Books Recommendation System

Introduction

A machine learning-based tool called the Books Recommendation System was created to help consumers find new books based on their likes and interests. Finding books that suit individual reading preferences might be difficult in today's society because there are so many books accessible. This recommendation system's goal is to give readers personalised book suggestions that will help them discover more books they would like and improve their reading experience as a whole. An overview of the Books Recommendation System, including its goal, approach, and distinguishing characteristics, is the goal of this paper. It will look into the fundamental formulas and methods employed to produce precise and pertinent book suggestions.

Research Question

The main goal of this project is to develop such an intelligent system which can recommend the books to the users based on their preferences and interest. To make the people more satisfying and engaged. With the help of this system, the users will be able to choose the books of their interest.

Dataset

The dataset has been taken from the Kaggle website and it contains three csv files e.g. Books, users and ratings data.

In [178]:

```
#Import the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#Import books dataset
books = pd.read_csv('Books.csv')
#Import ratings Dataset
ratings = pd.read_csv('Ratings.csv')
#Import users dataset
users = pd.read_csv('Users.csv')
```

```
/var/folders/qs/7h062p450sdb_ncy2h6f4_3c0000gq/T/ipykernel_18892/393
6091610.py:6: DtypeWarning: Columns (3) have mixed types. Specify dt
ype option on import or set low_memory=False.
  books = pd.read_csv('Books.csv')
```

In [179]:

```
books.head()
```

Out[179]:

	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	0195153448	Classical Mythology	Mark P. O. Morford	2002	Oxford University Press	http://images.amazon.com/image
1	0002005018	Clara Callan	Richard Bruce Wright	2001	HarperFlamingo Canada	http://images.amazon.com/image
2	0060973129	Decision in Normandy	Carlo D'Este	1991	HarperPerennial	http://images.amazon.com/image
3	0374157065	Flu: The Story of the Great Influenza Pandemic...	Gina Bari Kolata	1999	Farrar Straus Giroux	http://images.amazon.com/image
4	0393045218	The Mummies of Urumchi	E. J. W. Barber	1999	W. W. Norton & Company	http://images.amazon.com/image

In [180]:

```
ratings.head()
```

Out[180]:

	User-ID	ISBN	Book-Rating
0	276725	034545104X	0
1	276726	0155061224	5
2	276727	0446520802	0
3	276729	052165615X	3
4	276729	0521795028	6

In [181]:

```
users.head()
```

Out[181]:

	User-ID	Location	Age
0	1	nyc, new york, usa	NaN
1	2	stockton, california, usa	18.000
2	3	moscow, yukon territory, russia	NaN
3	4	porto, v.n.gaia, portugal	17.000
4	5	farnborough, hants, united kingdom	NaN

Preliminary Analysis of the data

In the preliminary analysis, we get the idea about the how many books we have and the number of users and the ratings we have. For each user, we have 11 ratings. The numbers in which users can rate between are from 0 to 10.

For the books dataset, we have almost 271360 books record and their description is mentioned in different columns e.g. 'ISBN', 'bookTitle', 'bookAuthor', 'yearOfPublication', 'publisher', 'imageUrlS', 'imageUrlM', 'imageUrlL'.

For the users dataset, we have almost 278858 users dataset and their 'User-ID', 'Location' and 'Age' is mentioned in it.

For the ratings dataset, we have 527556 ratings of the books and 'User-ID', 'ISBN', and 'Book-Rating' is mentioned in it.

In [182]:

```
# Print out the number of users, movie titles and ratings
print('The books dataset contains',len(books),'books')
print('The ratings dataset contains', len(ratings["User-ID"].unique()), 'user
s,',len(ratings['User-ID'].unique()),'books and',len(ratings),'ratings.')
```

```
The books dataset contains 271360 books
The ratings dataset contains 105283 users, 105283 books and 1149780
ratings.
```

In [183]:

```
print('This is an average of', round(len(ratings)/len(ratings["User-ID"].unique
())), 'ratings per user.')
```

```
This is an average of 11 ratings per user.
```

In [184]:

```
# Get unique values for ratings
print('Users can rate books as:',sorted(ratings["Book-Rating"].unique()))
```

```
Users can rate books as: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

In [185]:

```
# Shape and columns of the books dataset
print(books.shape)
print(list(books.columns))
```

