Build movie recommendation system

- This project implements a movie recommendation system using both content-based and collaborative filtering techniques, providing personalized movie recommendations based on user preferences.

Project Outline

1. Import Dependencies

- Import necessary libraries such as pandas, numpy, and scikit-learn for data manipulation and modeling.

2. Load Dataset

- Load the movie dataset containing information about movies, users, and ratings.

3. Data Preprocessing

- Explore the dataset to understand its structure, features, and distributions.
- Check for missing values and outliers that may need to be addressed during data preprocessing.

4. Exploratory Data Analysis

- Perform any necessary data cleaning and transformation steps to prepare the dataset for modeling.

5. Build Recommendation System

- Build different types of recommendation systems:

  ### 5.1 Simple Recommendation System

  - Implement a basic recommendation system (e.g., top N most popular movies) to establish a baseline for comparison.

    ### 5.2 Content-Based Recommendation System

  - Implement a content-based recommendation system that suggests movies similar to those a user has liked in the past, based on movie features (e.g., genres, directors, actors).

    ### 5.3 Collaborative Filtering (CF) Recommendation System

  - Implement user-based or item-based collaborative filtering to recommend movies based on the preferences of similar users or items.

    ### 5.4 Hybrid Recommendation System

  - Combine the content-based and CF recommendation systems to create a hybrid model that provides more accurate and diverse recommendations.

6. Evaluate the performance

- Evaluation of each recommendation system using metrics such as accuracy, precision, recall, and F1-score.

1. Import libraries

In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import ast
from scipy import stats
from ast import literal_eval
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
from nltk.stem.snowball import SnowballStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import wordnet
from surprise.model_selection import cross_validate
from surprise import Reader, Dataset, SVD




import warnings; warnings.simplefilter('ignore')
```

2. Load dataset

We have MovieLens datasets.

The Full Dataset: Consists of 26,000,000 ratings and 750,000 tag applications applied to 45,000 movies by 270,000 users. Includes tag genome data with 12 million relevance scores across 1,100 tags.

The Small Dataset: Comprises of 100,000 ratings and 1,300 tag applications applied to 9,000 movies by 700 users.

We will build our Simple Recommender using movies from the Full Dataset

In [2]:
```
credits = pd.read_csv('credits.csv')
keywords = pd.read_csv('keywords.csv')
links_small = pd.read_csv('links_small.csv')
movies = pd.read_csv('movies_metadata.csv')
ratings = pd.read_csv('ratings_small.csv')
```

3. Data Preprocessing

Credits dataframe

In [3]:
```
credits.head()
```

Out[3]:

	cast	crew	id
0	[{'cast_id': 14, 'character': 'Woody (voice)',...	[{'credit_id': '52fe4284c3a36847f8024f49', 'de...	862
1	[{'cast_id': 1, 'character': 'Alan Parrish', '...	[{'credit_id': '52fe44bfc3a36847f80a7cd1', 'de...	8844
2	[{'cast_id': 2, 'character': 'Max Goldman', 'c...	[{'credit_id': '52fe466a9251416c75077a89', 'de...	15602
3	[{'cast_id': 1, 'character': "Savannah 'Vannah...	[{'credit_id': '52fe44779251416c91011acb', 'de...	31357
4	[{'cast_id': 1, 'character': 'George Banks', '...	[{'credit_id': '52fe44959251416c75039ed7', 'de...	11862

In [4]:
```
credits.columns
```

Out[4]:
```
Index(['cast', 'crew', 'id'], dtype='object')
```

In [5]:
```
credits.isnull().sum()
```

Out[5]:
```
cast    0
crew    0
id      0
dtype: int64
```

- **cast:** Information about casting. Name of actor, gender and it's character name in movie
- **crew:** Information about crew members. Like who directed the movie, editor of the movie and so on.
- **id:** It's movie ID given by TMDb

In [6]:
```
credits.shape
```

Out[6]:
```
(45476, 3)
```

In [7]:
```
credits.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45476 entries, 0 to 45475
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   cast    45476 non-null  object
 1   crew    45476 non-null  object
 2   id      45476 non-null  int64
dtypes: int64(1), object(2)
memory usage: 1.0+ MB
```

Keywords dataframe

In [8]:
```
keywords.head()
```

Out[8]:

	id	keywords
0	862	[{'id': 931, 'name': 'jealousy'}, {'id': 4290,...
1	8844	[{'id': 10090, 'name': 'board game'}, {'id': 1...
2	15602	[{'id': 1495, 'name': 'fishing'}, {'id': 12392...
3	31357	[{'id': 818, 'name': 'based on novel'}, {'id':...
4	11862	[{'id': 1009, 'name': 'baby'}, {'id': 1599, 'n...

In [9]:
```
keywords.columns
```

Out[9]:
```
Index(['id', 'keywords'], dtype='object')
```

- **id:** It's movie ID given by TMDb
- **Keywords:** Tags/keywords for the movie. It list of tags/keywords

In [10]:
```
keywords.shape
```

Out[10]:
```
(46419, 2)
```

In [11]:
```
keywords.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46419 entries, 0 to 46418
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   id        46419 non-null  int64
 1   keywords  46419 non-null  object
dtypes: int64(1), object(1)
memory usage: 725.4+ KB
```

Link dataframe

In [12]:
```
links_small.head()
```

Out[12]:

	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

In [13]:
```
links_small.columns
```

Out[13]:
```
Index(['movieId', 'imdbId', 'tmdbId'], dtype='object')
```

In [14]:
```
links_small.isnull().sum()
```

Out[14]:
```
movieId     0
imdbId      0
tmdbId     13
dtype: int64
```

In [15]:
```
links_small.dropna(inplace=True)
```

In [16]:
```
links_small.isnull().sum()
```

Out[16]:
```
movieId    0
imdbId     0
tmdbId     0
dtype: int64
```

- **movieId:** It's serial number for movie
- **imdbId:** Movie id given on IMDb platform
- **tmdbId**: Movie id given on TMDb platform

In [17]:
```
links_small.shape
```

Out[17]:
```
(9112, 3)
```

In [18]:
```
links_small.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9112 entries, 0 to 9124
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   movieId  9112 non-null   int64  
 1   imdbId   9112 non-null   int64  
 2   tmdbId   9112 non-null   float64
dtypes: float64(1), int64(2)
memory usage: 284.8 KB
```

Metadata dataframe

In [19]:
```
movies.iloc[0:3].transpose()
```

Out[19]:

	0	1	
adult	False	False	
belongs_to_collection	{'id': 10194, 'name': 'Toy Story Collection', ...	NaN	{'i
budget	30000000	65000000	
genres	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	[{'id'
homepage	http://toystory.disney.com/toy-story	NaN	
id	862	8844	
imdb_id	tt0114709	tt0113497	
original_language	en	en	
original_title	Toy Story	Jumanji	
overview	Led by Woody, Andy's toys live happily in his ...	When siblings Judy and Peter discover an encha...	
popularity	21.946943	17.015539	
poster_path	/rhIRbceoE9lR4veEXuwCC2wARtG.jpg	/vzmL6fP7aPKNKPRTFnZmiUfciyV.jpg	/6ksm
production_companies	[{'name': 'Pixar Animation Studios', 'id': 3}]	[{'name': 'TriStar Pictures', 'id': 559}, {'na...	[{'
production_countries	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'
release_date	1995-10-30	1995-12-15	
revenue	373554033.0	262797249.0	
runtime	81.0	104.0	
spoken_languages	[{'iso_639_1': 'en', 'name': 'English'}]	[{'iso_639_1': 'en', 'name': 'English'}, {'iso...	[{'is
status	Released	Released	
tagline	NaN	Roll the dice and unleash the excitement!	Still
title	Toy Story	Jumanji	
video	False	False	
vote_average	7.7	6.9	
vote_count	5415.0	2413.0	

In [20]:

```
movies.columns
```

Out[20]:

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

Features

- **adult:** Indicates if the movie is X-Rated or Adult.
- **belongs_to_collection:** A stringified dictionary that gives information on the movie series the particular film belongs to.
- **budget:** The budget of the movie in dollars.
- **genres:** A stringified list of dictionaries that list out all the genres associated with the movie.
- **homepage:** The Official Homepage of the move.
- **id:** The ID of the movie.
- **imdb_id:** The IMDB ID of the movie.
- **original_language:** The language in which the movie was originally shot in.
- **original_title:** The original title of the movie.
- **overview:** A brief blurb of the movie.
- **popularity:** The Popularity Score assigned by TMDB.
- **poster_path:** The URL of the poster image.
- **production_companies:** A stringified list of production companies involved with the making of the movie.
- **production_countries:** A stringified list of countries where the movie was shot/produced in.
- **release_date:** Theatrical Release Date of the movie.
- **revenue:** The total revenue of the movie in dollars.
- **runtime:** The runtime of the movie in minutes.
- **spoken_languages:** A stringified list of spoken languages in the film.
- **status:** The status of the movie (Released, To Be Released, Announced, etc.)
- **tagline:** The tagline of the movie.
- **title:** The Official Title of the movie.
- **video:** Indicates if there is a video present of the movie with TMDB.
- **vote_average:** The average rating of the movie.
- **vote_count:** The number of votes by users, as counted by TMDB.

In [21]:
```
movies.columns
```

Out[21]:
```
Index(['adult', 'belongs_to_collection', 'budget', 'genres', 'homepage', 'id',
       'imdb_id', 'original_language', 'original_title', 'overview',
       'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title', 'video',
       'vote_average', 'vote_count'],
      dtype='object')
```

In [22]:
```
movies.shape
```

Out[22]:
```
(45466, 24)
```

In [23]:
```
movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45466 entries, 0 to 45465
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   adult                  45466 non-null  object
 1   belongs_to_collection  4494 non-null   object
 2   budget                 45466 non-null  object
 3   genres                 45466 non-null  object
 4   homepage               7782 non-null   object
 5   id                     45466 non-null  object
 6   imdb_id                45449 non-null  object
 7   original_language      45455 non-null  object
 8   original_title         45466 non-null  object
 9   overview               44512 non-null  object
 10  popularity             45461 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                45460 non-null  float64
 16  runtime                45203 non-null  float64
 17  spoken_languages       45460 non-null  object
 18  status                 45379 non-null  object
 19  tagline                20412 non-null  object
 20  title                  45460 non-null  object
 21  video                  45460 non-null  object
 22  vote_average           45460 non-null  float64
 23  vote_count             45460 non-null  float64
dtypes: float64(4), object(20)
memory usage: 8.3+ MB
```

In [24]:

```
movies.isnull().sum()
```

Out[24]:

```
adult                        0
belongs_to_collection    40972
budget                       0
genres                       0
homepage                 37684
id                           0
imdb_id                     17
original_language           11
original_title               0
overview                   954
popularity                   5
poster_path                386
production_companies         3
production_countries         3
release_date                87
revenue                      6
runtime                    263
spoken_languages             6
status                      87
tagline                  25054
title                        6
video                        6
vote_average                 6
vote_count                   6
dtype: int64
```

In [25]:

```
## Pre-processing step

def convert_int(x):
    try:
```

```
        return int(x)
    except:
        return np.nan
```

In [26]:
```
movies['id'] = movies['id'].apply(convert_int)
movies[movies['id'].isnull()]
```

Out[26]:

	adult	belongs_to_collection	budget	genres	home
19730	- Written by Ørnås	0.065736	/ff9qCepilowshEtG2GYWwzt2bs4.jpg	[{'name': 'Carousel Productions', 'id': 11176}...	[{'iso_31 'CA', 'r 'Car
29503	Rune Balot goes to a casino connected to the ...	1.931659	/zV8bHuSL6WXoD6FWogP9j4x80bL.jpg	[{'name': 'Aniplex', 'id': 2883}, {'name': 'Go...	[{'iso_31 'US', 'r 'U Stat
35587	Avalanche Sharks tells the story of a bikini ...	2.185485	/zaSf5OG7V8X8gqFvly88zDdRm46.jpg	[{'name': 'Odyssey Media', 'id': 17161}, {'nam...	[{'iso_31 'CA', 'r 'Can

3 rows × 24 columns

In [27]:
```
movies = movies.drop([19730, 29503, 35587])
```

In [28]:
```
movies['id'] = movies['id'].astype('int')
```

In [29]:
```
movies.fillna({'revenue': 0, 'runtime': 0, 'vote_average': 0, 'vote_count': 0}, inp
```

In [30]:
```
keywords['id'] = keywords['id'].astype('int')
credits['id'] = credits['id'].astype('int')
movies['id'] = movies['id'].astype('int')
```

In [31]:
```
movies.iloc[0:3].transpose()
```

Out[31]:

	0	1	
adult	False	False	
belongs_to_collection	{'id': 10194, 'name': 'Toy Story Collection', ...	NaN	{'i
budget	30000000	65000000	
genres	[{'id': 16, 'name': 'Animation'}, {'id': 35, '...	[{'id': 12, 'name': 'Adventure'}, {'id': 14, '...	[{'id'
homepage	http://toystory.disney.com/toy-story	NaN	
id	862	8844	
imdb_id	tt0114709	tt0113497	
original_language	en	en	
original_title	Toy Story	Jumanji	
overview	Led by Woody, Andy's toys live happily in his ...	When siblings Judy and Peter discover an encha...	
popularity	21.946943	17.015539	
poster_path	/rhIRbceoE9lR4veEXuwCC2wARtG.jpg	/vzmL6fP7aPKNKPRTFnZmiUfciyV.jpg	/6ksm
production_companies	[{'name': 'Pixar Animation Studios', 'id': 3}]	[{'name': 'TriStar Pictures', 'id': 559}, {'na...	[{'
production_countries	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'
release_date	1995-10-30	1995-12-15	
revenue	373554033.0	262797249.0	
runtime	81.0	104.0	
spoken_languages	[{'iso_639_1': 'en', 'name': 'English'}]	[{'iso_639_1': 'en', 'name': 'English'}, {'iso...	[{'is
status	Released	Released	
tagline	NaN	Roll the dice and unleash the excitement!	Still
title	Toy Story	Jumanji	
video	False	False	
vote_average	7.7	6.9	
vote_count	5415.0	2413.0	

Ratings dataframe

In [32]:

```
ratings.head()
```

Out[32]:

	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

In [33]:
```
ratings.columns
```

Out[33]:
```
Index(['userId', 'movieId', 'rating', 'timestamp'], dtype='object')
```

- **userId:** It is id for User
- **movieId:** It is TMDb movie id.
- **rating:** Rating given for the particular movie by specific user
- **timestamp:** Time stamp when rating has been given by user

In [34]:
```
ratings.shape
```

Out[34]:
```
(100004, 4)
```

In [35]:
```
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
```

In [36]:
```
ratings.isnull().sum()
```

Out[36]:
```
userId       0
movieId      0
rating       0
timestamp    0
dtype: int64
```

Data Preprocessing

In [37]:
```
movies.iloc[0].genres
```

Out[37]:
```
"[{'id': 16, 'name': 'Animation'}, {'id': 35, 'name': 'Comedy'}, {'id': 10751, 'na
me': 'Family'}]"
```

In [38]:
```
def convert(obj):
    l=[]
    for i in ast.literal_eval(obj):
        l.append(i['name'])
    return l
```

In [39]:
```
keywords['keywords'] = keywords['keywords'].apply(convert)
```

In [40]:
```
keywords.head()
```

Out[40]:

	id	keywords
0	862	[jealousy, toy, boy, friendship, friends, riva...
1	8844	[board game, disappearance, based on children'...
2	15602	[fishing, best friend, duringcreditsstinger, o...
3	31357	[based on novel, interracial relationship, sin...
4	11862	[baby, midlife crisis, confidence, aging, daug...

In [41]:
```
import ast
import numpy as np

def convert(obj):
    if pd.isna(obj):
        return []
    l = []
    for i in ast.literal_eval(obj):
        l.append(i['name'])
    return l

movies['production_companies'] = movies['production_companies'].apply(convert)
```

In [42]:
```
def convert(obj):
    l=[]
    counter=0
    for i in ast.literal_eval(obj):
        if counter != 3:
            l.append(i['name'])
            counter+=1
        else:
            break
    return l
```

In [43]:
```
movies['genres'] = movies['genres'].apply(convert)
```

1. Crew: From the crew, we will only pick the director as our feature since the others don't contribute that much to the feel of the movie.

2. Cast: Choosing Cast is a little more tricky. Lesser known actors and minor roles do not really affect people's opinion of a movie. Therefore, we must only select the major characters and their respective actors. Arbitrarily we will choose the top 3 actors that appear in the credits list.

In [44]:
```
credits['cast'] = credits['cast'].apply(convert)
```

In [45]:
```
def fetch_director(obj):
    l=[]
    for i in ast.literal_eval(obj):
        if i['job'] == 'Director':
            l.append(i['name'])
```

```
            break
    return l
```

In [46]:
```
credits['crew'] = credits['crew'].apply(fetch_director)
```

In [47]:
```
credits.head()
```

Out[47]:

	cast	crew	id
0	[Tom Hanks, Tim Allen, Don Rickles]	[John Lasseter]	862
1	[Robin Williams, Jonathan Hyde, Kirsten Dunst]	[Joe Johnston]	8844
2	[Walter Matthau, Jack Lemmon, Ann-Margret]	[Howard Deutch]	15602
3	[Whitney Houston, Angela Bassett, Loretta Devine]	[Forest Whitaker]	31357
4	[Steve Martin, Diane Keaton, Martin Short]	[Charles Shyer]	11862

In [48]:
```
movies['overview'] = movies['overview'].fillna('').apply(lambda x: x.split())
```

In [49]:
```
movies['tagline'] = movies['tagline'].fillna('').apply(lambda x: x.split())
```

In [50]:
```
movies.head()
```

Out[50]:

	adult	belongs_to_collection	budget	genres	homepage	id	imdb_
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[Animation, Comedy, Family]	http://toystory.disney.com/toy-story	862	tt01147
1	False	NaN	65000000	[Adventure, Fantasy, Family]	NaN	8844	tt01134
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[Romance, Comedy]	NaN	15602	tt01132
3	False	NaN	16000000	[Comedy, Drama, Romance]	NaN	31357	tt01148
4	False	{'id': 96871, 'name': 'Father of the Bride Col...	0	[Comedy]	NaN	11862	tt0113C

5 rows × 24 columns

In [51]:
```
movies.shape
```

Out[51]:
```
(45463, 24)
```

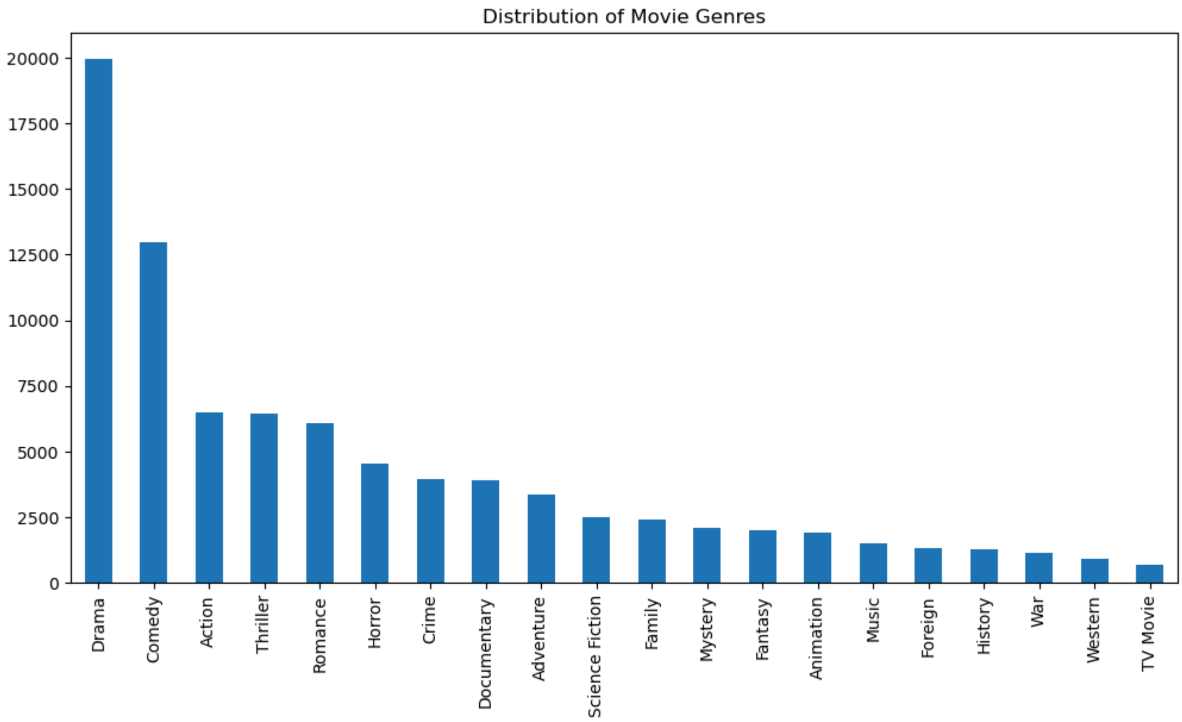
4. Exploratory Data Analysis

1. What is the distribution of movie genres in the dataset?
2. How many unique users and movies are present in the ratings dataset?
3. How has the popularity of movies changed over the years?
4. What is the distribution of movie ratings (vote_average) in the dataset?
5. Are there any correlations between movie budget, revenue, and ratings?
6. Are there any trends in movie release dates over the years?
7. What is the distribution of user ratings (or votes) per movie?
8. What are the top keywords used to describe movies in the keywords dataset?
9. What are the top production companies in the dataset?

1. Distribution of movie genres

In [52]:
```
genres_list = movies['genres'].explode()

