Week10 Assignment – Building a Movie Recommendation System

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<u>DSC630-T302: Predictive Analysis</u>

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February 18, 2024

Building a Movie Recommendation System

Introduction

Recommendation systems are like prediction systems designed to predict what the users may like when there are various options to choose from. Some classic examples are item recommendations from Amazon and movie recommendations from Netflix, among others. Recommendation systems are essential for businesses as they can keep customers on the platform longer than originally intended. This can be very relatable while shopping on Amazon. How the customers get lured into buying more when they see recommendations such as "Customers who bought this also bought this."

Source of the Data:

In this project, a movie recommendation system is built using the datasets from the Movie Lens website (MovieLens, 2013). As there are different flavors of datasets available on the website, to keep things simple, a small version of the dataset is used. Two datasets are used in this project, one being “movies.csv” which contains the details of movies such as the movie ID, title, and genre. The other file is "ratings.csv", as the name suggests, includes the movie ratings' details and the user ID of the users that rated the movies.

Data Exploration and Feature extraction:

As an initial step of exploring the dataset, exploratory data analysis is performed to understand the data distribution better. Some of the analyses performed in this step include finding the unique number of movies in the ratings and the movie datasets, the unique number of users, the average number of ratings for the movies, the most popular genre of movies, etc.

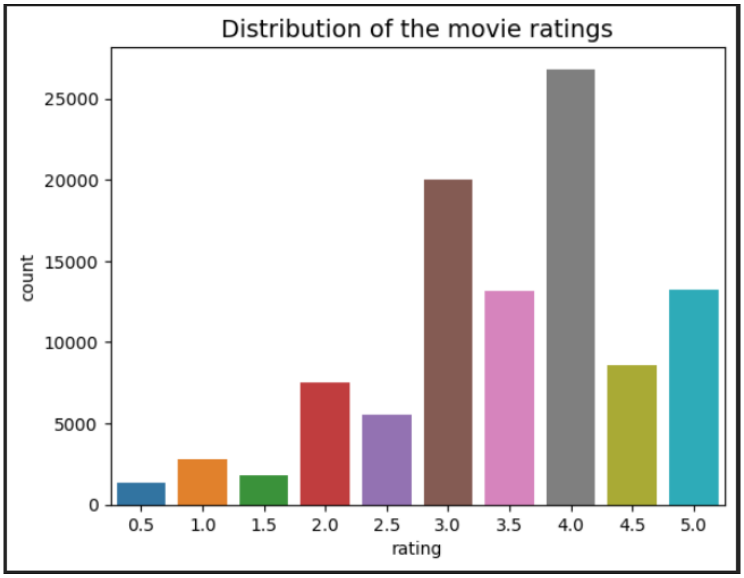


Figure 1: Distribution of the movie Ratings

A histogram of the distribution of the movies by ratings and a Bar plot of the movie distribution by Genres are also plotted to understand the data visually.

