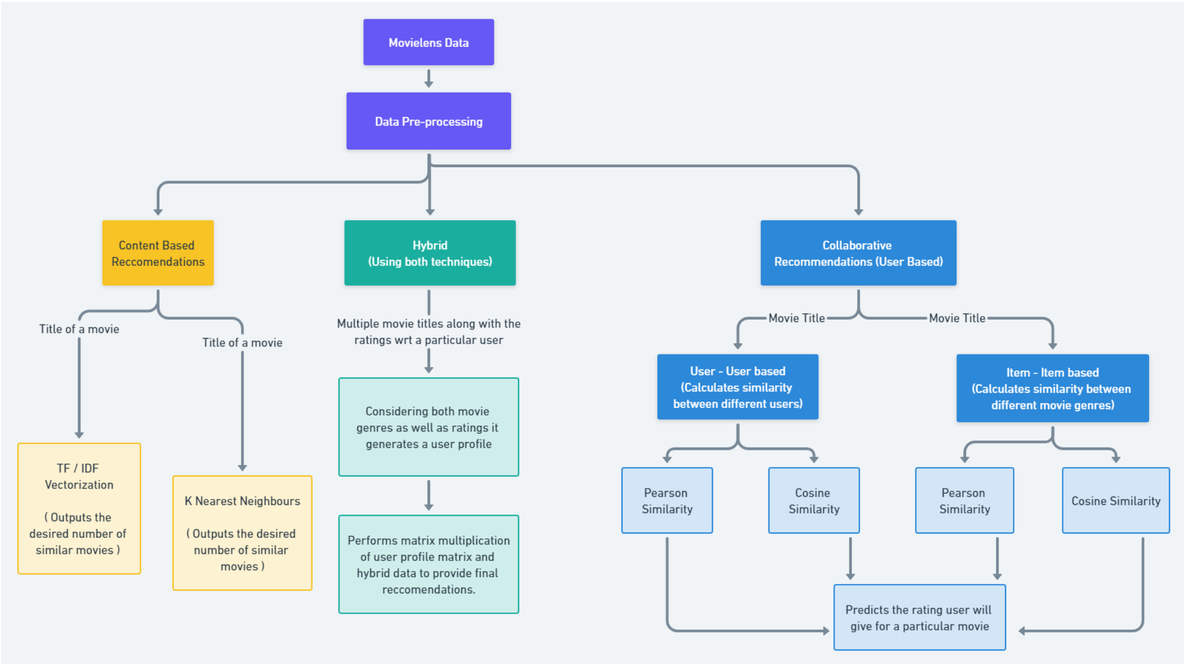
Project Overview

In [ ]:

```
from IPython.display import Image
Image(filename='/content/Project_Overview.png')
```

Out[76]:



User-User Collaborative Filtering using Nearest Neighbours

In [78]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Importing all the necessary data files.
links = pd.read_csv('/content/links.csv')
movies = pd.read_csv('/content/movies.csv')
ratings = pd.read_csv('/content/ratings.csv')
tags = pd.read_csv('/content/tags.csv')

display(links)
print()

display(movies)
print()

display(ratings)
print()

display(tags)
print()
```

	movieId	imdbId	tmdbId
0	1	114709	862.0
1	2	113497	8844.0
2	3	113228	15602.0
3	4	114885	31357.0
4	5	113041	11862.0
...	...	...	...
9737	193581	5476944	432131.0
9738	193583	5914996	445030.0
9739	193585	6397426	479308.0
9740	193587	8391976	483455.0
9741	193609	101726	37891.0

9742 rows × 3 columns

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy
...	...	...	...
9737	193581	Black Butler: Book of the Atlantic (2017)	Action|Animation|Comedy|Fantasy

	movieId	title	genres
9738	193583	No Game No Life: Zero (2017)	Animation|Comedy|Fantasy
9739	193585	Flint (2017)	Drama
9740	193587	Bungo Stray Dogs: Dead Apple (2018)	Action|Animation
9741	193609	Andrew Dice Clay: Dice Rules (1991)	Comedy

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931
...	...	...	...	...
100831	610	166534	4.0	1493848402
100832	610	168248	5.0	1493850091
100833	610	168250	5.0	1494273047
100834	610	168252	5.0	1493846352
100835	610	170875	3.0	1493846415

100836 rows × 4 columns

	userId	movieId	tag	timestamp
0	2	60756	funny	1445714994
1	2	60756	Highly quotable	1445714996
2	2	60756	will ferrell	1445714992
3	2	89774	Boxing story	1445715207
4	2	89774	MMA	1445715200
...	...	...	...	...
3678	606	7382	for katie	1171234019
3679	606	7936	austere	1173392334
3680	610	3265	gun fu	1493843984
3681	610	3265	heroic bloodshed	1493843978
3682	610	168248	Heroic Bloodshed	1493844270

3683 rows × 4 columns

In [79]:

```
# From the ratings dataset, we will create another dataset, where, for each movie,
# all the ratings given by the 610 users are displayed.
df = ratings.pivot(index='movieId',columns='userId',values='rating')
display(df)
print()

# The NaN values correspond to the users that have not rated a particular movie.
# We will replace them with zeroes to create a sparse matrix.
df = df.fillna(0)
display(df)
```

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604
movieId															
1	4.0	NaN	NaN	NaN	4.0	NaN	4.5	NaN	NaN	NaN	...	4.0	NaN	4.0	3.0
2	NaN	NaN	NaN	NaN	NaN	4.0	NaN	4.0	NaN	NaN	...	NaN	4.0	NaN	5.0
3	4.0	NaN	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	3.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN	5.0	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	3.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
193581	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
193583	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
193585	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
193587	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
193609	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN

9724 rows × 610 columns

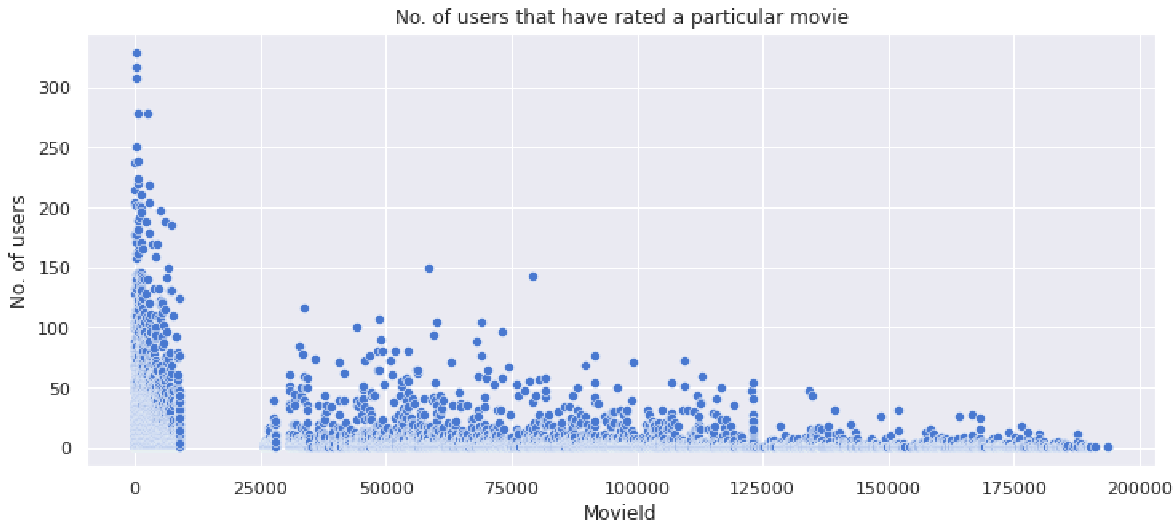
userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604	605	606
movieId																	
1	4.0	0.0	0.0	0.0	4.0	0.0	4.5	0.0	0.0	0.0	...	4.0	0.0	4.0	3.0	4.0	2.5
2	0.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0	0.0	0.0	...	0.0	4.0	0.0	5.0	3.5	0.0
3	4.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	3.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
193581	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	0.0
193583	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	0.0
193585	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	0.0
193587	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	0.0
193609	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	0.0

9724 rows × 610 columns

In [80]:

```
# This will give us the number of users who have voted for a particular movie
no_user_voted = ratings.groupby('movieId')['rating'].agg('count')

sns.set_palette("muted")
f,ax = plt.subplots(1,1,figsize=(12,5))
sns.scatterplot(no_user_voted.index,no_user_voted)
plt.xlabel('MovieId')
plt.ylabel('No. of users')
plt.title("No. of users that have rated a particular movie")
plt.show()
```

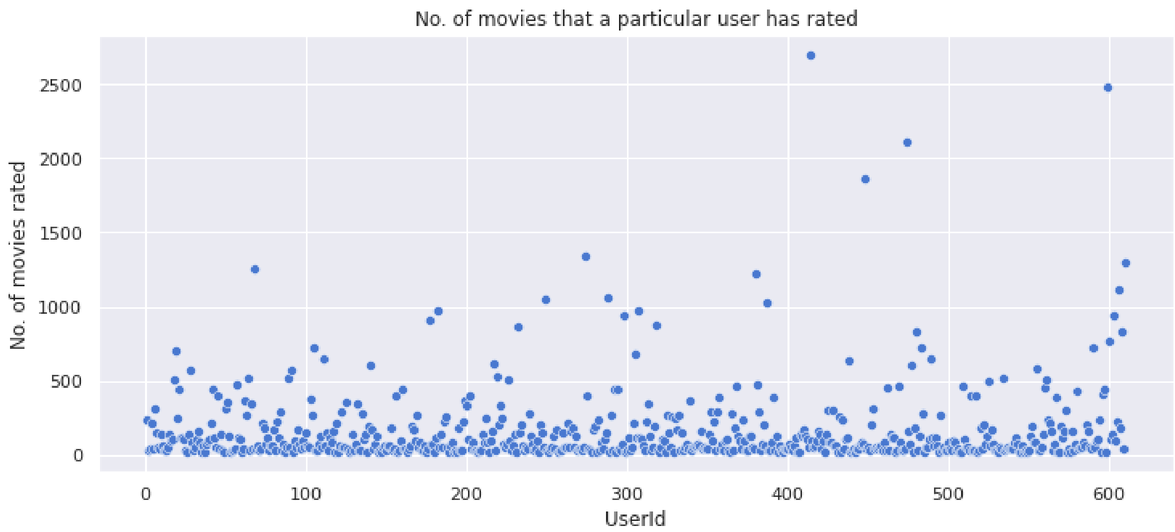
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarn
ing: Pass the following variables as keyword args: x, y. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



In [81]:

```
# This will give us the number of movies a user has rated
no_movies_voted = ratings.groupby('userId')['rating'].agg('count')

f,ax = plt.subplots(1,1,figsize=(12,5))
sns.scatterplot(no_movies_voted.index,no_movies_voted)
plt.xlabel('UserId')
plt.ylabel('No. of movies rated')
plt.title("No. of movies that a particular user has rated")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarn
ing: Pass the following variables as keyword args: x, y. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



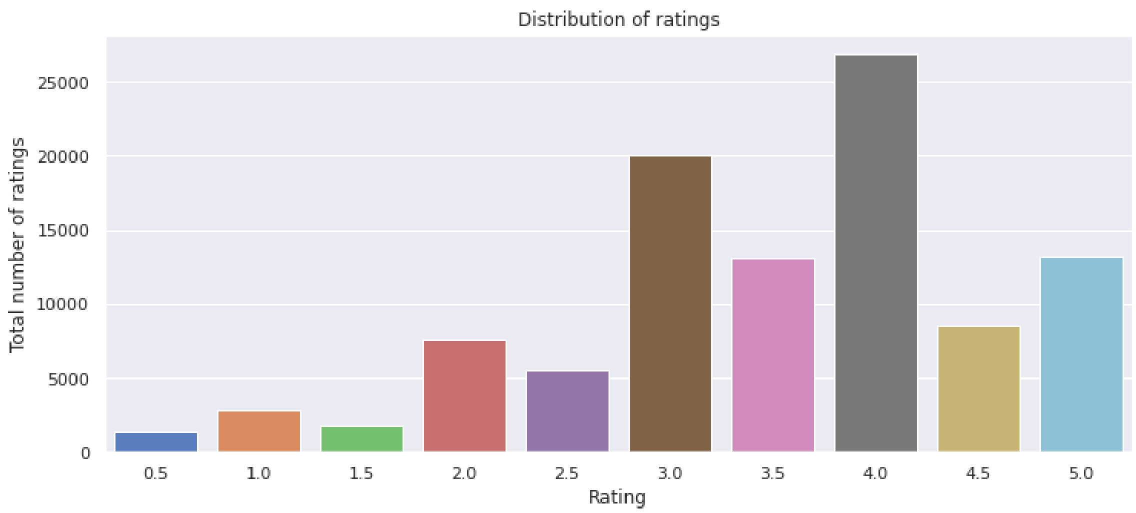
In [82]:

```
display(df)

# Plotting the distribution of ratings
fig, ax = plt.subplots(figsize=(12,5))
ax.set_title('Distribution of ratings')
sns.countplot(ratings['rating'])
ax.set_xlabel("Rating")
ax.set_ylabel("Total number of ratings")
plt.show()
```

userId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604	605	606	607
movieId																		
1	4.0	0.0	0.0	0.0	4.0	0.0	4.5	0.0	0.0	0.0	...	4.0	0.0	4.0	3.0	4.0	2.5	4.0
2	0.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0	0.0	0.0	...	0.0	4.0	0.0	5.0	3.5	0.0	0.0
3	4.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	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	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	3.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
193581	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	0.0	0.0
193583	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	0.0	0.0
193585	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	0.0	0.0
193587	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	0.0	0.0
193609	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	0.0	0.0

9724 rows × 610 columns

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the
only valid positional argument will be `data`, and passing other arguments w
ithout an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