# Count the occurrences of each genre
genre_counts = genres_list.value_counts()

# Plot the distribution of movie genres
genre_counts.plot(kind='bar', figsize=(12, 6), title='Distribution of Movie Genres'
```

Out[52]:
```
<Axes: title={'center': 'Distribution of Movie Genres'}>
```



The most common genres in movies are drama, followed by comedy, action, and thriller.

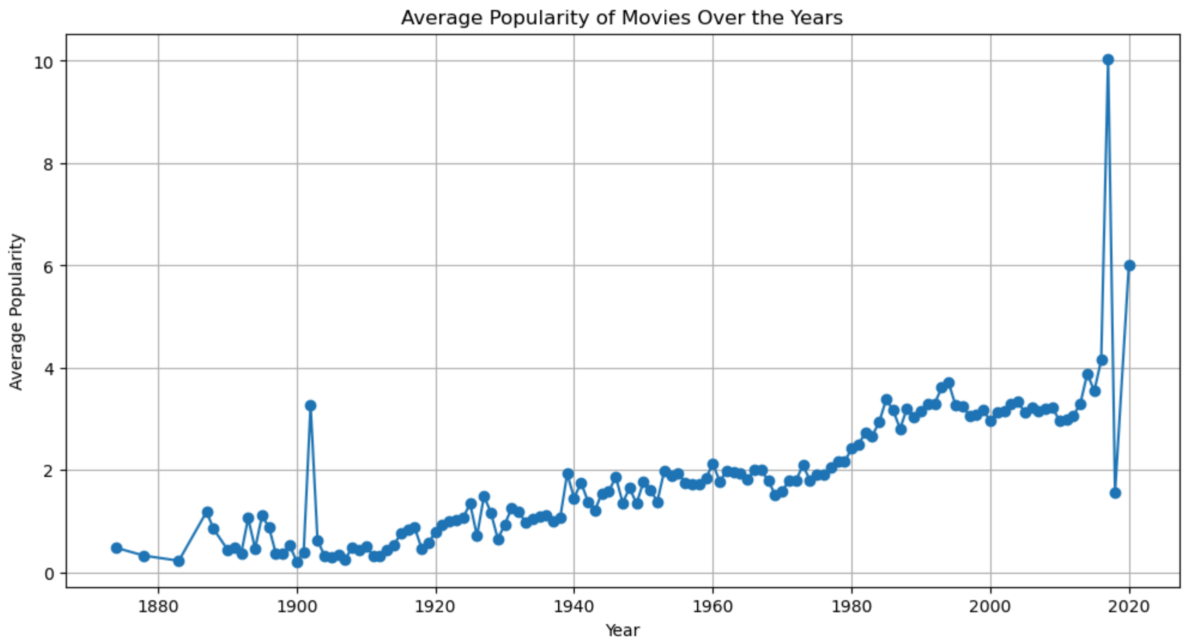
2. Unique number of users and movies

In [53]:
```
unique_users = ratings['userId'].nunique()
unique_movies = ratings['movieId'].nunique()

print(f"Number of unique users: {unique_users}")
print(f"Number of unique movies: {unique_movies}")
```

```
Number of unique users: 671
Number of unique movies: 9066
```

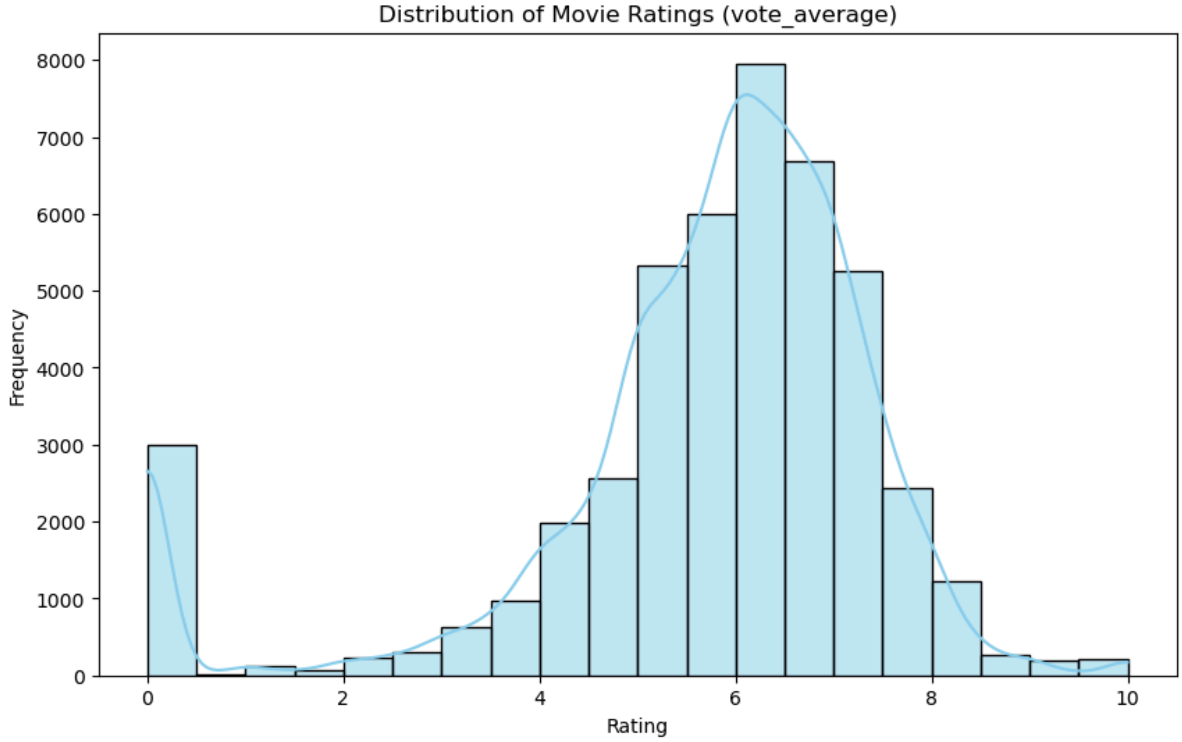
3. Average Popularity Of Movies Over Years

In [54]:
```
movies['popularity'] = pd.to_numeric(movies['popularity'], errors='coerce')
mean_popularity = movies['popularity'].mean()
movies['popularity'].fillna(mean_popularity, inplace=True)

movies['release_date'] = pd.to_datetime(movies['release_date'])

# Extract year from 'release_date'
movies['release_year'] = movies['release_date'].dt.year

# Group by 'release_year' and calculate the average popularity for each year
popularity_by_year = movies.groupby('release_year')['popularity'].mean()