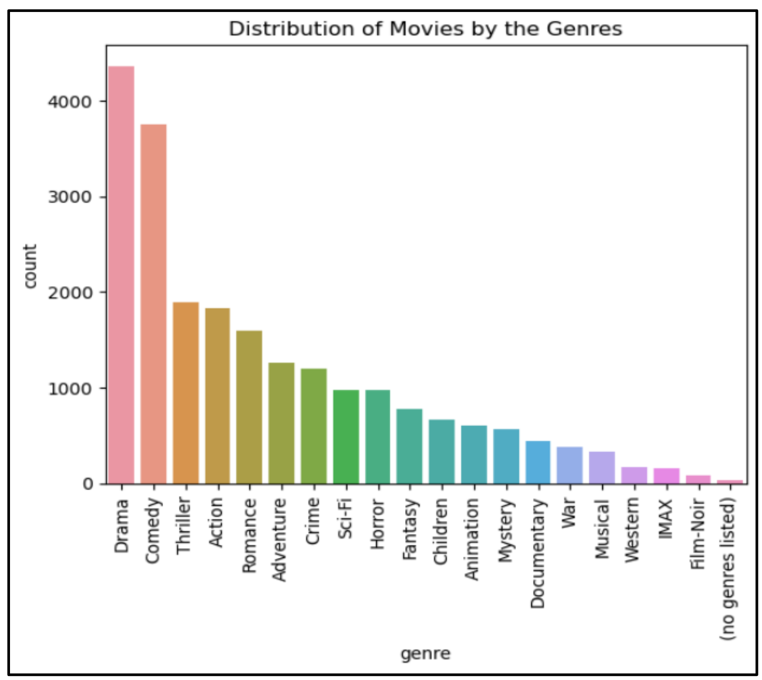


Figure 2: Distribution of the movies by Genre

Further analysis is done by joining the two datasets to find the movies that are rated the highest and lowest. While doing this analysis, it is found that merely calculating the mean ratings of the movies may not be enough as some movies may have one or two 5.0 ratings and can be rated highest, while some popular movies with 200 ratings with an average of rating of 4.0 can be rated as less popular. To avoid this problem, the Bayesian average method is employed to find the average rating using the model weights.

Recommendation system

Two methods were used to build the movie recommendation system in this project as discussed in this section.

Pairwise Correlation Method:

The first one was with the simpler pairwise correlation method, where the ratings and the movie dataset were merged, and the resulting dataset was reshaped to contain the user ID and movie titles with the user ratings. Then pairwise correlation was then computed for the movie of interest and after removing nulls, it was merged with the dataset that contains the count of movie ratings. The movies with more ratings and with higher correlations were chosen and displayed to the user. One big downside of this approach is that the outcome is based on the number of reviews that the movie received, though on the positive side, it is easier to deploy. (Nair, 2019)

K-Nearest Neighbors algorithm using Cosine distance Method:

In the second approach, first a sparse matrix is calculated on the user ratings of the ratings dataset. Then a function is built using K-nearest neighbors to find the similarity using the cosine distance method. The function sorts the results based on the similarity distance and returns the top 10 movies. Though this method can be slightly complicated, it can be more efficient with the results compared to the first method. (says, 2020)

Observations and Conclusion

In this project, the recommendation system was built using two different methods. For illustration purposes, the algorithms were tested with the horror movie "The Shining" released in 1980. The recommendation results are more satisfactory with the KNN method compared to the correlation method. However, as this was built only with a small subset of movies, the project can be expanded further by testing on bigger datasets to compare the performance.

References:

MovieLens. (2013, September 6). GroupLens. https://grouplens.org/datasets/movielens

Nair, A. (2019, September 25). How To Build Your First Recommender System Using Python & MovieLens Dataset. Analytics India Magazine. https://analyticsindiamag.com/how-to-build-your-first-recommender-system-using-python-movielens-dataset/

says, D. S. (2020, November 9). Build A Movie Recommendation System on Your Own. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2020/11/create-your-own-movie-movie-recommendation-system/

Building Recommendation system using Python

In [1]:
```
# Importing the Required Libraries
import pandas as pd
import numpy as np
import os
import sys
import re
from datetime import datetime
# Importing the required packages for plotting graphs
import matplotlib.pyplot as plt
import seaborn as sns
# Importing libraries for model building and standardization
from sklearn import preprocessing
from scipy.spatial.distance import cdist
from sklearn.cluster import KMeans
import sklearn.metrics as metrics
from collections import Counter
from sklearn.neighbors import NearestNeighbors
```

In [2]:
```
# Setting global options for the notebook such as maxrows
pd.set_option('display.max_columns', 50)
pd.set_option('display.max_colwidth', None)
pd.set_option("display.max_rows", 100)
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Importing the Dataset
path=os.getcwd()
# Assigning a path for the file
ratings_path=path+"\\ratings.csv"
movies_path=path+"\\movies.csv"
```

In [4]:
```
# Loading the source file into Pandas DataFrame
ratings_df=pd.read_csv(ratings_path)
# Printing the shape of the dataframe
ratings_df.shape
```

Out[4]: (100836, 4)

In [5]:
```
# Loading the source file into Pandas DataFrame
movies_df=pd.read_csv(movies_path)
# Printing the shape of the dataframe
movies_df.shape
```