In [83]:

```
# We have obtained a dataset of shape (2121,378) after the previous steps. However,
# most of the values are still zero. We will attempt to reduce the sparsity in the dataset.
from scipy.sparse import csr_matrix

data = csr_matrix(df.values)
df.reset_index(inplace=True)

display(df)
```

userId	movieId	1	2	3	4	5	6	7	8	9	...	601	602	603	604	605	606
0	1	4.0	0.0	0.0	0.0	4.0	0.0	4.5	0.0	0.0	...	4.0	0.0	4.0	3.0	4.0	2.5
1	2	0.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0	0.0	...	0.0	4.0	0.0	5.0	3.5	0.0
2	3	4.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
3	4	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	0.0
4	5	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	...	0.0	0.0	0.0	3.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9719	193581	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
9720	193583	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
9721	193585	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
9722	193587	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
9723	193609	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

9724 rows × 611 columns

In [84]:

```
# To make the movie recommendation model, we will use Nearest Neighbours.
from sklearn.neighbors import NearestNeighbors

knn = NearestNeighbors(n_neighbors=10, algorithm='auto', n_jobs=-1)
knn.fit(data)

# We will first take a particular movie input movie from the user
# We will then output 10 movies with the most similarities to the input movie.
def recommend(inp):
  movie_list = movies[movies['title'].str.contains(inp)]
  if(len(movie_list)==0):
    print("This movie is not in the database. Try another one!")
    return
  movie_idx= movie_list.iloc[0]['movieId']
  movie_idx = df[df['movieId'] == movie_idx].index[0]
  distances , indices = knn.kneighbors(data[movie_idx],n_neighbors=11)
  rec_movie_indices = sorted(list(zip(indices.squeeze().tolist(),distances.squeeze().tolist
  recommend_frame = []
  for val in rec_movie_indices:
    movie_idx = df.iloc[val[0]]['movieId']
    idx = movies[movies['movieId'] == movie_idx].index
    recommend_frame.append({'Title':movies.iloc[idx]['title'].values[0],'Distance':val[1]/1
  recommendations = pd.DataFrame(recommend_frame,index=range(1,11))
  return recommendations
```

In [85]:

```
# Testing the recommendation system
input = "Iron Man"
print("The top ten movies similar to", input, "are -")
recommend(input)
```

```
The top ten movies similar to Iron Man are -
```

Out[85]:

	Title	Distance
1	Guardians of the Galaxy (2014)	0.320819
2	Pirates of the Caribbean: At World's End (2007)	0.320156
3	Star Trek (2009)	0.319257
4	Kung Fu Panda (2008)	0.316978
5	X-Men: First Class (2011)	0.316109
6	Watchmen (2009)	0.315278
7	Iron Man 3 (2013)	0.313010
8	Thor (2011)	0.306839
9	Avengers, The (2012)	0.297027
10	Iron Man 2 (2010)	0.290990

User-User and Item-Item based Collaborative Filtering using Pearson and Cosine Similarity

In [ ]:

```
import pandas as pd
import numpy as np
```

In [ ]:

```
ratings = pd.read_csv('/content/ratings.csv')
```

In [ ]:

```
ratings
```

Out[42]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931
...	...	...	...	...
100831	610	166534	4.0	1493848402
100832	610	168248	5.0	1493850091
100833	610	168250	5.0	1494273047
100834	610	168252	5.0	1493846352
100835	610	170875	3.0	1493846415

100836 rows × 4 columns

In [ ]:

```
ratings.drop('timestamp', axis = 1, inplace = True)
```

In [ ]:

```
ratings
```

Out[44]:

	userId	movieId	rating
0	1	1	4.0
1	1	3	4.0
2	1	6	4.0
3	1	47	5.0
4	1	50	5.0
...	...	...	...
100831	610	166534	4.0
100832	610	168248	5.0
100833	610	168250	5.0
100834	610	168252	5.0
100835	610	170875	3.0

100836 rows × 3 columns

In [ ]:

```
# From the ratings dataset, we will create another dataset, where, for each movie,
# all the ratings given by the 610 users are displayed.
ratings = ratings.pivot(index='movieId',columns='userId',values='rating')

# The NaN values correspond to the users that have not rated a particular movie.
# We will replace them with zeroes to create a sparse matrix.
ratings = ratings.fillna(0)
display(ratings)
```

userId movieId	1	2	3	4	5	6	7	8	9	10	...	601	602	603	604	605	606	607
1	4.0	0.0	0.0	0.0	4.0	0.0	4.5	0.0	0.0	0.0	...	4.0	0.0	4.0	3.0	4.0	2.5	4.0
2	0.0	0.0	0.0	0.0	0.0	4.0	0.0	4.0	0.0	0.0	...	0.0	4.0	0.0	5.0	3.5	0.0	0.0
3	4.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	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	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	3.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
193581	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	0.0	0.0
193583	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	0.0	0.0
193585	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	0.0	0.0
193587	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	0.0	0.0
193609	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	0.0	0.0

9724 rows × 610 columns

In [ ]:

```
# Shuffling the data and dividing into train and test sets, where size of
# test set = 0.2
ratings = ratings.sample(frac = 1)

train_data = ratings[0:7780]
test_data = ratings[7780:]
```

In [ ]:

```
print(train_data.shape)
print(test_data.shape)
```

```
(7780, 610)
(1944, 610)
```

In [ ]:

```
# Create two user-item matrices, one for training and another for testing
train_data_matrix = train_data.values
test_data_matrix = test_data.values

# Check their shape
print(train_data_matrix.shape)
print(test_data_matrix.shape)
```

```
(7780, 610)
(1944, 610)
```

Using Pearson similarity and calculating pairwise distances:

In [ ]:

```
from sklearn.metrics.pairwise import pairwise_distances

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

```
[[ 1.         -0.00164204 -0.00164204 ... -0.00226439 -0.00164204
  -0.00655432]
 [-0.00164204  1.         -0.00164204 ... -0.00226439 -0.00164204
  -0.00655432]
 [-0.00164204 -0.00164204  1.         ... -0.00226439 -0.00164204
   0.10450497]
 ...
 [-0.00226439 -0.00226439 -0.00226439 ...  1.         -0.00226439
  -0.00903851]
 [-0.00164204 -0.00164204 -0.00164204 ... -0.00226439  1.
  -0.00655432]
 [-0.00655432 -0.00655432  0.10450497 ... -0.00903851 -0.00655432
   1.        ]]
```

In [ ]:

```
user_correlation.shape
```

Out[50]:

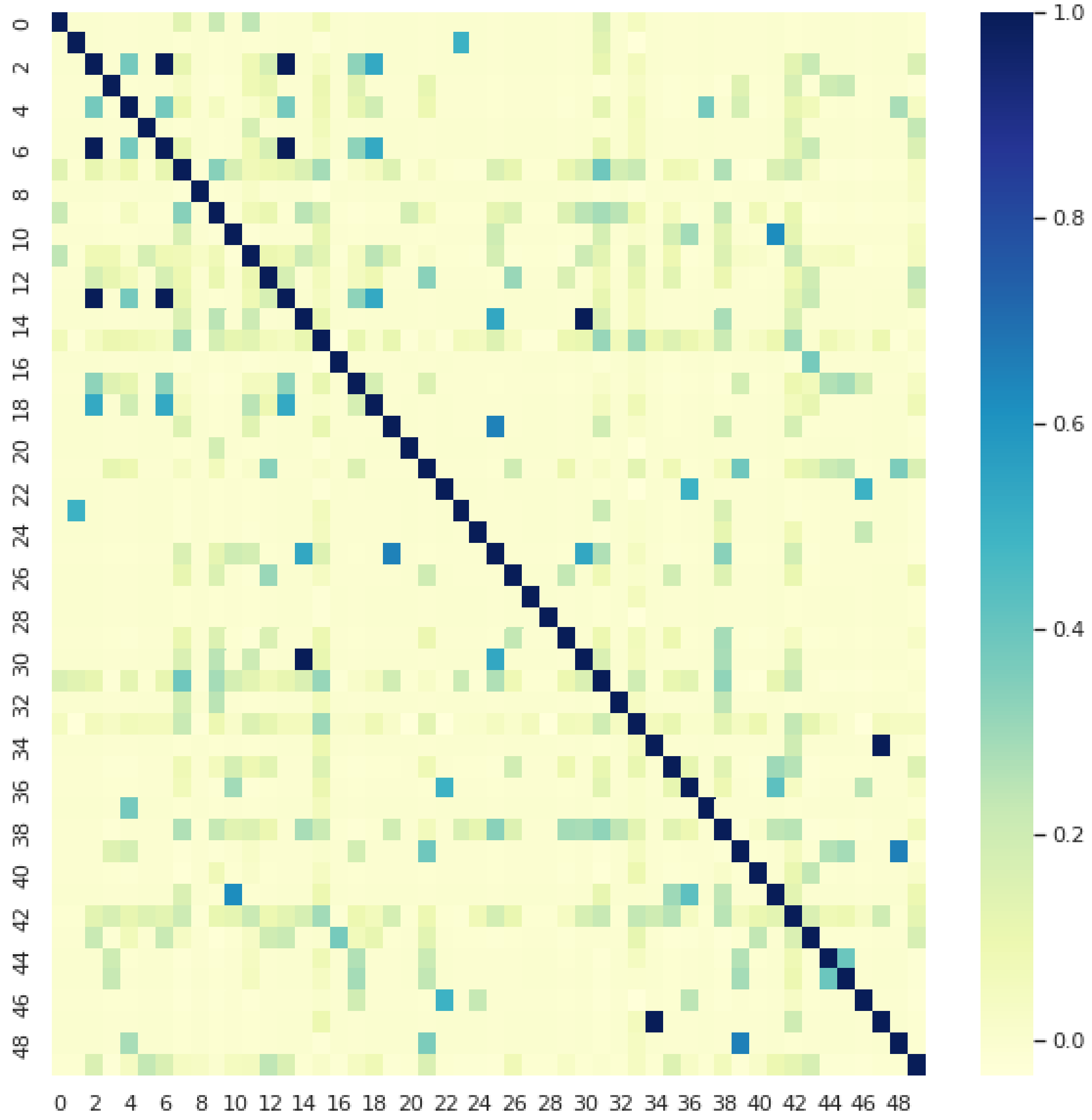
```
(7780, 7780)
```

In [ ]:

```
# Visualization of similarity in user behaviours.
# Darker colour represents that the users are more similar.

import seaborn as sns

user_correlation_reduced = user_correlation[0:50, 0:50]

sns.set(rc={'figure.figsize':(10,10)})

sns.heatmap(user_correlation_reduced, cmap="YlGnBu")
```

Out[51]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b2cf36f90>
```



In [ ]:

```
# Item Similarity Matrix
from sklearn.metrics.pairwise import pairwise_distances

item_correlation = 1 - pairwise_distances(train_data_matrix.T, metric='correlation')
item_correlation[np.isnan(item_correlation)] = 0
print(item_correlation)
```

```
[[ 1.          0.00825542  0.05938132 ...  0.26457636  0.06173917
   0.08488299]
 [ 0.00825542  1.         -0.0027605  ...  0.03399946  0.03058079
   0.09397368]
 [ 0.05938132 -0.0027605   1.         ...  0.01003191 -0.00306509
   0.02081813]
 ...
 [ 0.26457636  0.03399946  0.01003191 ...  1.          0.09988048
   0.24047064]
 [ 0.06173917  0.03058079 -0.00306509 ...  0.09988048  1.
   0.03328595]
 [ 0.08488299  0.09397368  0.02081813 ...  0.24047064  0.03328595
   1.        ]]
```

In [ ]:

```
item_correlation.shape
```

Out[53]:

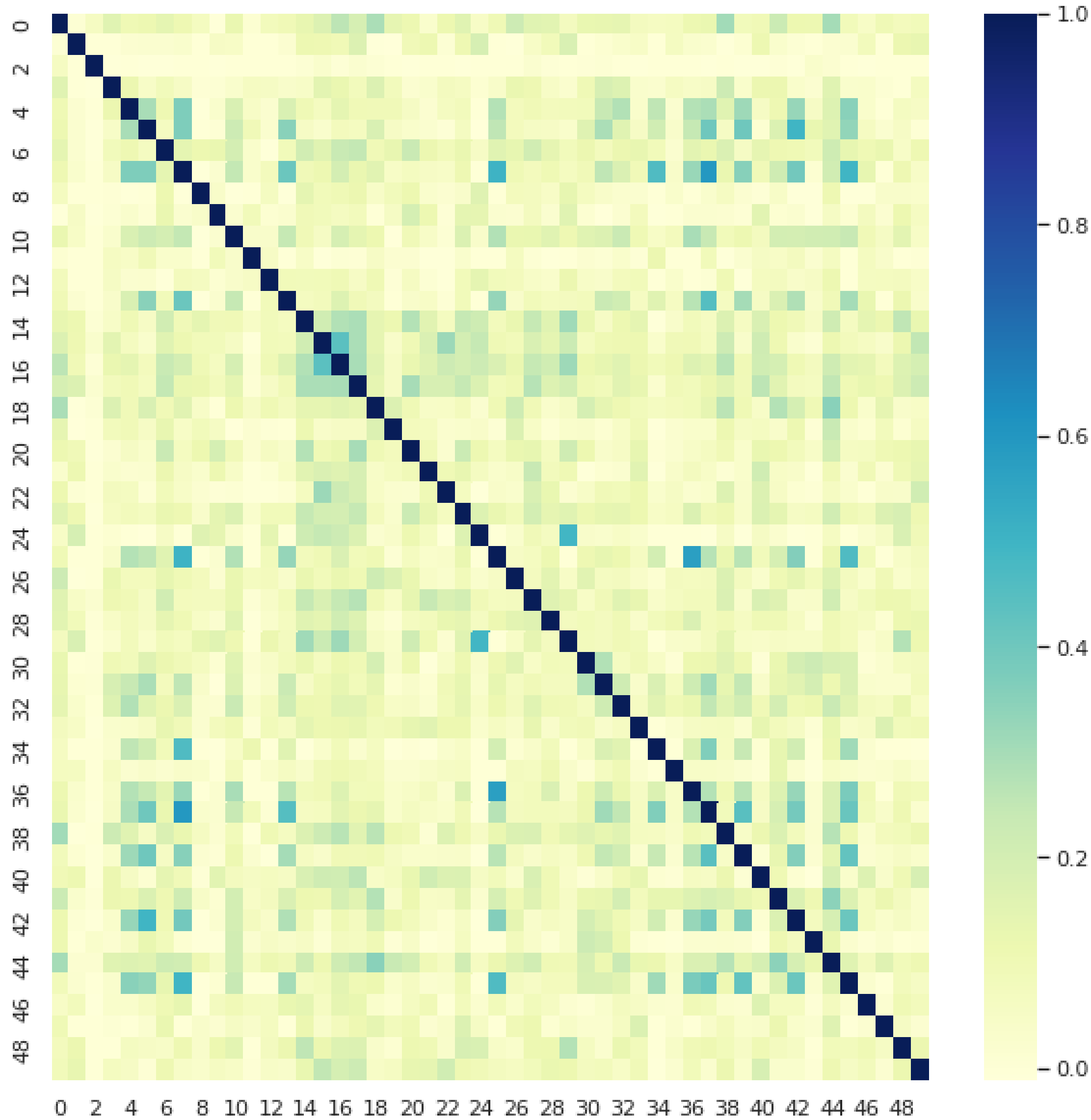
```
(610, 610)
```

In [ ]:

```
# Visualization of similarity in movie genres.
# Darker colour represents that the movies are more similar.

item_correaltion_reduced = item_correlation[0:50, 0:50]

sns.set(rc={'figure.figsize':(10,10)})

sns.heatmap(item_correaltion_reduced, cmap="YlGnBu")
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b2ce39890>
```



In [ ]:

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

    if type == 'user':
        mean_user_rating = ratings.mean(axis=1)
        ratings_diff = (ratings - mean_user_rating[:, np.newaxis]) #np.newaxis is used to a

        pred = mean_user_rating[:, np.newaxis] + similarity.dot(ratings_diff) / np.array([n

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

    return pred
```

Evaluating the model:

In [ ]:

```
from sklearn.metrics import mean_squared_error
from math import sqrt


def rmse(pred, actual):

    pred = pred[actual.nonzero()].flatten()
    actual = actual[actual.nonzero()].flatten()

    return sqrt(mean_squared_error(pred, actual))
```

In [ ]:

```
user_prediction = predict(train_data_matrix, user_correlation, type='user')
item_prediction = predict(train_data_matrix, item_correlation, type='item')

print('RMSE for Train data :')

print('User-based CF RMSE: ', rmse(user_prediction, test_data_matrix))
print('Item-based CF RMSE: ', rmse(item_prediction, test_data_matrix))
```

```
RMSE for Train data :
User-based CF RMSE:  3.478160795900392
Item-based CF RMSE:  3.5814993437345244
```

In [ ]:

```
print('RMSE for Test data :')

print('User-based CF RMSE: ' ,rmse(user_prediction, train_data_matrix))
print('Item-based CF RMSE: ' ,rmse(item_prediction, train_data_matrix))
```

```
RMSE for Test data :
User-based CF RMSE:  2.9143215301119656
Item-based CF RMSE:  3.0692804088035825
```

Using Cosine Similarity:

In [ ]:

```
# User Similarity Matrix
user_correlation_2 = 1 - pairwise_distances(train_data, metric='cosine')
user_correlation_2[np.isnan(user_correlation_2)] = 0
print(user_correlation_2)
```

```
[[1.         0.         0.         ... 0.         0.         0.        ]
 [0.         1.         0.         ... 0.         0.         0.        ]
 [0.         0.         1.         ... 0.         0.         0.10954451]
 ...
 [0.         0.         0.         ... 1.         0.         0.        ]
 [0.         0.         0.         ... 0.         1.         0.        ]
 [0.         0.         0.10954451 ... 0.         0.         1.        ]]
```

In [ ]:

```
# Item Similarity Matrix

item_correlation_2 = 1 - pairwise_distances(train_data_matrix.T, metric='cosine')
item_correlation_2[np.isnan(item_correlation_2)] = 0
print(item_correlation_2)
```

```
[[1.         0.01668289 0.06623956 ... 0.29345494 0.07036485 0.13326595]
 [0.01668289 1.         0.         ... 0.04776859 0.03389141 0.10744564]
 [0.06623956 0.         1.         ... 0.02315252 0.         0.03712886]
 ...
 [0.29345494 0.04776859 0.02315252 ... 1.         0.11268921 0.31329845]
 [0.07036485 0.03389141 0.         ... 0.11268921 1.         0.05300382]
 [0.13326595 0.10744564 0.03712886 ... 0.31329845 0.05300382 1.        ]]
```

Evaluating the model:

In [ ]:

```
user_prediction_2 = predict(train_data_matrix, user_correlation_2, type='user')
item_prediction_2 = predict(train_data_matrix, item_correlation_2, type='item')

print('RMSE for Train data :')

print('User-based CF RMSE: ', rmse(user_prediction_2, test_data_matrix))
print('Item-based CF RMSE: ', rmse(item_prediction_2, test_data_matrix))
```

```
RMSE for Train data :
User-based CF RMSE:  3.423444527257832
Item-based CF RMSE:  3.5781338527742768
```

In [ ]:

```
print('RMSE for Test data :')

print('User-based CF RMSE: ' ,rmse(user_prediction_2, train_data_matrix))
print('Item-based CF RMSE: ' ,rmse(item_prediction_2, train_data_matrix))
```

```
RMSE for Test data :
User-based CF RMSE:  2.8901775055418644
Item-based CF RMSE:  3.0744584748341746
```

In [ ]:

```

```

Content Based model using Term Frequency (TF), Inverse Document Frequency (IDF) and Cosine Similarity

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel

import matplotlib.pyplot as plt
```

In [ ]:

```
movies = pd.read_csv('/content/movies.csv')
```

In [ ]:

```
movies
```

Out[65]:

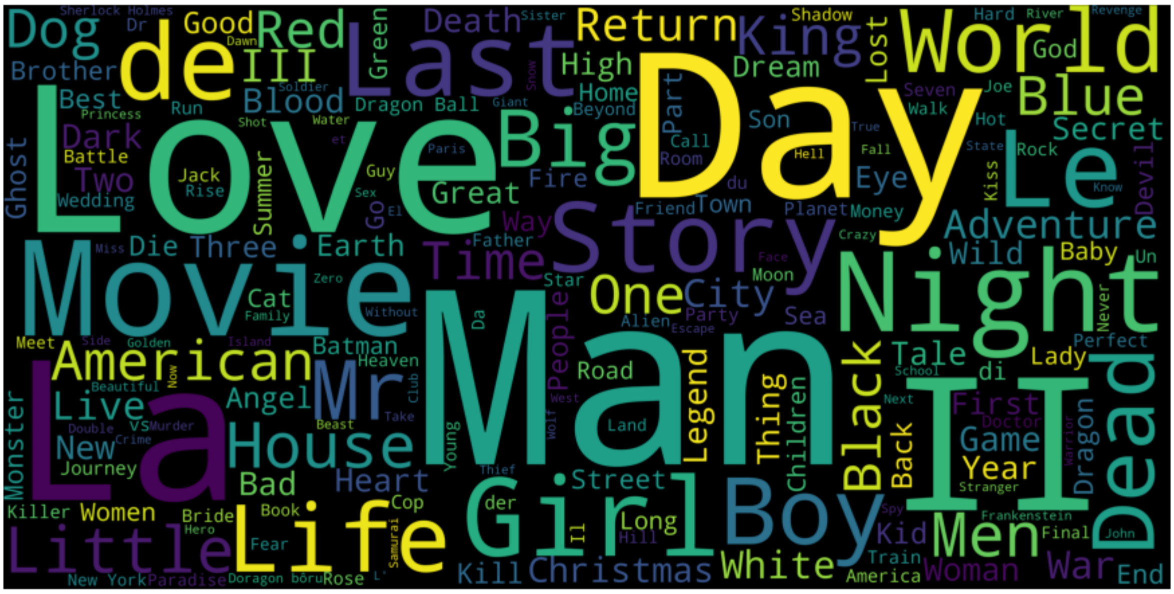
	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy
...	...	...	...
9737	193581	Black Butler: Book of the Atlantic (2017)	Action|Animation|Comedy|Fantasy
9738	193583	No Game No Life: Zero (2017)	Animation|Comedy|Fantasy
9739	193585	Flint (2017)	Drama
9740	193587	Bungo Stray Dogs: Dead Apple (2018)	Action|Animation
9741	193609	Andrew Dice Clay: Dice Rules (1991)	Comedy