```
(271360, 8)
['ISBN', 'Book-Title', 'Book-Author', 'Year-Of-Publication', 'Publis
her', 'Image-URL-S', 'Image-URL-M', 'Image-URL-L']
```

In [186]:

```
# Shape anf columns of the users dataset
print(users.shape)
print(list(users.columns))
```

```
(278858, 3)
['User-ID', 'Location', 'Age']
```

In [187]:

```
# Shape and columns of the ratings dataset
print(ratings.shape)
print(list(ratings.columns))
```

```
(1149780, 3)
['User-ID', 'ISBN', 'Book-Rating']
```

Data Cleaning steps

In [188]:

```
# Checking the sum of the null values in the books dataset
books.isnull().sum()
```

Out[188]:

```
ISBN                   0
Book-Title             0
Book-Author            1
Year-Of-Publication    0
Publisher              2
Image-URL-S            0
Image-URL-M            0
Image-URL-L            3
dtype: int64
```

In [189]:

```
# Checking the sum of null values in users dataset
users.isnull().sum()
```

Out[189]:

```
User-ID          0
Location         0
Age         110762
dtype: int64
```

In [190]:

```
# Checking the null value sin the ratings dataset
ratings.isnull().sum()
```

Out[190]:

```
User-ID        0
ISBN           0
Book-Rating    0
dtype: int64
```

It can be seen from the above three cells that books dataset has some null values but their effect is negligible. In the users dataset, there is large null values in age column, we cannot use much this column in this analysis. There is no null values in ratings column.

In [191]:

```
# Duplicated values in the books dataset
books.duplicated().sum()
```

Out[191]:

```
0
```

In [192]:

```
# Duplicated values in the users data
users.duplicated().sum()
```

Out[192]:

```
0
```

In [193]:

```
# Duplicates values in the ratings data
ratings.duplicated().sum()
```

Out[193]:

```
0
```

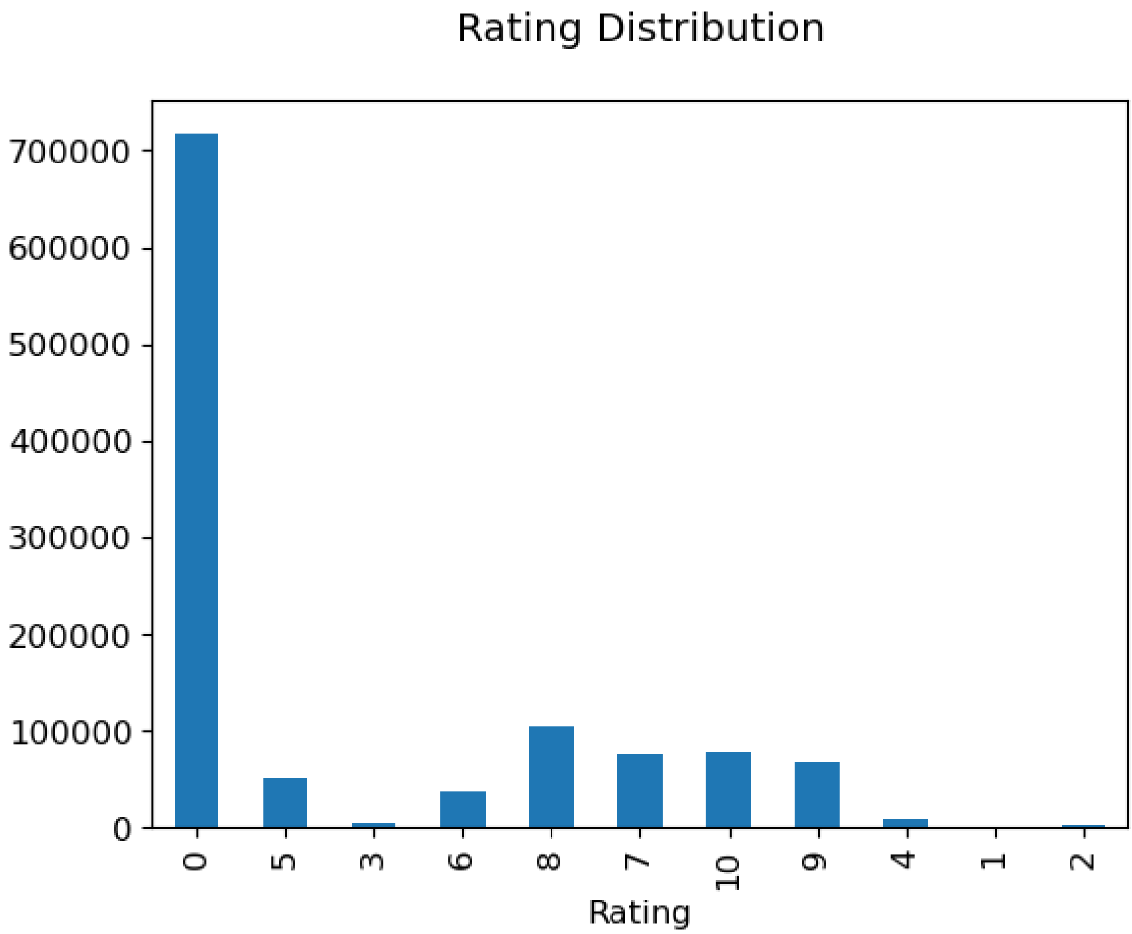
Exploratory Data Analysis

After the cleaning process, the data has been explored in the different ways through graphs.

In the first way, ratings distribution has been observed and their counts. Most of the books have zero ratings.

In [194]:

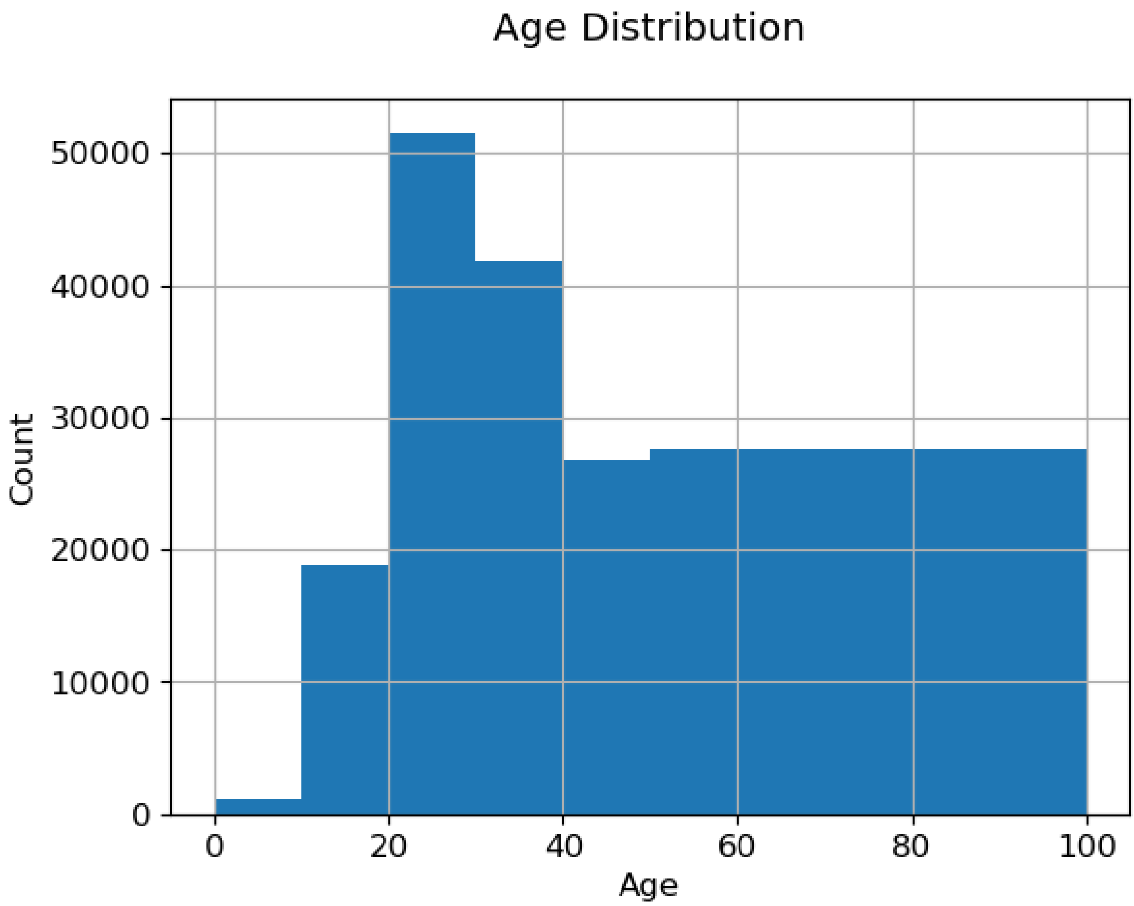
```
plt.rc("font", size=12)
ratings['Book-Rating'].value_counts(sort=False).plot(kind='bar')
plt.title('Rating Distribution\n')
plt.xlabel('Rating')
plt.show()
```



In the plot below, it basically shows the distribution of age which gives more number of ratings. It can be shown from the graph that people from 20 to 40 have given more number of ratings.