Out[5]: (9742, 3)

In [6]:
```
# Printing top 5 rows from ratings dataframe
ratings_df.head()
```

Out[6]:

	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

In [7]:
```
# Printing top 5 rows from movies dataframe
movies_df.head()
```

Out[7]:

	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

In [8]:
```python
# Joining the Ratings and Movies dataframe
merged_df1=ratings_df.merge(movies_df,on='movieId', how='left')
```

In [9]:
```python
# Printing top few rows of merged dataframe
merged_df1.head()
```

Out[9]:

	userId	movieId	rating	timestamp	title	genres
0	1	1	4.0	964982703	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	1	3	4.0	964981247	Grumpier Old Men (1995)	Comedy|Romance
2	1	6	4.0	964982224	Heat (1995)	Action|Crime|Thriller
3	1	47	5.0	964983815	Seven (a.k.a. Se7en) (1995)	Mystery|Thriller
4	1	50	5.0	964982931	Usual Suspects, The (1995)	Crime|Mystery|Thriller

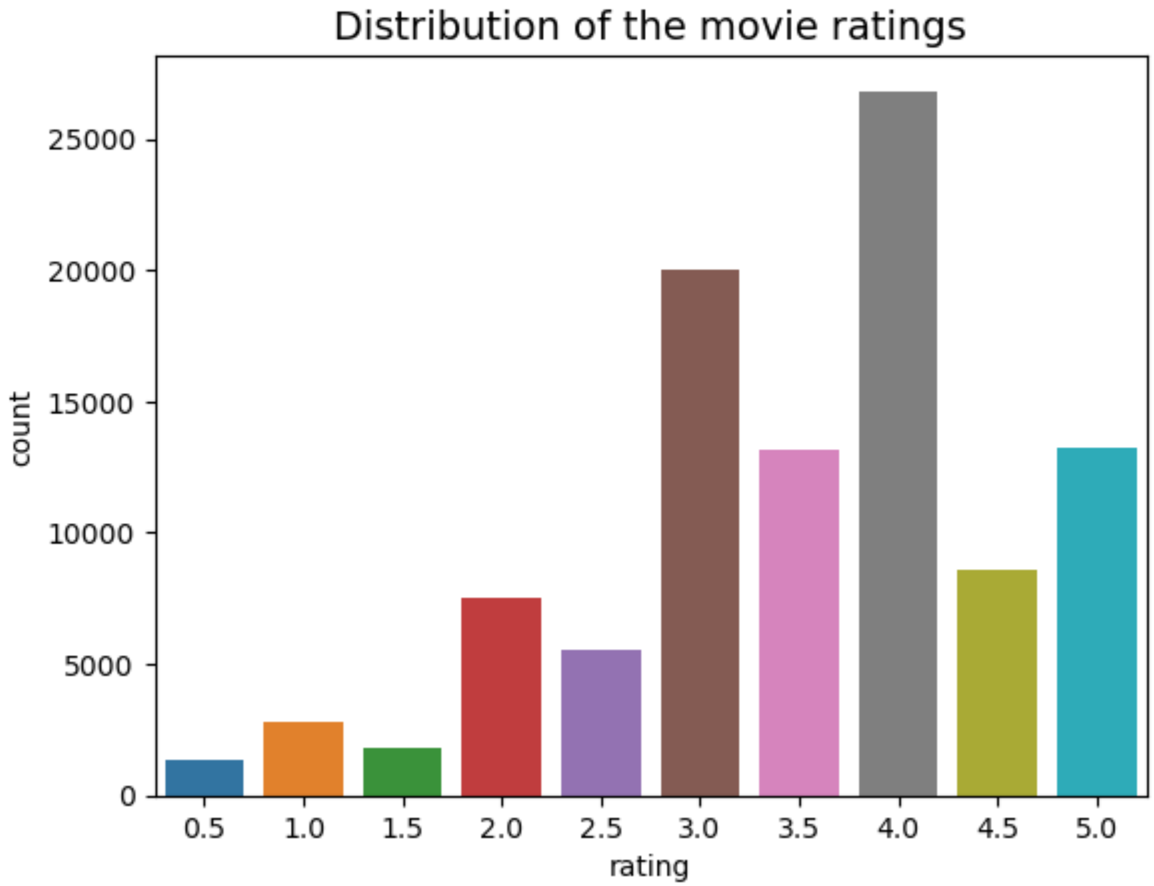
EDA and Feature Engineering

In [10]:
```python
# Calculating the number of ratings, number of movies and users
num_ratings = len(ratings_df)
num_movies = ratings_df['movieId'].nunique()
num_users = ratings_df['userId'].nunique()
# Printing the results
print(f"Number of ratings: {num_ratings}")
print(f"Number of unique movies: {num_movies}")
print(f"Number of unique users: {num_users}")
print(f"Average number of ratings per user: {round(num_ratings/num_users, 2)}")
print(f"Average number of ratings per movie: {round(num_ratings/num_movies, 2)}")
```

```
Number of ratings: 100836
Number of unique movies: 9724
Number of unique users: 610
Average number of ratings per user: 165.3
Average number of ratings per movie: 10.37
```

In [11]:
```python
# Platting the results of Ratings as a Histogram
sns.countplot(x="rating",data=ratings_df)
plt.title("Distribution of the movie ratings", fontsize=14)
```

```
plt.show()
```



In [12]:
```
# Printing the Mean rating of all movies
print(f"Mean rating: {round(ratings_df['rating'].mean(),2)}")
```

```
Mean rating: 3.5
```

In [13]:
```
# Calculating the mean ratings per user
mean_ratings = ratings_df.groupby('userId')['rating'].mean()
print(f"Mean rating per user: {round(mean_ratings.mean(),2)}")
```

```
Mean rating per user: 3.66
```

In [14]:
```