9742 rows × 3 columns

Visualizaing the frequency of different words in movie titles:

In [ ]:

```
# Import new libraries
%matplotlib inline
import wordcloud
from wordcloud import WordCloud, STOPWORDS

# Create a wordcloud of the movie titles
movies['title'] = movies['title'].fillna("").astype('str')
title_corpus = ' '.join(movies['title'])
title_wordcloud = WordCloud(stopwords=STOPWORDS, background_color='black', height=2000, wid

# Plot the wordcloud
plt.figure(figsize=(16,8))
plt.imshow(title_wordcloud)
plt.axis('off')
plt.show()
```



In [ ]:

```
# Cleaning the genre column and converting the values to string

movies['genres'] = movies['genres'].str.split('|')

movies['genres'] = movies['genres'].fillna("").astype('str')

movies
```

Out[67]:

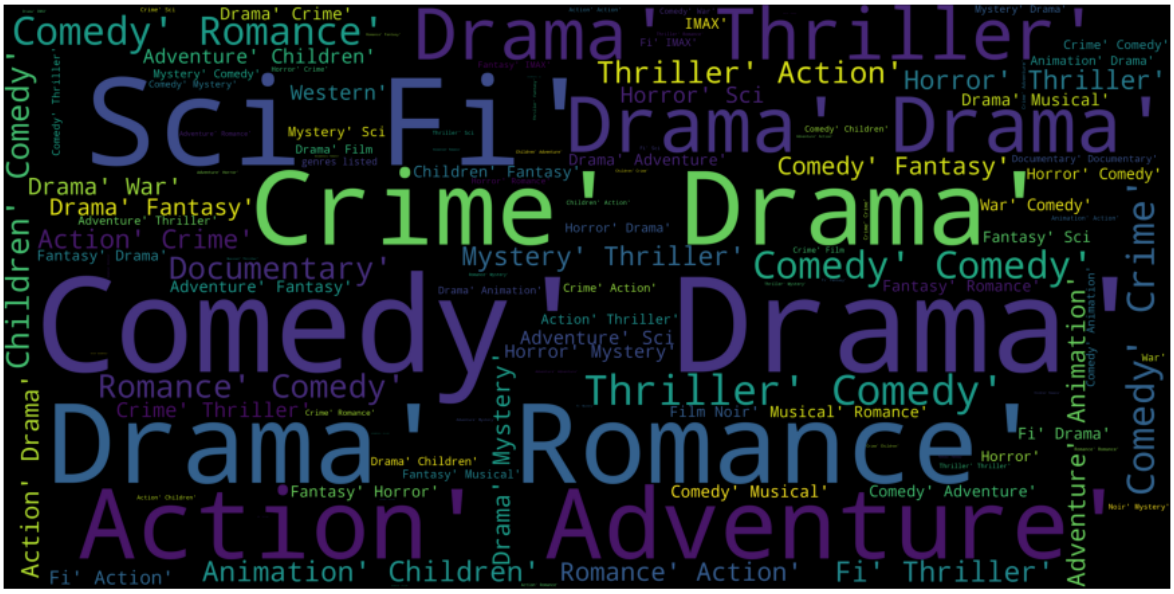
	movieId	title	genres
0	1	Toy Story (1995)	['Adventure', 'Animation', 'Children', 'Comedy...
1	2	Jumanji (1995)	['Adventure', 'Children', 'Fantasy']
2	3	Grumpier Old Men (1995)	['Comedy', 'Romance']
3	4	Waiting to Exhale (1995)	['Comedy', 'Drama', 'Romance']
4	5	Father of the Bride Part II (1995)	['Comedy']
...	...	...	...
9737	193581	Black Butler: Book of the Atlantic (2017)	['Action', 'Animation', 'Comedy', 'Fantasy']
9738	193583	No Game No Life: Zero (2017)	['Animation', 'Comedy', 'Fantasy']
9739	193585	Flint (2017)	['Drama']
9740	193587	Bungo Stray Dogs: Dead Apple (2018)	['Action', 'Animation']
9741	193609	Andrew Dice Clay: Dice Rules (1991)	['Comedy']

9742 rows × 3 columns

Visualizaing the frequency of different Genres present in the dataset:

In [ ]:

```
# Create a wordcloud of the movie genres

title_corpus = ' '.join(movies['genres'])
title_wordcloud = WordCloud(stopwords=STOPWORDS, background_color='black', height=2000, wid

# Plot the wordcloud
plt.figure(figsize=(16,8))
plt.imshow(title_wordcloud)
plt.axis('off')
plt.show()
```



In [ ]:

```
tf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2),min_df=0, stop_words='english')
tfidf_matrix = tf.fit_transform(movies['genres'])
tfidf_matrix.shape
```

Out[69]:

```
(9742, 177)
```

In [ ]:

```
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
cosine_sim
```

Out[70]:

```
array([[1.        , 0.31379419, 0.0611029 , ..., 0.        , 0.16123168,
        0.16761358],
       [0.31379419, 1.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.0611029 , 0.        , 1.        , ..., 0.        , 0.        ,
        0.36454626],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.16123168, 0.        , 0.        , ..., 0.        , 1.        ,
        0.        ],
       [0.16761358, 0.        , 0.36454626, ..., 0.        , 0.        ,
        1.        ]])
```

In [ ]:

```
# Build a 1-dimensional array with movie titles
titles = movies['title']
indices = pd.Series(movies.index, index=movies['title'])

# Function that get movie recommendations based on the cosine similarity score of movie gen
def recommendations_based_on_genre(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[1:21]
    movie_indices = [i[0] for i in sim_scores]

    return titles.iloc[movie_indices]
```