# Plot the popularity trend over the years
plt.figure(figsize=(12, 6))
plt.plot(popularity_by_year.index, popularity_by_year.values, marker='o')
plt.xlabel('Year')
plt.ylabel('Average Popularity')
plt.title('Average Popularity of Movies Over the Years')
plt.grid(True)
plt.show()
```



4. Distribution of movie ratings

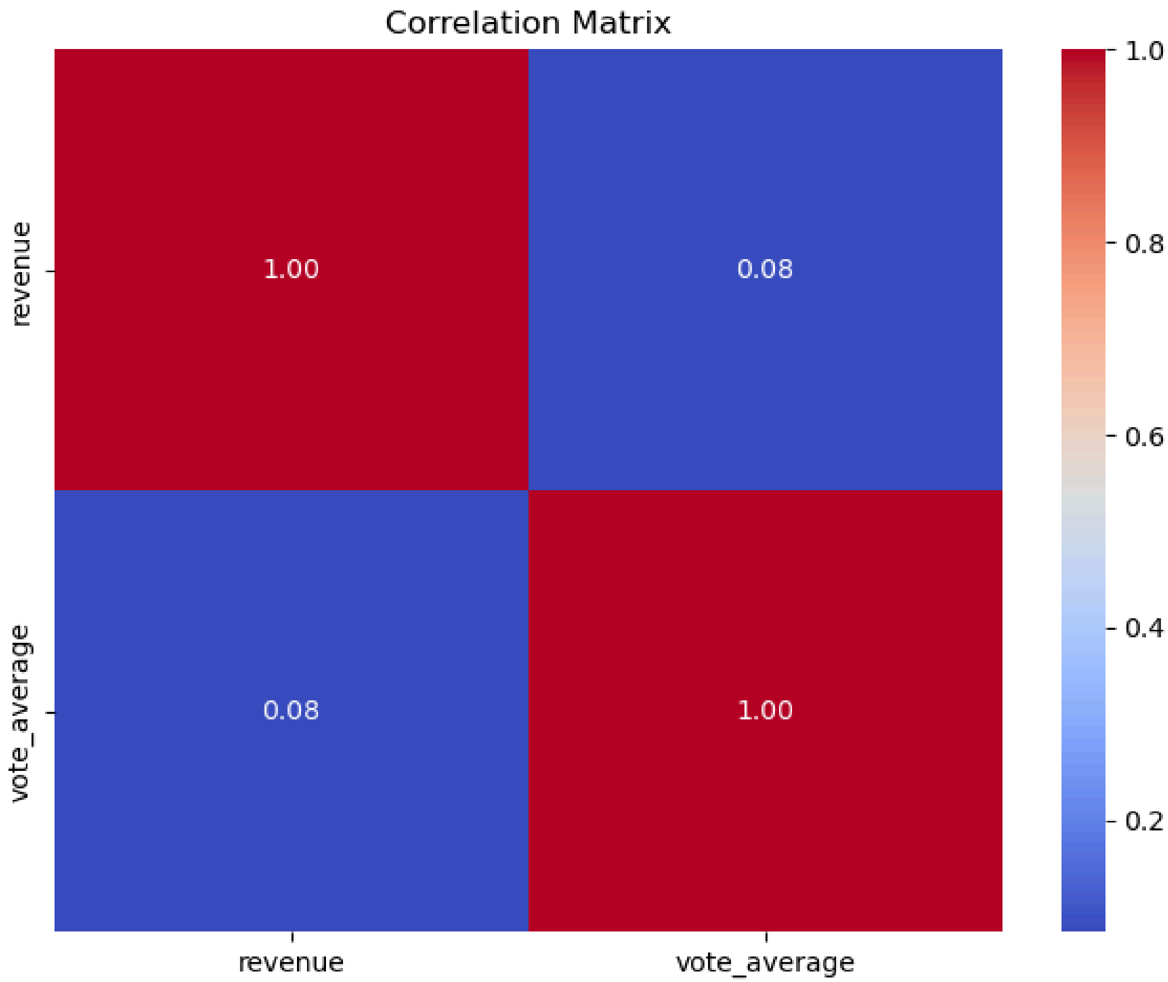
In [55]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=movies, x='vote_average', bins=20, kde=True, color='skyblue')
plt.title('Distribution of Movie Ratings (vote_average)')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```



5. Correlations between movie budget, revenue, and ratings

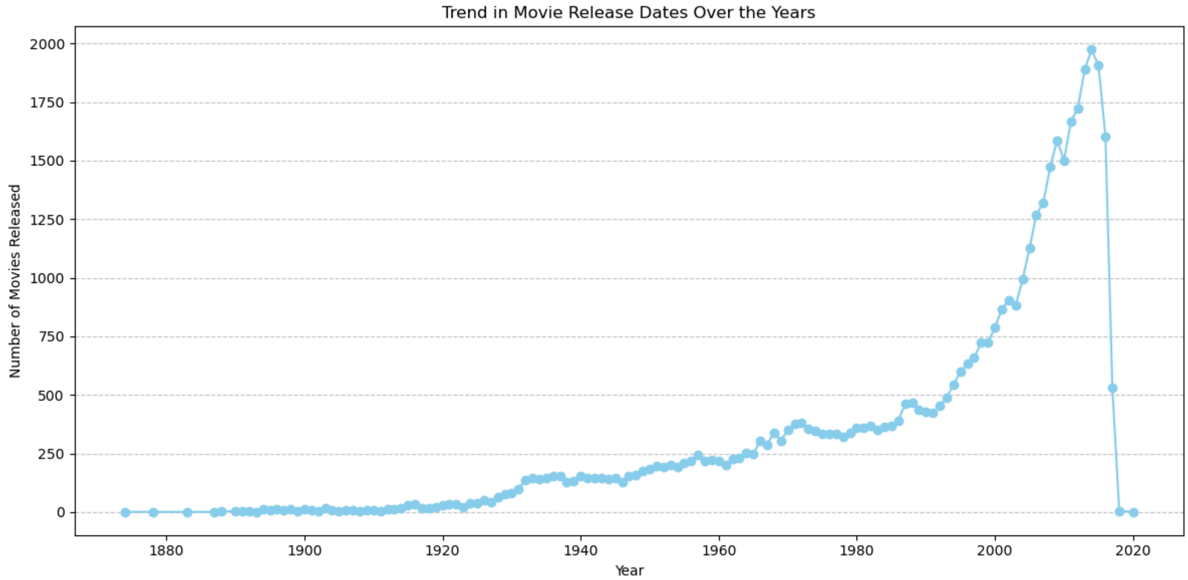
In [56]:

```
# Selecting relevant columns
numerical_columns = ['budget', 'revenue', 'vote_average']
numerical_data = movies[numerical_columns]

# Calculating the correlation matrix
correlation_matrix = numerical_data.corr()

# Plotting the heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



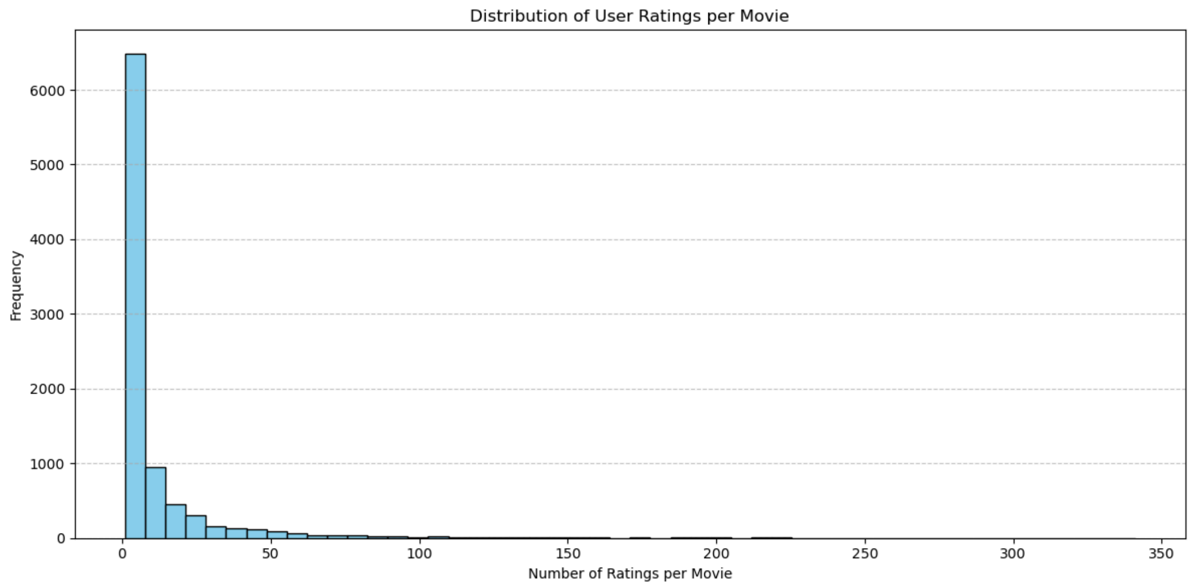
6. Trends in movie release dates over the years

In [57]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming you have loaded the dataset into 'movies'

# Extract the year from the release_date column
movies['release_year'] = pd.to_datetime(movies['release_date']).dt.year

# Group the movies by release year to get the count of movies released each year
movies_per_year = movies.groupby('release_year').size()

# Visualize the trend in movie release dates over the years
plt.figure(figsize=(12, 6))
movies_per_year.plot(kind='line', marker='o', color='skyblue')
plt.title('Trend in Movie Release Dates Over the Years')
plt.xlabel('Year')
plt.ylabel('Number of Movies Released')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



7. Distribution of user ratings (or votes) per movie

In [58]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming you have loaded the dataset into 'ratings_df'

# Group the ratings dataset by movieId to get the count of ratings for each movie
ratings_per_movie = ratings.groupby('movieId').size()

# Visualize the distribution of ratings per movie
plt.figure(figsize=(12, 6))
plt.hist(ratings_per_movie, bins=50, color='skyblue', edgecolor='black')
plt.title('Distribution of User Ratings per Movie')
plt.xlabel('Number of Ratings per Movie')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