# Joining the ratings and movies dataframe using inner join
movie_ratings=ratings_df.merge(movies_df,on="movieId")
```

```python
# Printing the list of movies with higher number of reviews
movie_ratings['title'].value_counts()[0:10]
```

Out[14]:

```
Forrest Gump (1994)                          329
Shawshank Redemption, The (1994)             317
Pulp Fiction (1994)                          307
Silence of the Lambs, The (1991)             279
Matrix, The (1999)                           278
Star Wars: Episode IV - A New Hope (1977)    251
Jurassic Park (1993)                         238
Braveheart (1995)                            237
Terminator 2: Judgment Day (1991)            224
Schindler's List (1993)                      220
Name: title, dtype: int64
```

In [15]:

```python
# Calculating the mean ratings for each movie
mean_movie_ratings=ratings_df.groupby('movieId').mean()[['rating']]
```

In [16]:

```python
# Getting the lowest rated movie
lowest_rated=mean_movie_ratings['rating'].idxmin()
# Printing the name of the movie with lowest rating
movies_df[movies_df["movieId"]==lowest_rated]
```

Out[16]:

	movieId	title	genres
2689	3604	Gypsy (1962)	Musical

In [17]:

```python
# Getting the lowest rated movie
highest_rated=mean_movie_ratings['rating'].idxmax()
# Printing the name of the movie with highest rating
movies_df[movies_df["movieId"]==highest_rated]
```

Out[17]:

	movieId	title	genres
48	53	Lamerica (1994)	Adventure|Drama

In [18]:

```python
# Grouping the ratings datfarme by movies and get the count and mean of ratings
movie_stats=ratings_df.groupby('movieId')['rating'].agg(['count','mean'])
movie_stats.head()
```

Out[18]:

movieId	count	mean
1	215	3.920930
2	110	3.431818
3	52	3.259615
4	7	2.357143
5	49	3.071429

In [19]:

```
# Finding the mean value of ratings for each movie
cnt=movie_stats['count'].mean()
# Finding the average ratings for each movie
mean=movie_stats['mean'].mean()
print(f"Average number of ratings for a given movie: {cnt:.2f}")
print(f"Average rating for a given movie: {mean:.2f}")
# Calculating the average using Bayesian average method using weights
def bayesian_avg(ratings):
    bayesian_avg = (cnt*mean+ratings.sum())/(cnt+ratings.count())
    return round(bayesian_avg, 3)
```

```
Average number of ratings for a given movie: 10.37
Average rating for a given movie: 3.26
```