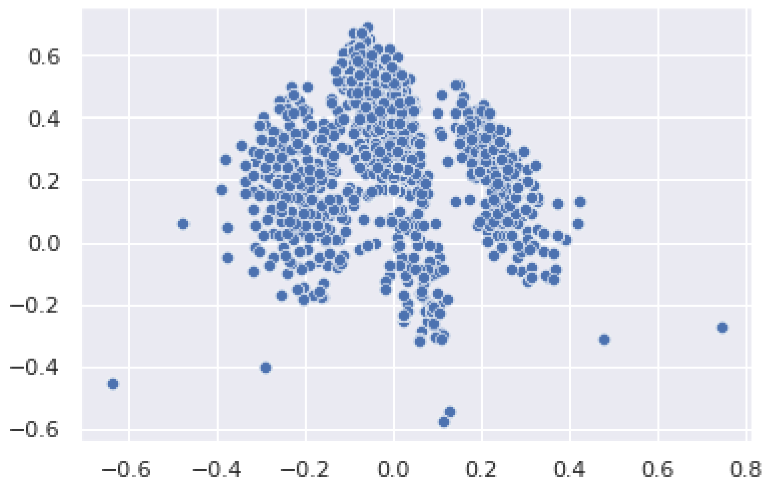
In [ ]:

```
# Plot to represent all the vectors in 2 dimensions using PCA

from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('vect', CountVectorizer()),
    ('tfidf', TfidfTransformer()),
])

X = pipeline.fit_transform(movies['genres']).todense()

pca = PCA(n_components=2).fit(X)
data2D = pca.transform(X)
sns.scatterplot(data2D[:,0], data2D[:,1] )
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:598: Futu
reWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError i
n 1.2. Please convert to a numpy array with np.asarray. For more information
see: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html (htt
ps://numpy.org/doc/stable/reference/generated/numpy.matrix.html)
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:598: Futu
reWarning: np.matrix usage is deprecated in 1.0 and will raise a TypeError i
n 1.2. Please convert to a numpy array with np.asarray. For more information
see: https://numpy.org/doc/stable/reference/generated/numpy.matrix.html (htt
ps://numpy.org/doc/stable/reference/generated/numpy.matrix.html)
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarn
ing: Pass the following variables as keyword args: x, y. From version 0.12,
 the only valid positional argument will be `data`, and passing other argume
nts without an explicit keyword will result in an error or misinterpretatio
n.
  FutureWarning
```

Out[72]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1b2cd4cc90>
```



In [ ]:

```
recommendations_based_on_genre('Good Will Hunting (1997)').head(10)
```

Out[73]:

```
24                              Leaving Las Vegas (1995)
27                                     Persuasion (1995)
42                    How to Make an American Quilt (1995)
45                           When Night Is Falling (1995)
66                                  Bed of Roses (1996)
75         Once Upon a Time... When We Were Colored (1995)
76                             Angels and Insects (1995)
93                    Bridges of Madison County, The (1995)
115                          Up Close and Personal (1996)
151                                      Mad Love (1995)
Name: title, dtype: object
```

In [ ]:

```
recommendations_based_on_genre('Jumanji (1995)').head(10)
```

Out[74]:

```
53                      Indian in the Cupboard, The (1995)
109                       NeverEnding Story III, The (1994)
767                         Escape to Witch Mountain (1975)
1514              Darby O'Gill and the Little People (1959)
1556                                    Return to Oz (1985)
1617                           NeverEnding Story, The (1984)
1618    NeverEnding Story II: The Next Chapter, The (1...
1799                           Santa Claus: The Movie (1985)
3574    Harry Potter and the Sorcerer's Stone (a.k.a. ...
6075    Chronicles of Narnia: The Lion, the Witch and ...
Name: title, dtype: object
```

In [ ]:

```
recommendations_based_on_genre('Iron Man (2008)').head(10)
```

Out[75]:

```
224               Star Wars: Episode IV - A New Hope (1977)
275                                        Stargate (1994)
385                                  Demolition Man (1993)
898     Star Wars: Episode V - The Empire Strikes Back...
911     Star Wars: Episode VI - Return of the Jedi (1983)
1058             Star Trek III: The Search for Spock (1984)
1346                                   Lost in Space (1998)
1557                                  Rocketeer, The (1991)
1567                                            Tron (1982)
1692                              Six-String Samurai (1998)
Name: title, dtype: object
```

In [ ]:

Hybrid Filtering using Linear Regression

In [ ]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import linear_kernel
from sklearn.metrics.pairwise import cosine_similarity
from ast import literal_eval
```

In [ ]:

```
#Using regular expressions to find a year stored between parentheses
#We specify the parantheses so we don't conflict with movies that have years in their title
movies['year'] = movies.title.str.extract('(\(\d\d\d\d\))',expand=False)
#Removing the parentheses
movies['year'] = movies.year.str.extract('(\d\d\d\d)',expand=False)
#Removing the years from the 'title' column
movies['title'] = movies.title.str.replace('(\(\d\d\d\d\))', '')
#Applying the strip function to get rid of any ending whitespace characters that may have a
movies['title'] = movies['title'].apply(lambda x: x.strip())
movies.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: FutureWarnin
g: The default value of regex will change from True to False in a future ver
sion.
  import sys
```

Out[5]:

	movieId	title	genres	year
0	1	Toy Story	Adventure|Animation|Children|Comedy|Fantasy	1995
1	2	Jumanji	Adventure|Children|Fantasy	1995
2	3	Grumpier Old Men	Comedy|Romance	1995
3	4	Waiting to Exhale	Comedy|Drama|Romance	1995
4	5	Father of the Bride Part II	Comedy	1995

In [ ]:

```
#Every genre is separated by a | so we simply have to call the split function on |
movies['genres'] = movies.genres.str.split('|')
movies.head()
```

Out[6]:

	movieId	title	genres	year
0	1	Toy Story	[Adventure, Animation, Children, Comedy, Fantasy]	1995
1	2	Jumanji	[Adventure, Children, Fantasy]	1995
2	3	Grumpier Old Men	[Comedy, Romance]	1995
3	4	Waiting to Exhale	[Comedy, Drama, Romance]	1995
4	5	Father of the Bride Part II	[Comedy]	1995

In [ ]:

```
#Copying the movie dataframe into a new one since we won't need to use the genre informatio
moviesWithGenres_df = movies.copy()

#For every row in the dataframe, iterate through the list of genres and place a 1 into the
for index, row in movies.iterrows():
    for genre in row['genres']:
        moviesWithGenres_df.at[index, genre] = 1
#Filling in the NaN values with 0 to show that a movie doesn't have that column's genre
moviesWithGenres_df = moviesWithGenres_df.fillna(0)
moviesWithGenres_df.head()
```

Out[8]:

	movieId	title	genres	year	Adventure	Animation	Children	Comedy	Fantasy	Ro
0	1	Toy Story	[Adventure, Animation, Children, Comedy, Fantasy]	1995	1.0	1.0	1.0	1.0	1.0	
1	2	Jumanji	[Adventure, Children, Fantasy]	1995	1.0	0.0	1.0	0.0	1.0	
2	3	Grumpier Old Men	[Comedy, Romance]	1995	0.0	0.0	0.0	1.0	0.0	
3	4	Waiting to Exhale	[Comedy, Drama, Romance]	1995	0.0	0.0	0.0	1.0	0.0	
4	5	Father of the Bride Part II	[Comedy]	1995	0.0	0.0	0.0	1.0	0.0	