In [195]:

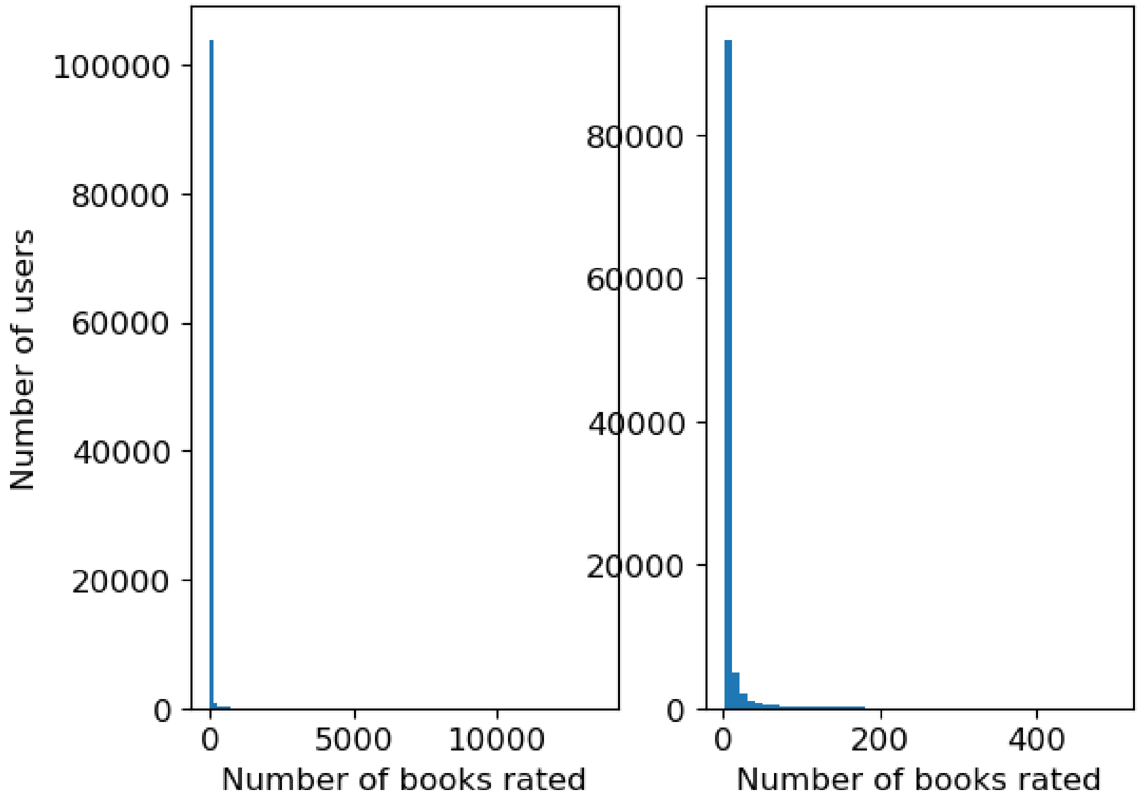
```
users.Age.hist(bins=[0, 10, 20, 30, 40, 50, 100])
plt.title('Age Distribution\n')
plt.xlabel('Age')
plt.ylabel('Count')
plt.savefig('system2.png', bbox_inches='tight')
plt.show()
```



In the plot below, we have seen the distribution of user ratings. This bar chat shows the number of books rated by each user. It has been seen from the graph that it is (positive)right skewed. Most users rate around 20 books, with a fewer rating reaching to the 10000 or more books.

In [196]:

```
ratings_by_user = ratings["User-ID"].value_counts()
fig, (ax1, ax2) = plt.subplots(1, 2)
# Plot all the data
ax1.hist(ratings_by_user,bins=100)
ax1.set_xlabel('Number of books rated')
ax1.set_ylabel('Number of users')
# Zoom in
ax2.hist(ratings_by_user,bins=50,range=(min(ratings_by_user),500))
ax2.set_xlabel('Number of books rated')
plt.show()
```



Methods

There are methods which have been applied to the dataset for getting the recommendation system of the books in many ways.

Rating Counts based Recommendation of books

From the ratings dataset, we get the counts on the basis of each of the ISBN. The book with ISBN 0971880107 receives the most rating counts.

In [197]:

```
# ratings dataframe grouped by ISBN and its counts
rat_count = pd.DataFrame(ratings.groupby('ISBN')['Book-Rating'].count())
#Sorting the values of the rating count
rat_count.sort_values('Book-Rating', ascending=False).head()
```

Out[197]:

ISBN	Book-Rating
0971880107	2502
0316666343	1295
0385504209	883
0060928336	732
0312195516	723

In [198]:

```
# Finding out what is name of this book
rated_books = pd.DataFrame(['0971880107', '0316666343', '0385504209', '006092833
6', '0312195516'], index=np.arange(5), columns = ['ISBN'])
# merging the rated books to ISBN column of books dataset
rated_books_summary = pd.merge(rated_books, books, on='ISBN')
# See the summary of most rated books
rated_books_summary
```

Out[198]:

	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	0971880107	Wild Animus	Rich Shapero	2004	Too Far	http://images.amazon.com/images/P/
1	0316666343	The Lovely Bones: A Novel	Alice Sebold	2002	Little, Brown	http://images.amazon.com/images/P/
2	0385504209	The Da Vinci Code	Dan Brown	2003	Doubleday	http://images.amazon.com/images/P/
3	0060928336	Divine Secrets of the Ya-Ya Sisterhood: A Novel	Rebecca Wells	1997	Perennial	http://images.amazon.com/images/P/
4	0312195516	The Red Tent (Bestselling Backlist)	Anita Diamant	1998	Picador USA	http://images.amazon.com/images/P/

With the help of rating count, it can be shown that those books can be famous which have high ratings so we can recommend on the basis of that rating.

Popularity Based Recommendation System

In [199]:

```
#merges the 'ratings' and 'books' datasets based on the 'ISBN' column, combining
the rating information with the corresponding book details.
name_with_ratings= ratings.merge(books,on='ISBN')
name_with_ratings.head()
```

Out[199]:

	User-ID	ISBN	Book-Rating	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	276725	034545104X	0	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com
1	2313	034545104X	5	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com
2	6543	034545104X	0	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com
3	8680	034545104X	5	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com
4	10314	034545104X	9	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com

In [200]:

```
rating_df = name_with_ratings.groupby('Book-Title').count()['Book-Rating'].reset
_index()
#renames the 'Book-Rating' column in the 'rating_df' DataFrame to 'num_ratings'
rating_df.rename(columns={'Book-Rating':'num_ratings'},inplace=True)
rating_df
```

Out[200]:

	Book-Title	num_ratings
0	A Light in the Storm: The Civil War Diary of ...	4
1	Always Have Popsicles	1
2	Apple Magic (The Collector's series)	1
3	Ask Lily (Young Women of Faith: Lily Series, ...	1
4	Beyond IBM: Leadership Marketing and Finance ...	1
...	...	...
241066	Ã?Â?lpiraten.	2
241067	Ã?Â?rger mit Produkt X. Roman.	4
241068	Ã?Â?sterlich leben.	1
241069	Ã?Â?stlich der Berge.	3
241070	Ã?Â?thique en toc	2

241071 rows × 2 columns

In [201]:

```
avg_rating = name_with_ratings.groupby('Book-Title').mean()['Book-Rating'].reset
_index()
avg_rating.rename(columns={'Book-Rating':'avg_rating'},inplace=True)
avg_rating
```