In [20]:

```
# Applying the Bayesian average function on all the movies in the ratings dataset
bayesian_avg_ratings = ratings_df.groupby('movieId')['rating'].agg(bayesian_avg).reset_index()
# Rennaming the columns in the bayesian_avg_ratings dataframe
bayesian_avg_ratings.columns = ['movieId', 'bayesian_avg']
# Joining bayesian_avg_ratings and movie stats dataframe
movie_stats = movie_stats.merge(bayesian_avg_ratings, on='movieId')
```

In [21]:

```
# Joining the movie_stats dataframe with movies dataframe based on movieid and title
movie_stats = movie_stats.merge(movies_df[['movieId', 'title']])
# Sorting the results to find the most popular movie
movie_stats.sort_values('bayesian_avg', ascending=False).head()
```

Out[21]:

	movieId	count	mean	bayesian_avg	title
277	318	317	4.429022	4.392	Shawshank Redemption, The (1994)
659	858	192	4.289062	4.236	Godfather, The (1972)
2224	2959	218	4.272936	4.227	Fight Club (1999)
224	260	251	4.231076	4.193	Star Wars: Episode IV - A New Hope (1977)
46	50	204	4.237745	4.191	Usual Suspects, The (1995)

In [22]:

```
# Sorting the results to find the least popular movies
movie_stats.sort_values('bayesian_avg', ascending=True).head()
```

Out[22]:

	movieId	count	mean	bayesian_avg	title
1172	1556	19	1.605263	2.190	Speed 2: Cruise Control (1997)
2679	3593	19	1.657895	2.224	Battlefield Earth (2000)
1372	1882	33	1.954545	2.267	Godzilla (1998)
1144	1499	27	1.925926	2.297	Anaconda (1997)
1988	2643	16	1.687500	2.307	Superman IV: The Quest for Peace (1987)

In [23]:
```python
#  Formatting the genres in the movies dataset by extracting the values split by pipes into a list
movies_df['genres'] = movies_df['genres'].apply(lambda x: x.split("|"))
movies_df.head()
```

Out[23]:

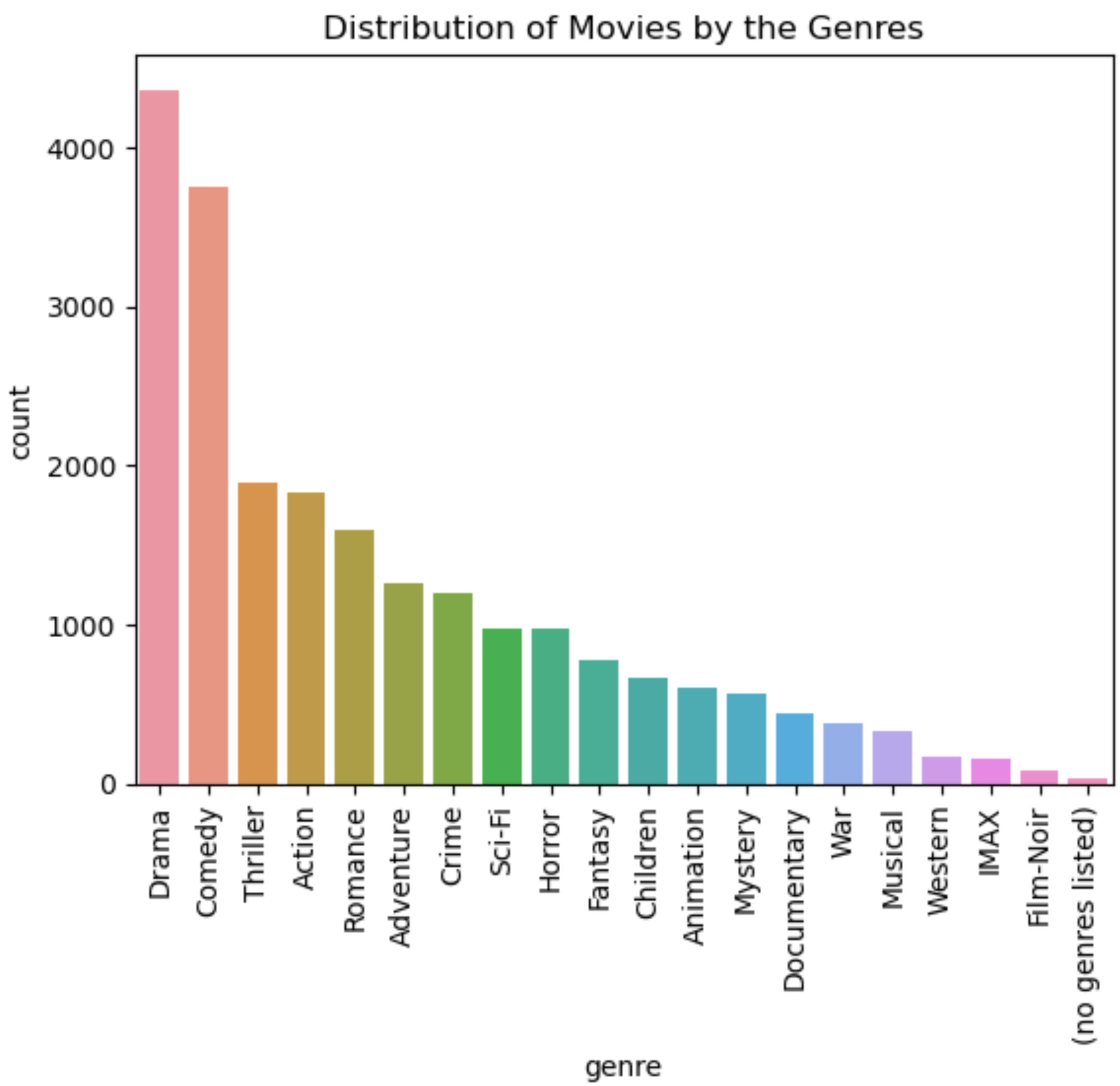
	movieId	title	genres
0	1	Toy Story (1995)	[Adventure, Animation, Children, Comedy, Fantasy]
1	2	Jumanji (1995)	[Adventure, Children, Fantasy]
2	3	Grumpier Old Men (1995)	[Comedy, Romance]
3	4	Waiting to Exhale (1995)	[Comedy, Drama, Romance]
4	5	Father of the Bride Part II (1995)	[Comedy]

In [24]:
```python
# Using collections to get the count of genre in the dataset
genre_frequency = Counter(g for genres in movies_df['genres'] for g in genres)
# Printing the total number of genres
print(f"There are {len(genre_frequency)} genres.")
# Printing all the genres with the frequency in the dataset
genre_frequency
```

```
There are 20 genres.
```

Out[24]:
```
Counter({'Adventure': 1263,
         'Animation': 611,
         'Children': 664,
         'Comedy': 3756,
         'Fantasy': 779,
         'Romance': 1596,
         'Drama': 4361,
         'Action': 1828,
         'Crime': 1199,
         'Thriller': 1894,
         'Horror': 978,
         'Mystery': 573,
         'Sci-Fi': 980,
         'War': 382,
         'Musical': 334,
         'Documentary': 440,
         'IMAX': 158,
         'Western': 167,
         'Film-Noir': 87,
         '(no genres listed)': 34})
```

In [25]:
```
# Creating a dataframe with genre name and its frequency
genre_frequency_df = pd.DataFrame([genre_frequency]).T.reset_index()
genre_frequency_df.columns = ['genre', 'count']
# Creating bar plot to illustrate the distribution of genre and its counts in the dataset.
sns.barplot(x='genre', y='count', data=genre_frequency_df.sort_values(by='count', ascending=False))
plt.xticks(rotation=90)
plt.title("Distribution of Movies by the Genres")
plt.show()
```