5 rows × 24 columns

In [ ]:

```
#Drop removes a specified row or column from a dataframe
ratings = ratings.drop('timestamp', 1)
ratings.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarnin
g: In a future version of pandas all arguments of DataFrame.drop except for
the argument 'labels' will be keyword-only
```

Out[9]:

	userId	movieId	rating
0	1	1	4.0
1	1	3	4.0
2	1	6	4.0
3	1	47	5.0
4	1	50	5.0

In [ ]:

```
userInput = [
            {'title':'Breakfast Club, The', 'rating':5},
            {'title':'Toy Story', 'rating':3.5},
            {'title':'Jumanji', 'rating':2},
            {'title':"Pulp Fiction", 'rating':5},
            {'title':'Akira', 'rating':4.5}
         ]
inputMovies = pd.DataFrame(userInput)
inputMovies
```

Out[10]:

	title	rating
0	Breakfast Club, The	5.0
1	Toy Story	3.5
2	Jumanji	2.0
3	Pulp Fiction	5.0
4	Akira	4.5

In [ ]:

```
#Filtering out the movies by title
inputId = movies[movies['title'].isin(inputMovies['title'].tolist())]
#Then merging it so we can get the movieId. It's implicitly merging it by title.
inputMovies = pd.merge(inputId, inputMovies)
#Dropping information we won't use from the input dataframe
inputMovies = inputMovies.drop('genres', 1).drop('year', 1)
#Final input dataframe
#If a movie you added in above isn't here, then it might not be in the original
#dataframe or it might spelled differently, please check capitalisation.
inputMovies
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: FutureWarnin
g: In a future version of pandas all arguments of DataFrame.drop except for
the argument 'labels' will be keyword-only
```

Out[11]:

	movieId	title	rating
0	1	Toy Story	3.5
1	2	Jumanji	2.0
2	296	Pulp Fiction	5.0
3	1274	Akira	4.5
4	1968	Breakfast Club, The	5.0

In [ ]:

```
#Filtering out the movies from the input
userMovies = moviesWithGenres_df[moviesWithGenres_df['movieId'].isin(inputMovies['movieId']
userMovies
```

Out[12]:

	movieId	title	genres	year	Adventure	Animation	Children	Comedy	Fantasy
0	1	Toy Story	[Adventure, Animation, Children, Comedy, Fantasy]	1995	1.0	1.0	1.0	1.0	1.0
1	2	Jumanji	[Adventure, Children, Fantasy]	1995	1.0	0.0	1.0	0.0	1.0
257	296	Pulp Fiction	[Comedy, Crime, Drama, Thriller]	1994	0.0	0.0	0.0	1.0	0.0
973	1274	Akira	[Action, Adventure, Animation, Sci-Fi]	1988	1.0	1.0	0.0	0.0	0.0
1445	1968	Breakfast Club, The	[Comedy, Drama]	1985	0.0	0.0	0.0	1.0	0.0

5 rows × 24 columns

In [ ]:

```
#Resetting the index to avoid future issues
userMovies = userMovies.reset_index(drop=True)
#Dropping unnecessary issues due to save memory and to avoid issues
userGenreTable = userMovies.drop('movieId', 1).drop('title', 1).drop('genres', 1).drop('yea
userGenreTable
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: FutureWarnin
g: In a future version of pandas all arguments of DataFrame.drop except for
the argument 'labels' will be keyword-only
  after removing the cwd from sys.path.
```

Out[13]:

	Adventure	Animation	Children	Comedy	Fantasy	Romance	Drama	Action	Crime	Thrille
0	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.(
1	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.(
2	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	1.(
3	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.(
4	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.(

In [ ]:

```
inputMovies['rating']
```

Out[14]:

```
0    3.5
1    2.0
2    5.0
3    4.5
4    5.0
Name: rating, dtype: float64
```

In [ ]:

```
#Dot produt to get weights
userProfile = userGenreTable.transpose().dot(inputMovies['rating'])
#The user profile
userProfile
```

Out[15]:

```
Adventure             10.0
Animation              8.0
Children               5.5
Comedy                13.5
Fantasy                5.5
Romance                0.0
Drama                 10.0
Action                 4.5
Crime                  5.0
Thriller               5.0
Horror                 0.0
Mystery                0.0
Sci-Fi                 4.5
War                    0.0
Musical                0.0
Documentary            0.0
IMAX                   0.0
Western                0.0
Film-Noir              0.0
(no genres listed)     0.0
dtype: float64
```

In [ ]:

```
#Now let's get the genres of every movie in our original dataframe
genreTable = moviesWithGenres_df.set_index(moviesWithGenres_df['movieId'])
#And drop the unnecessary information
genreTable = genreTable.drop('movieId', 1).drop('title', 1).drop('genres', 1).drop('year',
genreTable.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: FutureWarnin
g: In a future version of pandas all arguments of DataFrame.drop except for
the argument 'labels' will be keyword-only
  after removing the cwd from sys.path.
```

Out[16]:

	Adventure	Animation	Children	Comedy	Fantasy	Romance	Drama	Action	Crime
movieId									
1	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0
2	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0
4	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0
5	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0

In [ ]:

```
genreTable.shape
```

Out[17]:

```
(9742, 20)
```

In [ ]:

```
#Multiply the genres by the weights and then take the weighted average
recommendationTable_df = ((genreTable*userProfile).sum(axis=1))/(userProfile.sum())
recommendationTable_df.head()
```

Out[18]:

```
movieId
1    0.594406
2    0.293706
3    0.188811
4    0.328671
5    0.188811
dtype: float64
```

In [ ]:

```
#Sort our recommendations in descending order
recommendationTable_df = recommendationTable_df.sort_values(ascending=False)
#Just a peek at the values
recommendationTable_df.head()
```

Out[19]:

```
movieId
134853    0.734266
148775    0.685315
117646    0.678322
6902      0.678322
81132     0.671329
dtype: float64
```

In [ ]:

```
#The final recommendation table
movies.loc[movies['movieId'].isin(recommendationTable_df.head(10).keys())]
```

Out[20]:

	movieId	title	genres	year
1390	1907	Mulan	[Adventure, Animation, Children, Comedy, Drama...	1998
2250	2987	Who Framed Roger Rabbit?	[Adventure, Animation, Children, Comedy, Crime...	1988
4631	6902	Interstate 60	[Adventure, Comedy, Drama, Fantasy, Mystery, S...	2002
5490	26340	Twelve Tasks of Asterix, The (Les douze travau...	[Action, Adventure, Animation, Children, Comed...	1976
7441	81132	Rubber	[Action, Adventure, Comedy, Crime, Drama, Film...	2010
8349	108540	Ernest & Célestine (Ernest et Célestine)	[Adventure, Animation, Children, Comedy, Drama...	2012
8357	108932	The Lego Movie	[Action, Adventure, Animation, Children, Comed...	2014
8597	117646	Dragonheart 2: A New Beginning	[Action, Adventure, Comedy, Drama, Fantasy, Th...	2000
8900	134853	Inside Out	[Adventure, Animation, Children, Comedy, Drama...	2015
9169	148775	Wizards of Waverly Place: The Movie	[Adventure, Children, Comedy, Drama, Fantasy, ...	2009