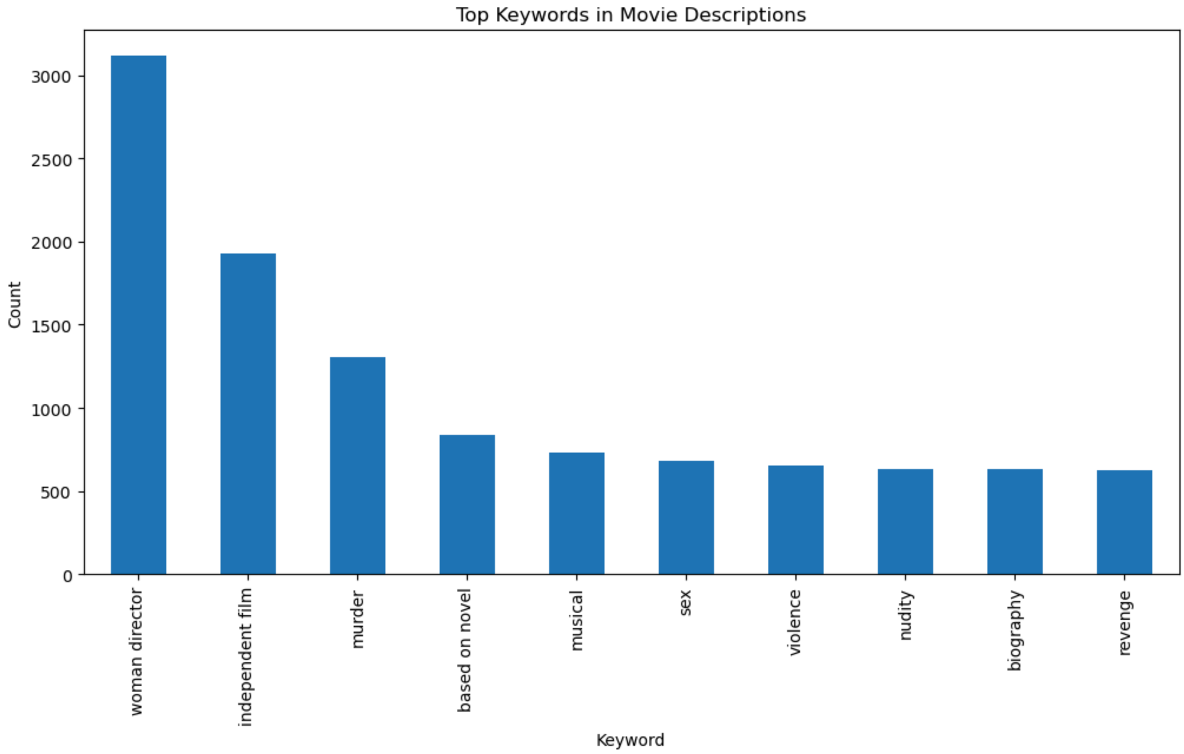


8.Top Keywords

In [59]:
```
keywords_list = keywords['keywords'].explode()

# Count the occurrences of each keyword
keyword_counts = keywords_list.value_counts()

# Print the top keywords
print("Top keywords:")
print(keyword_counts.head(10))
```

```
Top keywords:
woman director      3115
independent film    1930
murder              1308
based on novel       835
musical              734
sex                  685
violence             651
nudity               636
biography            629
revenge              626
Name: keywords, dtype: int64
```

In [60]:
```
plt.figure(figsize=(12, 6))
keyword_counts.head(10).plot(kind='bar', title='Top Keywords in Movie Descriptions'
plt.xlabel('Keyword')
plt.ylabel('Count')
plt.show()
```



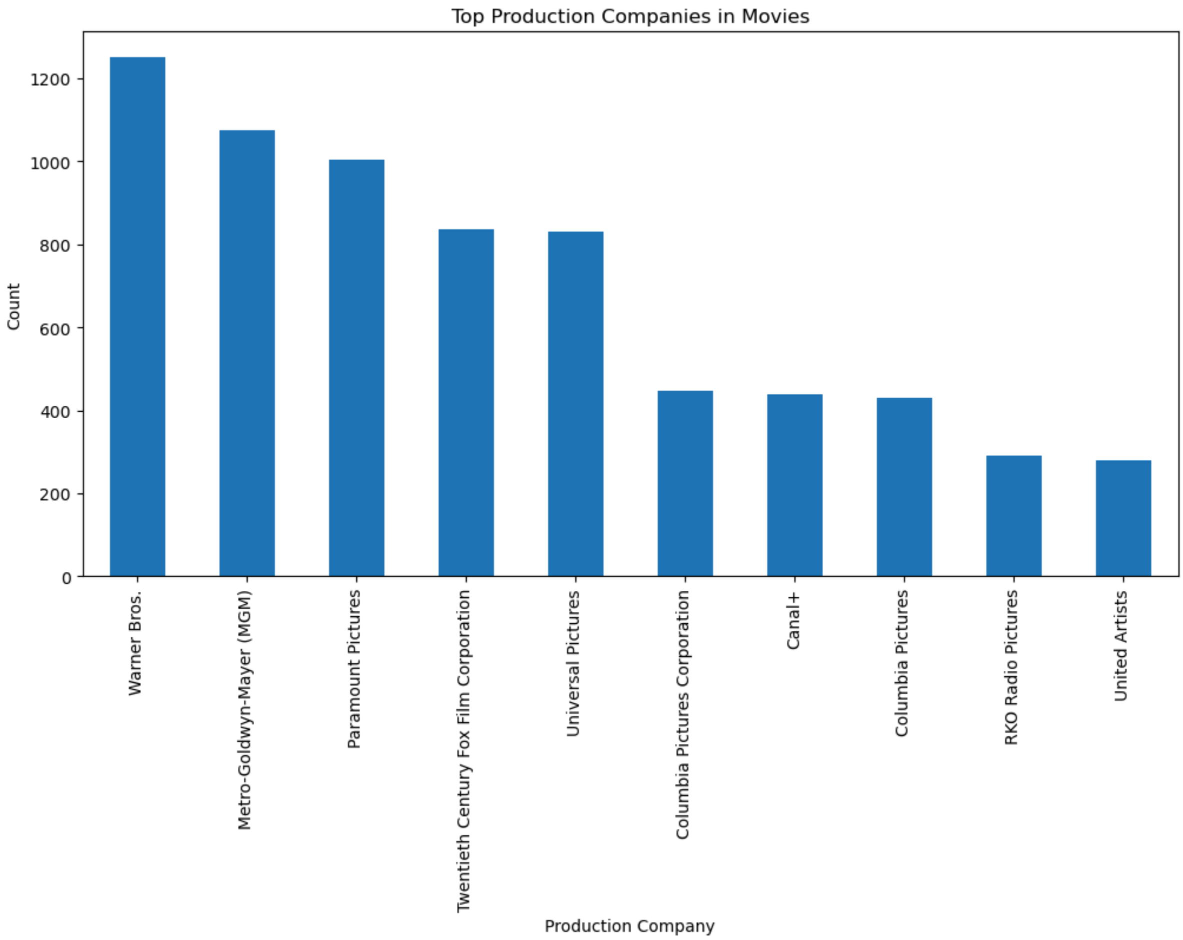
9.Top Production Companies

In [61]:
```
production_companies_list = movies['production_companies'].explode()

# Count the occurrences of each production company
production_company_counts = production_companies_list.value_counts()

# Print the top production companies
print("Top production companies:")
print(production_company_counts.head(10))
```

```
Top production companies:
Warner Bros.                            1250
Metro-Goldwyn-Mayer (MGM)               1076
Paramount Pictures                      1003
Twentieth Century Fox Film Corporation   836
Universal Pictures                       830
Columbia Pictures Corporation            448
Canal+                                   438
Columbia Pictures                        431
RKO Radio Pictures                       290
United Artists                           279
Name: production_companies, dtype: int64
```

In [62]:
```
# Plot the top 10 production companies
plt.figure(figsize=(12, 6))
production_company_counts.head(10).plot(kind='bar', title='Top Production Companies
plt.xlabel('Production Company')
plt.ylabel('Count')
```

Out[62]:
```
Text(0, 0.5, 'Count')
```



In [63]:
```
movies_df_exploded = movies.explode('production_companies')

# Group by production company and calculate the average rating
production_company_ratings = movies_df_exploded.groupby('production_companies')['vo

# Print the top production companies according to ratings
print("Top production companies according to ratings:")
print(production_company_ratings.sort_values(ascending=False).head(10))
```

```
Top production companies according to ratings:
production_companies
Vanguardia Films                 10.0
Roberto Me Dejó Films            10.0
One Small Instrument Pictures    10.0
Marquise                         10.0
Chase Productions                10.0
INCAA                            10.0
Rhino Media                      10.0
AMV Production                   10.0
Wood-Thomas Pictures             10.0
Les Films Fauves                 10.0
Name: vote_average, dtype: float64
```

6. Build recommendation system

6.1. Simple recommendation system

Approach:

- The Simple Recommender offers **generalized recommendations** to every user **based on movie popularity and (sometimes) genre**.
- The **basic idea** behind this recommender is that **movies that are more popular and more critically acclaimed will have a higher probability of being liked by the average audience.**
- This model **does not give personalized recommendations** based on the user.

What we are actually doing:

- The implementation of this model is extremely trivial.
- All we have to do is **sort our movies based on ratings and popularity** and display the top movies of our list.
- As an added step, we can **pass in a genre argument to get the top movies of a particular genre.**

I will build our overall Top 250 Chart and will define a function to build charts for a particular genre. Let's begin!