Recommendation system: Approach 1 using Correlation Method

In [26]:
```
# Finding the average rating of each movie in the Dataset
avg_ratings=pd.DataFrame(merged_df1.groupby('title').mean()['rating'])
# Adding a new column named count ratings
avg_ratings['count_ratings']=pd.DataFrame(merged_df1.groupby('title').count()['rating'])
avg_ratings.head()
```

Out[26]:

title	rating	count_ratings
'71 (2014)	4.0	1
'Hellboy': The Seeds of Creation (2004)	4.0	1
'Round Midnight (1986)	3.5	2
'Salem's Lot (2004)	5.0	1
'Til There Was You (1997)	4.0	2

In [27]:
```
# Using pivot table function to reshape the dataframe
pivot_df=merged_df1.pivot_table(index='userId',columns='title',values='rating')
pivot_df.head()
```

Out[27]:

title	'71 (2014)	'Hellboy': The Seeds of Creation (2004)	'Round Midnight (1986)	'Salem's Lot (2004)	'Til There Was You (1997)	'Tis the Season for Love (2015)	'burbs, The (1989)	'night Mother (1986)	(500) Days of Summer (2009)	*batteries not included (1987)	...All the Marbles (1981)	...And Justice for All (1979)	(Schneid - Jag auf Nik Baxt (199
userId													
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 9719 columns

In [28]:

```
# Calculating pairwise correlation using corrwith function and calculating results for "The shining"
corr_results=pivot_df.corrwith(pivot_df['Shining, The (1980)'])
corr_results
```

Out[28]:
```
title
'71 (2014)                                         NaN
'Hellboy': The Seeds of Creation (2004)            NaN
'Round Midnight (1986)                             NaN
'Salem's Lot (2004)                                NaN
'Til There Was You (1997)                          NaN
                                                  ...
eXistenZ (1999)                              -0.504770
xXx (2002)                                    0.058187
xXx: State of the Union (2005)               -0.190693
¡Three Amigos! (1986)                         0.118727
À nous la liberté (Freedom for Us) (1931)          NaN
Length: 9719, dtype: float64
```

In [29]:
```
# Calculating the recommendations and cleansing it by dropping nulls
recommendation = pd.DataFrame(corr_results,columns=['Correlation'])
recommendation.dropna(inplace=True)
# The recommendation results are then joined with average ratings
recommendation = recommendation.join(avg_ratings['count_ratings'])
recommendation.head()
```

Out[29]:

title	Correlation	count_ratings
'burbs, The (1989)	0.476152	17
(500) Days of Summer (2009)	0.239143	42
***batteries not included (1987)**	0.870388	7
...And Justice for All (1979)	-1.000000	3
10 Cloverfield Lane (2016)	0.184289	14

In [30]:
```
# The resulting dataframe with the count of reviews more then 100 with higher correlation are extracted
recc = recommendation[recommendation['count_ratings']>100].sort_values('Correlation',ascending=False).reset_index()
# The results are joined with movies dataframe to get the movie titles and genre
final_recommendation = recc.merge(movies_df,on='title', how='left')
final_recommendation.head(10)
```

Out[30]:

	title	Correlation	count_ratings	movieId	genres
0	Shining, The (1980)	1.000000	109	1258	[Horror]
1	Waterworld (1995)	0.515491	115	208	[Action, Adventure, Sci-Fi]
2	Léon: The Professional (a.k.a. The Professional) (Léon) (1994)	0.515057	133	293	[Action, Crime, Drama, Thriller]
3	Donnie Darko (2001)	0.468267	109	4878	[Drama, Mystery, Sci-Fi, Thriller]
4	Outbreak (1995)	0.459459	101	292	[Action, Drama, Sci-Fi, Thriller]
5	Crimson Tide (1995)	0.445512	103	161	[Drama, Thriller, War]
6	Trainspotting (1996)	0.411779	102	778	[Comedy, Crime, Drama]
7	Breakfast Club, The (1985)	0.391780	113	1968	[Comedy, Drama]
8	Braveheart (1995)	0.370874	237	110	[Action, Drama, War]
9	Stargate (1994)	0.365455	140	316	[Action, Adventure, Sci-Fi]

Recommendation system: Approach 2 using Sparse Matrix and KNN method

In [31]:

```
# imporing csr_matrix to create sparse matrix
from scipy.sparse import csr_matrix
# Getting the list of unique elements in the User id and movie id of ratings dataframe
user_count = ratings_df['userId'].nunique()
movie_count = ratings_df['movieId'].nunique()
# Creating User mapper, movie mapper and the inverse mappers using zip and dict functions
user_mapper = dict(zip(np.unique(ratings_df["userId"]), list(range(user_count))))
movie_mapper = dict(zip(np.unique(ratings_df["movieId"]), list(range(movie_count))))
user_inv_mapper = dict(zip(list(range(user_count)), np.unique(ratings_df["userId"])))
movie_inv_mapper = dict(zip(list(range(movie_count)), np.unique(ratings_df["movieId"])))
# Extracting the row and column index to be used for sparse matric
user_index = [user_mapper[i] for i in ratings_df['userId']]
item_index = [movie_mapper[i] for i in ratings_df['movieId']]
# Creating sparse matrix using csr_matrix from rating data and shape , row and column index are also provided
sparse_matrix = csr_matrix((ratings_df["rating"], (user_index,item_index)), shape=(user_count,movie_count))
```

In [32]:

```
# Printing the shape of sparse matrix
```

```
sparse_matrix.shape
```

Out[32]: (610, 9724)

In [33]:
```
# Creating function to find movie recommendations
def find_movie_recommendations(movie_id, sparse_matrix, movie_mapper, movie_inv_mapper, k, metric='cosine'):
    """
    Finds k-nearest neighbours for a given movie id.

    Args:
        movie_id: id of the movie of interest
        X: user-item utility matrix
        k: number of similar movies to retrieve
        metric: distance metric for kNN calculations

    Output: returns list of k similar movie ID's
    """
    # Transposing the sparse matrix
    sparse_matrix = sparse_matrix.T
    # Creating empty list to capture the neighbor results
    neighbour_ids = []
    # Find the index of the movie of intesrest
    movie_ind = movie_mapper[movie_id]
    # Creating a vector of the ratings of the movie from the sparse matrix
    movie_vec = sparse_matrix[movie_ind]
    if isinstance(movie_vec, (np.ndarray)):
        movie_vec = movie_vec.reshape(1,-1)
    # use k+1 since kNN output includes the movieId of interest
    kNN = NearestNeighbors(n_neighbors=k+1, algorithm="brute", metric=metric)
    # Fitting the KNN model for the sparse matrix data
    kNN.fit(sparse_matrix)
    # FInding the neighbors using the kneighbors method of KNN model
    neighbour = kNN.kneighbors(movie_vec, return_distance=False)
    # Appending the results of neighbors to the neighbor_ids list
    for i in range(0,k):
        n = neighbour.item(i)
        neighbour_ids.append(movie_inv_mapper[n])
    # Removing the first item of the list to exclude the movie being searched.
    neighbour_ids.pop(0)
    # Returning the movie ids of the nearest movies of interest.
    return neighbour_ids
```

In [35]:
```python
# Testing the function using "The Shining"
movie_name='Shining, The (1980)'
# Creating dictionary of Movie Id and names
movie_ids = dict(zip(movies_df['title'],movies_df['movieId']))
# Extracting the movie id of the movie of interest
movie_id = movie_ids[movie_name]
# Finding similar movies using find_movie_recommendations function
similar_movies = find_movie_recommendations(movie_id, sparse_matrix, movie_mapper, movie_inv_mapper,
metric='cosine', k=10)
movie_titles = dict(zip(movies_df['movieId'],movies_df['title']))
# Printing the movie recommendations
print(f"Because you watched {movie_name}:")
for i in similar_movies:
    print(movie_titles[i])
```

```
Because you watched Shining, The (1980):
Psycho (1960)
Clockwork Orange, A (1971)
Goodfellas (1990)
Alien (1979)
Sixth Sense, The (1999)
Reservoir Dogs (1992)
Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1964)
Fight Club (1999)
Fargo (1996)
```