- I use the TMDB Ratings to come up with our Top Movies Chart.
- I will use IMDB's weighted rating formula to construct my chart.
- Mathematically, it is represented as follows:

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

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

In [64]:
```
# this is V
vote_counts = movies[movies['vote_count'].notnull()]['vote_count'].astype('int')

# this is R
vote_averages = movies[movies['vote_average'].notnull()]['vote_average'].astype('ir

# this is C
C = vote_averages.mean()
C
```

Out[64]:
```
5.244550513604469
```

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

In [65]:
```
m = vote_counts.quantile(0.95)
m
```

Out[65]:
```
433.90000000000146
```

In [66]:
```
# Pre-processing step for getting year from date by splliting it using '-'

movies['year'] = pd.to_datetime(movies['release_date'], errors='coerce').apply(
    lambda x: str(x).split('-')[0] if x != np.nan else np.nan)
```

In [67]:
```
qualified = movies[(movies['vote_count'] >= m) &
               (movies['vote_count'].notnull()) &
               (movies['vote_average'].notnull())][['title',
                                                    'year',
                                                    'vote_count',
                                                    'vote_average',
                                                    'popularity',
                                                    'genres']]

qualified['vote_count'] = qualified['vote_count'].astype('int')
qualified['vote_average'] = qualified['vote_average'].astype('int')
qualified.shape
```

Out[67]:
```
(2274, 6)
```

- Therefore, to qualify to be considered for the chart, a movie has to have at least **434 votes** on TMDB.
- We also see that the **average rating** for **a movie on TMDB** is **5.244 on a scale of 10**.
- Here, only **2274 movies** are qualify to be on our chart.

In [68]:
```
def weighted_rating(x):
    v = x['vote_count']
    R = x['vote_average']
    return (v/(v+m) * R) + (m/(m+v) * C)
```

In [69]:
```
qualified['wr'] = qualified.apply(weighted_rating, axis=1)
```

In [70]:
```
qualified = qualified.sort_values('wr', ascending=False).head(250)
```

Top Movies

In [71]:
```
qualified.head(15)
```

Out[71]:

	title	year	vote_count	vote_average	popularity	genres	wr
15480	Inception	2010	14075	8	29.108149	[Action, Thriller, Science Fiction]	7.917596
12481	The Dark Knight	2008	12269	8	123.167259	[Drama, Action, Crime]	7.905881
22879	Interstellar	2014	11187	8	32.213481	[Adventure, Drama, Science Fiction]	7.897117
2843	Fight Club	1999	9678	8	63.869599	[Drama]	7.881764
4863	The Lord of the Rings: The Fellowship of the Ring	2001	8892	8	32.070725	[Adventure, Fantasy, Action]	7.871799
292	Pulp Fiction	1994	8670	8	140.950236	[Thriller, Crime]	7.868673
314	The Shawshank Redemption	1994	8358	8	51.645403	[Drama, Crime]	7.864012
7000	The Lord of the Rings: The Return of the King	2003	8226	8	29.324358	[Adventure, Fantasy, Action]	7.861940
351	Forrest Gump	1994	8147	8	48.307194	[Comedy, Drama, Romance]	7.860669
5814	The Lord of the Rings: The Two Towers	2002	7641	8	29.423537	[Adventure, Fantasy, Action]	7.851938
256	Star Wars	1977	6778	8	42.149697	[Adventure, Action, Science Fiction]	7.834220
1225	Back to the Future	1985	6239	8	25.778509	[Adventure, Comedy, Science Fiction]	7.820829
834	The Godfather	1972	6024	8	41.109264	[Drama, Crime]	7.814864
1154	The Empire Strikes Back	1980	5998	8	19.470959	[Adventure, Action, Science Fiction]	7.814116
46	Se7en	1995	5915	8	18.457430	[Crime, Mystery, Thriller]	7.811686

- We see that three Christopher Nolan Films, **Inception**, **The Dark Knight** and **Interstellar** occur at the very top of our chart.

- The chart also indicates a strong bias of TMDB Users towards particular genres and directors.

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

In [72]:
```
s = movies.apply(lambda x: pd.Series(x['genres']),axis=1).stack().reset_index(level
s.name = 'genre'
gen_md = movies.drop('genres', axis=1).join(s)
gen_md.head(3).transpose()
```

Out[72]:

	0	0	
adult	False	False	
belongs_to_collection	{'id': 10194, 'name': 'Toy Story Collection', ...	{'id': 10194, 'name': 'Toy Story Collection', ...	
budget	30000000	30000000	
homepage	http://toystory.disney.com/toy-story	http://toystory.disney.com/toy-story	http:
id	862	862	
imdb_id	tt0114709	tt0114709	
original_language	en	en	
original_title	Toy Story	Toy Story	
overview	[Led, by, Woody,, Andy's, toys, live, happily,...	[Led, by, Woody,, Andy's, toys, live, happily,...	[Le
popularity	21.946943	21.946943	
poster_path	/rhIRbceoE9lR4veEXuwCC2wARtG.jpg	/rhIRbceoE9lR4veEXuwCC2wARtG.jpg	/rhIRb
production_companies	[Pixar Animation Studios]	[Pixar Animation Studios]	
production_countries	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'iso_3166_1': 'US', 'name': 'United States o...	[{'i
release_date	1995-10-30 00:00:00	1995-10-30 00:00:00	
revenue	373554033.0	373554033.0	
runtime	81.0	81.0	
spoken_languages	[{'iso_639_1': 'en', 'name': 'English'}]	[{'iso_639_1': 'en', 'name': 'English'}]	[{'is
status	Released	Released	
tagline	[]	[]	
title	Toy Story	Toy Story	
video	False	False	
vote_average	7.7	7.7	
vote_count	5415.0	5415.0	
release_year	1995.0	1995.0	
year	1995	1995	
genre	Animation	Comedy	

In [73]:
```
def build_chart(genre, percentile=0.85):
    df = gen_md[gen_md['genre'] == genre]
    vote_counts = df[df['vote_count'].notnull()]['vote_count'].astype('int')
    vote_averages = df[df['vote_average'].notnull()]['vote_average'].astype('int')
    C = vote_averages.mean()
    m = vote_counts.quantile(percentile)

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

```
    qualified['wr'] = qualified.apply(lambda x:
                        (x['vote_count']/(x['vote_count']+m) * x['vote_average']) +
                        axis=1)
    qualified = qualified.sort_values('wr', ascending=False).head(250)

    return qualified
```

Let us see our method in action by displaying the **Top 15 Romance Movies** (Romance almost didn't feature at all in our Generic Top Chart despite being one of the most popular movie genres).

Top 15 Romantic Movies

In [74]:
```
build_chart('Romance').head(5)
```

Out[74]:

	title	year	vote_count	vote_average	popularity	wr
10309	Dilwale Dulhania Le Jayenge	1995	661	9	34.457024	8.593391
351	Forrest Gump	1994	8147	8	48.307194	7.973403
876	Vertigo	1958	1162	8	18.208220	7.824299
40251	Your Name.	2016	1030	8	34.461252	7.803480
883	Some Like It Hot	1959	835	8	11.845107	7.761781

In [75]:
```
build_chart('Action').head(5)
```

Out[75]:

	title	year	vote_count	vote_average	popularity	wr
15480	Inception	2010	14075	8	29.108149	7.955030
12481	The Dark Knight	2008	12269	8	123.167259	7.948530
4863	The Lord of the Rings: The Fellowship of the Ring	2001	8892	8	32.070725	7.929470
7000	The Lord of the Rings: The Return of the King	2003	8226	8	29.324358	7.923913
5814	The Lord of the Rings: The Two Towers	2002	7641	8	29.423537	7.918255

In [76]:
```
build_chart('Fantasy').head(5)
```

Out[76]:

	title	year	vote_count	vote_average	popularity	wr
4863	The Lord of the Rings: The Fellowship of the Ring	2001	8892	8	32.070725	7.898973
7000	The Lord of the Rings: The Return of the King	2003	8226	8	29.324358	7.891130
5814	The Lord of the Rings: The Two Towers	2002	7641	8	29.423537	7.883163
3030	The Green Mile	1999	4166	8	19.966780	7.793310
5481	Spirited Away	2001	3968	8	41.048867	7.783838

6.2 Content based recommendation system

In [77]:
```
links_small = links_small[links_small['tmdbId'].notnull()]['tmdbId'].astype('int')
```

In [78]:
```
movies = movies[movies['id'].isin(links_small)]
movies.shape
```

Out[78]:
```
(9099, 26)
```

We have **9099 movies** available in our small movies metadata dataset which is 5 times smaller than our original dataset of 45000 movies.

Content based recommendation system : Using movie overview and taglines

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

In [79]:
```
movies['description'] = movies['overview'] + movies['tagline']
```

In [80]:
```
movies.head()
```

Out[80]:

	adult	belongs_to_collection	budget	genres	homepage	id	imdb_
0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[Animation, Comedy, Family]	http://toystory.disney.com/toy-story	862	tt01147
1	False	NaN	65000000	[Adventure, Fantasy, Family]	NaN	8844	tt01134
2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[Romance, Comedy]	NaN	15602	tt01132
3	False	NaN	16000000	[Comedy, Drama, Romance]	NaN	31357	tt01148
4	False	{'id': 96871, 'name': 'Father of the Bride Col...	0	[Comedy]	NaN	11862	tt0113C

5 rows × 27 columns

In [82]:
```
tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='engli
movies['description'] = movies['description'].apply(lambda x: ' '.join(x) if isinst

tfidf_matrix = tf.fit_transform(movies['description'])
```

In [83]:
```
tfidf_matrix.shape
```

Out[83]:
```
(9099, 267952)
```

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

In [84]:
```
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

In [85]:
```
cosine_sim[0]
#cosine_sim.shape
```

Out[85]:
```
array([1.        , 0.00680491, 0.        , ..., 0.        , 0.00344926,
       0.        ])
```

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

In [89]:
```
movies.drop(columns=['level_0'], inplace=True, errors='ignore')
movies = movies.reset_index(drop=True)

titles = movies['title']
indices = pd.Series(movies.index, index=movies['title'])
indices.head(2)
```

Out[89]:
```
title
Toy Story    0
Jumanji      1
dtype: int64
```

In [90]:
```
def get_recommendations(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:31]
    movie_indices = [i[0] for i in sim_scores]
    return titles.iloc[movie_indices]
```

- We're all set...!
- Let us now try and get the top recommendations for a few movies and see how good the recommendations are.

In [91]:
```
get_recommendations('The Godfather').head(10)
```

Out[91]:
```
973      The Godfather: Part II
8387                 The Family
3509                       Made
4196        Johnny Dangerously
29               Shanghai Triad
5667                       Fury
2412             American Movie
1582    The Godfather: Part III
4221                    8 Women
2159             Summer of Sam
Name: title, dtype: object
```

In [92]:
```
get_recommendations('The Dark Knight').head(10)
```

Out[92]:
```
7931                      The Dark Knight Rises
132                              Batman Forever
1113                             Batman Returns
8227    Batman: The Dark Knight Returns, Part 2
7565                 Batman: Under the Red Hood
524                                      Batman
7901                           Batman: Year One
2579               Batman: Mask of the Phantasm
2696                                        JFK
8165    Batman: The Dark Knight Returns, Part 1
Name: title, dtype: object
```

- We see that for The **Dark Knight**, our system is able to identify it as a **Batman film and subsequently recommend other Batman films** as its top recommendations.

- But unfortunately, that is all this system can do at the moment.
- This is not of much use to most people as it doesn't take into considerations very important features such as cast, crew, director and genre, which determine the rating and the popularity of a movie.
- Someone who liked The Dark Knight probably likes it more because of Nolan and would hate Batman Forever and every other substandard movie in the Batman Franchise.

- Therefore, we are going to use much more suggestive metadata than Overview and Tagline.
- In the next subsection, we will build a more sophisticated recommender that takes **genre, keywords, cast and crew** into consideration.

In [93]:
```
movies = movies.merge(credits, on='id')
movies = movies.merge(keywords, on='id')
```

In [94]:
```
smd = movies[movies['id'].isin(links_small)]
smd.shape
```

Out[94]:
```
(9219, 31)
```

In [95]:
```
smd.head()
```

Out[95]:

	index	adult	belongs_to_collection	budget	genres	homepage	id
0	0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[Animation, Comedy, Family]	http://toystory.disney.com/toy-story	862
1	1	False	NaN	65000000	[Adventure, Fantasy, Family]	NaN	8844
2	2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[Romance, Comedy]	NaN	15602
3	3	False	NaN	16000000	[Comedy, Drama, Romance]	NaN	31357
4	4	False	{'id': 96871, 'name': 'Father of the Bride Col...	0	[Comedy]	NaN	11862

5 rows × 31 columns

We now have our cast, crew, genres and credits, all in one dataframe.

- Approach to building the recommender is going to be extremely hacky.
- What I plan on doing is creating a metadata dump for every movie which consists of genres, director, main actors and keywords.
- I then use a **Count Vectorizer** to create our **count matrix**
- The remaining steps are similar to what we did earlier: we calculate the cosine similarities and return movies that are most similar.

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

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

In [97]:
```
smd['cast'] = smd['cast'].apply(lambda x: [str.lower(i.replace(" ", "")) for i in x
smd['crew'] = smd['crew'].astype('str').apply(lambda x: str.lower(x.replace(" ", "
smd['crew'] = smd['crew'].apply(lambda x: [x,x, x])
```

Keywords

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

In [98]:
```
s = smd.apply(lambda x: pd.Series(x['keywords']),axis=1).stack().reset_index(level=
s.name = 'keyword'
s = s.value_counts()
s[:5]
```

Out[98]:
```
independent film        610
woman director          550
murder                  399
duringcreditsstinger    327
based on novel          318
Name: keyword, dtype: int64
```

- Keywords occur in frequencies ranging from 1 to 610.
- We do not have any use for keywords that occur only once.
- Therefore, these can be safely removed.
- Finally, we will convert every word to its stem so that words such as **Dogs** and **Dog** are considered the same.

In [99]:
```
s = s[s > 1]
```

In [100…
```
# Just an example
stemmer = SnowballStemmer('english')
stemmer.stem('dogs')
```

Out[100]:
```
'dog'
```

In [101…
```
def filter_keywords(x):
    words = []
    for i in x:
        if i in s:
            words.append(i)
    return words
```

In [102…
```
smd['tags'] = smd['overview'] + smd['genres']+ smd['cast'] + smd['crew'] + smd['key
```

In [103…
```
smd['tags'] = smd['tags'].apply(lambda x:" ".join(x))
```

In [104…
```
smd.head()
```

Out[104]:

	index	adult	belongs_to_collection	budget	genres	homepage	id
0	0	False	{'id': 10194, 'name': 'Toy Story Collection', ...	30000000	[Animation, Comedy, Family]	http://toystory.disney.com/toy-story	862
1	1	False	NaN	65000000	[Adventure, Fantasy, Family]	NaN	8844
2	2	False	{'id': 119050, 'name': 'Grumpy Old Men Collect...	0	[Romance, Comedy]	NaN	15602
3	3	False	NaN	16000000	[Comedy, Drama, Romance]	NaN	31357
4	4	False	{'id': 96871, 'name': 'Father of the Bride Col...	0	[Comedy]	NaN	11862

5 rows × 32 columns

In [105…

```
count = CountVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='er
count_matrix = count.fit_transform(smd['tags'])
```

In [106…

```
cosine_sim = cosine_similarity(count_matrix, count_matrix)
```

In [107…

```
movies = movies.reset_index()
titles = movies['title']
indices = pd.Series(movies.index, index=smd['title'])
```

- We will reuse the get_recommendations function that we had written earlier.
- Since our cosine similarity scores have changed, we expect it to give us different (and probably better) results.
- Let us check for **The Dark Knight** again and see what recommendations I get this time around.

In [108…

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

Out[108]:
```
6218                              Batman Begins
8031                      The Dark Knight Rises
7659                 Batman: Under the Red Hood
524                                      Batman
9024         Batman v Superman: Dawn of Justice
8265     Batman: The Dark Knight Returns, Part 1
132                              Batman Forever
1134                             Batman Returns
1260                             Batman & Robin
8334     Batman: The Dark Knight Returns, Part 2
Name: title, dtype: object
```

- I am much more satisfied with the results I get this time around. The recommendations seem to have recognized other Christopher Nolan movies (due to the high weightage given to director) and put them as top recommendations.
- I enjoyed watching **The Dark Knight** as well as some of the other ones in the list including **Batman Begins and The Dark Knight Rises.**

In [109…
```
get_recommendations('Inception').head(10)
```

Out[109]:
```
6623              The Prestige
8613              Interstellar
2085                 Following
6218             Batman Begins
8031     The Dark Knight Rises
6981           The Dark Knight
4145                  Insomnia
3381                   Memento
343                    Timecop
8500                   Don Jon
Name: title, dtype: object
```

In [110…
```
get_recommendations('Mean Girls').head(10)
```

Out[110]:
```
8883                     The DUFF
5163         Just One of the Guys
7382     The Curiosity of Chance
6811            Charlie Bartlett
5458            Napoleon Dynamite
4991               Summer School
8101              21 Jump Street
1056                   Heathers
7692                     Easy A
8090                  Project X
Name: title, dtype: object
```

In [111…
```
get_recommendations('Pulp Fiction').head(10)
```

Out[111]:
```
1381              Jackie Brown
5200         Kill Bill: Vol. 2
8905         The Hateful Eight
4903         Kill Bill: Vol. 1
646              Trainspotting
405                      Fresh
5545       Maria Full of Grace
1532     The French Connection
4952             New Jack City
20                  Get Shorty
Name: title, dtype: object
```

Add Popularity and Ratings

- One thing that we notice about our recommendation system is that it recommends movies regardless of ratings and popularity. It is true that Batman and Robin has a lot of similar characters as compared to The Dark Knight but
it was a terrible movie that shouldn't be recommended to anyone.
- Therefore, we will add a mechanism to remove bad movies and return movies which are popular and have had a good critical response.
- I will take the top 25 movies based on similarity scores and calculate the vote of the **60th percentile** movie. Then, using this as the value of m, we will calculate the weighted rating of each movie using IMDB's formula like we did in the Simple Recommender section.

In [112…

```
def improved_recommendations(title):
    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:26]
    movie_indices = [i[0] for i in sim_scores]

    movies = smd.iloc[movie_indices][['title', 'vote_count', 'vote_average', 'year'
    vote_counts = movies[movies['vote_count'].notnull()]['vote_count'].astype('int'
    vote_averages = movies[movies['vote_average'].notnull()]['vote_average'].astype
    C = vote_averages.mean()
    m = vote_counts.quantile(0.60)
    qualified = movies[(movies['vote_count'] >= m) & (movies['vote_count'].notnull(
                       (movies['vote_average'].notnull())]
    qualified['vote_count'] = qualified['vote_count'].astype('int')
    qualified['vote_average'] = qualified['vote_average'].astype('int')
    qualified['wr'] = qualified.apply(weighted_rating, axis=1)
    qualified = qualified.sort_values('wr', ascending=False).head(10)
    return qualified
```

In [113…

```
improved_recommendations('The Dark Knight')
```

Out[113]:

	title	vote_count	vote_average	year	wr
7648	Inception	14075	8	2010	7.917596
6623	The Prestige	4510	8	2006	7.758169
8031	The Dark Knight Rises	9263	7	2012	6.921450
6218	Batman Begins	7511	7	2005	6.904128
8033	Sherlock Holmes: A Game of Shadows	3971	7	2011	6.827081
7069	Watchmen	2892	7	2009	6.770982
524	Batman	2145	7	1989	6.704646
8419	Man of Steel	6462	6	2013	5.952466
9024	Batman v Superman: Dawn of Justice	7189	5	2016	5.013920
9004	Suicide Squad	7717	5	2016	5.013018

In [114…

```
improved_recommendations('Pulp Fiction')
```

Out[114]:

	title	vote_count	vote_average	year	wr
898	Reservoir Dogs	3821	8	1992	7.719009
4903	Kill Bill: Vol. 1	5091	7	2003	6.862135
8905	The Hateful Eight	4405	7	2015	6.842590
5200	Kill Bill: Vol. 2	4061	7	2004	6.830544
646	Trainspotting	2737	7	1996	6.759788
1381	Jackie Brown	1580	7	1997	6.621784
6016	Layer Cake	565	7	2004	6.237472
1532	The French Connection	435	7	1971	6.123386
6788	Death Proof	1359	6	2007	5.817174
3249	Traffic	573	6	2000	5.674457

- We will conclude our Content Based Recommender section here

6.3 Collaborative Filtering based recommendation system

Collaborative filtering is a technique used in recommendation systems to recommend items by comparing users' preferences. I have a ratings dataset that contains userId, movieId, rating, and timestamp

Our content based engine suffers from some severe limitations.

- It is only capable of suggesting movies which are close to a certain movie. That is, it is not capable of capturing tastes and providing recommendations across genres.

- Also, the engine that we built is not really personal in that it doesn't capture the personal tastes and biases of a user. Anyone querying our engine for recommendations based on a movie will receive the same recommendations for that movie, regardless of who (s)he is.

- Therefore, in this section, we will use Collaborative Filtering to make recommendations to Movie Watchers. Collaborative Filtering is based on the idea that users similar to a me can be used to predict how much I will like a particular product or service those users have used/experienced but I have not.

- I will not be implementing Collaborative Filtering from scratch. Instead, I will use the **Surprise library** that used extremely powerful algorithms like **Singular Value Decomposition (SVD) to minimise RMSE (Root Mean Square Error) and give great recommendations**.

- Implementation of SVD for surprise library is given on this link

In [115…
```
reader = Reader(rating_scale=(1, 10))
data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)
```

In [116…
```
from surprise.model_selection import train_test_split

trainset, testset = train_test_split(data, test_size=0.25)
```

In [117…
```
from surprise import SVD
from surprise import KNNBasic
from surprise import SlopeOne
from surprise import CoClustering
from surprise import Reader
from surprise import Dataset
from surprise.model_selection import cross_validate
# Define a list of algorithms to try
algos = [
    SVD(),
    KNNBasic(),
    CoClustering()
]

# Evaluate each algorithm
for algo in algos:
    print(f"Evaluating {algo.__class__.__name__}")
    results = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=Tr
    print(f"Mean RMSE: {results['test_rmse'].mean()}")
    print(f"Mean MAE: {results['test_mae'].mean()}")
    print("-" * 50)
```

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8908  0.8889  0.8986  0.9078  0.8941  0.8960  0.0067
MAE (testset)     0.6873  0.6850  0.6905  0.6986  0.6876  0.6898  0.0047
Fit time          2.01    2.00    2.24    1.76    1.76    1.95    0.18
Test time         0.33    1.30    0.35    0.25    0.25    0.50    0.40
Mean RMSE: 0.8960186575096113
Mean MAE: 0.6898121699406646
--------------------------------------------------
Evaluating KNNBasic
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Computing the msd similarity matrix...
Done computing similarity matrix.
Evaluating RMSE, MAE of algorithm KNNBasic on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.9565  0.9674  0.9687  0.9708  0.9756  0.9678  0.0063
MAE (testset)     0.7359  0.7417  0.7431  0.7478  0.7508  0.7438  0.0051
Fit time          0.39    0.40    0.43    0.55    0.40    0.44    0.06
Test time         2.36    2.37    2.67    2.61    3.21    2.64    0.31
Mean RMSE: 0.9677809159863852
Mean MAE: 0.7438445179101223
--------------------------------------------------
Evaluating CoClustering
Evaluating RMSE, MAE of algorithm CoClustering on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.9576  0.9696  0.9705  0.9675  0.9626  0.9656  0.0048
MAE (testset)     0.7419  0.7516  0.7517  0.7518  0.7484  0.7491  0.0038
Fit time          5.32    6.71    5.88    6.36    5.73    6.00    0.49
Test time         0.23    0.23    0.18    0.27    0.27    0.23    0.03
Mean RMSE: 0.9655568650734926
Mean MAE: 0.7490811913749187
--------------------------------------------------
```

In [121…

```
# Build the full training set
trainset = data.build_full_trainset()
algo= SVD()

# Train the model
algo.fit(trainset)
```

Out[121]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x14da61ad910>
```

In [122…

```
ratings[ratings['userId'] == 1]
```

Out[122]:

	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
5	1	1263	2.0	1260759151
6	1	1287	2.0	1260759187
7	1	1293	2.0	1260759148
8	1	1339	3.5	1260759125
9	1	1343	2.0	1260759131
10	1	1371	2.5	1260759135
11	1	1405	1.0	1260759203
12	1	1953	4.0	1260759191
13	1	2105	4.0	1260759139
14	1	2150	3.0	1260759194
15	1	2193	2.0	1260759198
16	1	2294	2.0	1260759108
17	1	2455	2.5	1260759113
18	1	2968	1.0	1260759200
19	1	3671	3.0	1260759117

In [123…

```
algo.predict(1, 302)
```

Out[123]:

```
Prediction(uid=1, iid=302, r_ui=None, est=2.6365281884909875, details={'was_imposs
ible': False})
```

- For movie with ID 302, we get an estimated prediction of 2.636. One startling feature of this recommender system is that it doesn't care what the movie is (or what it contains). It works purely on the basis of an assigned movie ID and tries to predict ratings based on how the other users have perceive the movie.

Hybrid recommendation system

- In this section, will try to build a simple hybrid recommender that brings together techniques we have implemented in the content based and collaborative filter based engines. This is how it will work:
- **Input:** User ID and the Title of a Movie
- **Output:** Similar movies sorted on the basis of expected ratings by that particular user.

In [124…
```
def convert_int(x):
    try:
        return int(x)
    except:
        return np.nan
```

In [125…
```
id_map = pd.read_csv('links_small.csv')[['movieId', 'tmdbId']]
id_map['tmdbId'] = id_map['tmdbId'].apply(convert_int)
id_map.columns = ['movieId', 'id']
id_map = id_map.merge(smd[['title', 'id']], on='id').set_index('title')
#id_map = id_map.set_index('tmdbId')
```

In [126…
```
indices_map = id_map.set_index('id')
```

In [146…
```
smd.rename(columns={'id': 'movieId'}, inplace=True)
```

In [154…
```
def hybrid(userId, title):
    idx = indices[title]
    tmdbId = id_map.loc[title]['id']
    movie_id = id_map.loc[title]['movieId']
    sim_scores = list(enumerate(cosine_sim[int(idx)]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:26]
    movie_indices = [i[0] for i in sim_scores]
    movies = smd.iloc[movie_indices][['title', 'vote_count', 'vote_average', 'relea
    movies['est'] = movies['movieId'].apply(lambda x: algo.predict(userId, indices_
    movies = movies.sort_values('est', ascending=False)
    return movies.head(10)
```

In [155…
```
hybrid(1, 'Avatar')
```

Out[155]:

	title	vote_count	vote_average	release_date	movieId	est
987	Alien	4564.0	7.9	1979-05-25	348	3.196518
974	Aliens	3282.0	7.7	1986-07-18	679	3.126991
7889	X-Men: First Class	5252.0	7.1	2011-05-24	49538	3.048741
7935	Rise of the Planet of the Apes	4452.0	7.0	2011-08-03	61791	2.869049
7065	Meet Dave	381.0	5.1	2008-07-08	11260	2.854473
9005	Independence Day: Resurgence	2550.0	4.9	2016-06-22	47933	2.844577
2920	Moonraker	551.0	5.9	1979-06-26	698	2.818261
8934	Home	1539.0	6.8	2015-03-18	228161	2.729838
648	Independence Day	3334.0	6.7	1996-06-25	602	2.728439
5215	Enemy Mine	253.0	6.7	1985-12-12	11864	2.706554

In [156…
```
hybrid(5000, 'Avatar')
```

Out[156]:

	title	vote_count	vote_average	release_date	movieId	est
7889	X-Men: First Class	5252.0	7.1	2011-05-24	49538	3.942168
987	Alien	4564.0	7.9	1979-05-25	348	3.916773
974	Aliens	3282.0	7.7	1986-07-18	679	3.892782
7935	Rise of the Planet of the Apes	4452.0	7.0	2011-08-03	61791	3.760815
9005	Independence Day: Resurgence	2550.0	4.9	2016-06-22	47933	3.698841
922	The Abyss	822.0	7.1	1989-08-09	2756	3.669620
8934	Home	1539.0	6.8	2015-03-18	228161	3.609384
5215	Enemy Mine	253.0	6.7	1985-12-12	11864	3.575928
2920	Moonraker	551.0	5.9	1979-06-26	698	3.547577
344	True Lies	1138.0	6.8	1994-07-14	36955	3.535983

In [157…

```
hybrid(3423, "The Terminator")
```

Out[157]:

	title	vote_count	vote_average	release_date	movieId	est
2079	The Matrix	9079.0	7.9	1999-03-30	603	4.126869
6179	A Trip to the Moon	314.0	7.9	1902-09-01	775	4.009961
522	Terminator 2: Judgment Day	4274.0	7.7	1991-07-01	280	3.935659
974	Aliens	3282.0	7.7	1986-07-18	679	3.892782
1024	The Day the Earth Stood Still	323.0	7.3	1951-09-17	828	3.888607
1589	Metropolis	666.0	8.0	1927-01-10	19	3.873797
7502	The Book of Eli	2207.0	6.6	2010-01-14	20504	3.781841
4173	Minority Report	2663.0	7.1	2002-06-20	180	3.772297
4214	Rollerball	115.0	6.0	1975-06-25	11484	3.763321
922	The Abyss	822.0	7.1	1989-08-09	2756	3.669620

We are done...!