```
/var/folders/qs/7h062p450sdb_ncy2h6f4_3c0000gq/T/ipykernel_18892/215
8557364.py:1: FutureWarning: The default value of numeric_only in Da
taFrameGroupBy.mean is deprecated. In a future version, numeric_only
will default to False. Either specify numeric_only or select only co
lumns which should be valid for the function.
  avg_rating = name_with_ratings.groupby('Book-Title').mean()['Book-
Rating'].reset_index()
```

Out[201]:

	Book-Title	avg_rating
0	A Light in the Storm: The Civil War Diary of ...	2.250
1	Always Have Popsicles	0.000
2	Apple Magic (The Collector's series)	0.000
3	Ask Lily (Young Women of Faith: Lily Series, ...	8.000
4	Beyond IBM: Leadership Marketing and Finance ...	0.000
...	...	...
241066	Ã?Â?lpiraten.	0.000
241067	Ã?Â?rger mit Produkt X. Roman.	5.250
241068	Ã?Â?sterlich leben.	7.000
241069	Ã?Â?stlich der Berge.	2.667
241070	Ã?Â?thique en toc	4.000

241071 rows × 2 columns

In [202]:

```
#merges the 'popular' DataFrame with the 'books' dataset based on the 'bookTitle' column. It then drops any duplicate rows based on the 'bookTitle' column and selects specific columns
popular_dta = rating_df.merge(avg_rating,on='Book-Title')

popular_dta
```

Out[202]:

	Book-Title	num_ratings	avg_rating
0	A Light in the Storm: The Civil War Diary of ...	4	2.250
1	Always Have Popsicles	1	0.000
2	Apple Magic (The Collector's series)	1	0.000
3	Ask Lily (Young Women of Faith: Lily Series, ...	1	8.000
4	Beyond IBM: Leadership Marketing and Finance ...	1	0.000
...	...	...	...
241066	Ã?Â?lpiraten.	2	0.000
241067	Ã?Â?rger mit Produkt X. Roman.	4	5.250
241068	Ã?Â?sterlich leben.	1	7.000
241069	Ã?Â?stlich der Berge.	3	2.667
241070	Ã?Â?thique en toc	2	4.000

241071 rows × 3 columns

In [203]:

```
popular = popular_dta[popular_dta['num_ratings']>=250].sort_values('avg_rating',ascending=False).head(50)
popular_df = popular.merge(books,on='Book-Title').drop_duplicates('Book-Title')[['Book-Title','num_ratings','avg_rating']]
```

In [204]:

```
popular_df['Book-Title'][0]
```

Out[204]:

```
'Harry Potter and the Prisoner of Azkaban (Book 3)'
```

Correlation Based Recommendation system of books

Correlation is the other way of seeing the recommendation of the books. By seeing the books who are more correlated with each other we can get their counts on the basis of that. The main purpose of taking book rating along with rating count is that if rating count is not highly rated at all but the rating of that book is higher then it will not be a better system.

In [205]:

```
# along with ratings count find the mean of those ratings
rating_avg1= pd.DataFrame(ratings.groupby('ISBN')['Book-Rating'].mean())

rating_avg1['ratingCount'] = pd.DataFrame(ratings.groupby('ISBN')['Book-Ratin
g'].count())
rating_avg1.sort_values('ratingCount', ascending=False).head()
```

Out[205]:

	Book-Rating	ratingCount
ISBN		
0971880107	1.020	2502
0316666343	4.469	1295
0385504209	4.652	883
0060928336	3.448	732
0312195516	4.335	723

In [206]:

```
# users with less than 200 rating and books less than 100 ratings are excluded
#Counts of the user ID
counts1 = ratings['User-ID'].value_counts()
ratings = ratings[ratings['User-ID'].isin(counts1[counts1 >= 200].index)]
counts = ratings['Book-Rating'].value_counts()
ratings = ratings[ratings['Book-Rating'].isin(counts[counts >= 100].index)]
```

In [207]:

```
# Making the rating matrix
# pivot converts the rating table to 2D matrix
pivot_rating = ratings.pivot(index='User-ID', columns='ISBN')['Book-Rating']
userID1 = pivot_rating.index
ISBN1 = pivot_rating.columns
print(pivot_rating.shape)
pivot_rating.head()
```

```
(905, 207699)
```

Out[207]:

ISBN	0330299891	0375404120	0586045007	9022906116	9032803328	9044922564	904492257
User-ID							
254	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2276	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2766	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2977	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3363	NaN	NaN	NaN	NaN	NaN	NaN	NaN

5 rows × 207699 columns

In [208]:

```
# corelating the pivot rating to the bones book
ratings_of_bones = pivot_rating['0316666343']
# corrwith function finds the correlation between two data frames
bones_similar = pivot_rating.corrwith(ratings_of_bones)
bones_corr = pd.DataFrame(bones_similar, columns=['pearsonR'])
# Dropping all the NAN calues
bones_corr.dropna(inplace=True)
#Joining all the correlation with average rating
corr_summ = bones_corr.join(rating_avg1['ratingCount'])
corr_summ[corr_summ['ratingCount']>=300].sort_values('pearsonR', ascending=Fals
e).head(10)
```

```
/Applications/anaconda3/lib/python3.10/site-packages/numpy/lib/funct
ion_base.py:2845: RuntimeWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar, dtype=dtype)
/Applications/anaconda3/lib/python3.10/site-packages/numpy/lib/funct
ion_base.py:2704: RuntimeWarning: divide by zero encountered in divi
de
  c *= np.true_divide(1, fact)
```

Out[208]:

ISBN	pearsonR	ratingCount
0316666343	1.000	1295
0312291639	0.472	354
0316601950	0.434	568
0446610038	0.430	391
0446672211	0.421	585
0385265700	0.352	319
0345342968	0.317	321
0060930535	0.310	494
0375707972	0.308	354
0684872153	0.272	326

In all the above process, the correlation is based on ratings. What ever book we include, it will correlate with all the other books in pivot rating table and find the values from 0 to 1. If the value is close to zero, it means it is not correlated. The more it is nearer to one, the more it will be correlated. It will follow pearson method of correlation. IT values ranging from -1 to +1. So correlation is found along with rating count and average rating.

In [209]:

```
# to see all the names of the books
remainingbooks_corr_to_bones = pd.DataFrame(['0312291639', '0316601950', '0446610038', '0446672211', '0385265700', '0345342968', '0060930535', '0375707972', '0684872153'],
                                            index=np.arange(9), columns=['ISBN'])
correlated_books = pd.merge(remainingbooks_corr_to_bones, books, on='ISBN')
correlated_books
```

Out[209]:

	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	0312291639	The Nanny Diaries: A Novel	Emma McLaughlin	2003	St. Martin's Griffin	http://images.amazon.com/images
1	0316601950	The Pilot's Wife : A Novel	Anita Shreve	1999	Back Bay Books	http://images.amazon.com/images
2	0446610038	1st to Die: A Novel	James Patterson	2002	Warner Vision	http://images.amazon.com/images
3	0446672211	Where the Heart Is (Oprah's Book Club (Paperba...	Billie Letts	1998	Warner Books	http://images.amazon.com/images
4	0385265700	The Book of Ruth (Oprah's Book Club (Paperback))	Jane Hamilton	1990	Anchor	http://images.amazon.com/images
5	0345342968	Fahrenheit 451	RAY BRADBURY	1987	Del Rey	http://images.amazon.com/images
6	0060930535	The Poisonwood Bible: A Novel	Barbara Kingsolver	1999	Perennial	http://images.amazon.com/images
7	0375707972	The Reader	Bernhard Schlink	1999	Vintage Books USA	http://images.amazon.com/images
8	0684872153	Angela's Ashes (MMP) : A Memoir	Frank McCourt	1999	Scribner	http://images.amazon.com/images

Collaborative Filtering Using k-Nearest Neighbors (kNN)

Collaborative filtering aims to predict user preferences based on the behavior and preferences of similar users. Collaborative filtering using k-Nearest Neighbors is a powerful technique for providing personalized recommendations. kNN is a memory-based algorithm that finds the k most similar users (or items) to a target user (or item). The similarity can be measured using distance metrics like cosine similarity or Euclidean distance. Once the most similar neighbors are identified, their preferences are used to make recommendations to the target user.

In [211]:

```
#merging of ratings and books dataset on basis of ISBN
combine_bookrating = pd.merge(ratings, books, on='ISBN')
combine_bookrating.head()
```

Out[211]:

	User-ID	ISBN	Book-Rating	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	277427	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
1	3363	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
2	11676	002542730X	6	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
3	12538	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
4	13552	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c

In [212]:

```
# Adding anew column for total rating count and group by book titles
combine_book_rating = combine_bookrating.dropna(axis = 0, subset = ['Book-Titl
e'])

bookrating_Count1 = (combine_book_rating.
     groupby(by = ['Book-Title'])['Book-Rating'].
     count().
     reset_index().
     rename(columns = {'Book-Rating': 'totalRatingCount'})
     [['Book-Title', 'totalRatingCount']]
    )
bookrating_Count1.head()
```

Out[212]:

	Book-Title	totalRatingCount
0	A Light in the Storm: The Civil War Diary of ...	2
1	Always Have Popsicles	1
2	Apple Magic (The Collector's series)	1
3	Beyond IBM: Leadership Marketing and Finance ...	1
4	Clifford Visita El Hospital (Clifford El Gran...	1

In [213]:

```
#Combining and merging the rating data with total rating count data
rating_with_totalRating_Count = combine_book_rating.merge(bookrating_Count1, lef
t_on = 'Book-Title', right_on = 'Book-Title', how = 'left')
rating_with_totalRating_Count.head()
```

Out[213]:

	User-ID	ISBN	Book-Rating	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	277427	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
1	3363	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
2	11676	002542730X	6	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
3	12538	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
4	13552	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c

In [214]:

```
pd.set_option('display.float_format', lambda x: '%.3f' % x)
print(bookrating_Count1['totalRatingCount'].describe())
```

```
count   160576.000
mean         3.044
std          7.428
min          1.000
25%          1.000
50%          1.000
75%          2.000
max        365.000
Name: totalRatingCount, dtype: float64
```

In [215]:

```
print(bookrating_Count1['totalRatingCount'].quantile(np.arange(.9, 1, .01)))
```

```
0.900     5.000
0.910     6.000
0.920     7.000
0.930     7.000
0.940     8.000
0.950    10.000
0.960    11.000
0.970    14.000
0.980    19.000
0.990    31.000
Name: totalRatingCount, dtype: float64
```

In [235]:

```
# Setting the threshold for the popular books
popular_books_threshold = 50
rating_pop_book1= rating_with_totalRating_Count.query('totalRatingCount >= @popu
lar_books_threshold')
```

In [236]:

```
rating_pop_book1.head()
```

Out[236]:

	User-ID	ISBN	Book-Rating	Book-Title	Book-Author	Year-Of-Publication	Publisher	
0	277427	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
1	3363	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
2	11676	002542730X	6	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
3	12538	002542730X	10	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c
4	13552	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	James Finn Garner	1994	John Wiley & Sons Inc	http://images.amazon.c

In [231]:

```
rating_pop_book1.shape
```

Out[231]:

```
(62149, 5)
```

Recommendation for Users in UK and Canada

This is basically the analysis including only users based on the location. For this purpose, we chose UK and Canada users for recommendation. The K-nearest neighbors algorithm is implemented using the NearestNeighbors class from sklearn.neighbors. The algorithm uses the cosine distance metric and the brute-force algorithm. The model is trained on the "uk_canada_user_rating_matrix" sparse matrix.

To find the nearest neighbors, the cosine similarity metric was used. The cosine similarity calculates the similarity between rating vectors. The sklearn.neighbors library was utilized, and the kNN model was fitted to the data. It was necessary to transform the rating information into a matrix representation, where each row corresponded to a book and each column to a user. There were zeros to fill in the missing values. In order to distinguish popular books from obscure ones, the overall rating count for each book was determined.

In [219]:

```
combine= rating_pop_book1.merge(users, left_on = 'User-ID', right_on = 'User-ID', how = 'left')
#combining the data based for the users in UK and Canada
uk_canada_user_rating = combine[combine['Location'].str.contains("united Kingdom|canada")]
#Dropping the age column
uk_canada_user_rating=uk_canada_user_rating.drop('Age', axis=1)
uk_canada_user_rating.head()
```

Out[219]:

	User-ID	ISBN	Book-Rating	bookTitle	totalRatingCount	Location
9	28204	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	82	south ohio, nova scotia, canada
13	43246	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	82	toronto, ontario, canada
31	119575	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	82	north vancouver, british columbia, canada
53	188010	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	82	edmonton, alberta, canada
56	198711	002542730X	0	Politically Correct Bedtime Stories: Modern Ta...	82	little canada, minnesota, usa

Implementing KNN

Since we'll be measuring the separations between the rating vectors, we transform our table to a 2D matrix and replace the missing values with zeros. The values (ratings) of the matrix dataframe are then converted into a scipy sparse matrix for faster calculations.

Identifying Nearby Neighbours Sklearn.neighbors and unsupervised methods are used. We use the "brute" technique to find the nearest neighbours, and we set the "metric=cosine" option to force the programme to determine the cosine similarity between the rating vectors. We finally fitted the model.

In [220]:

```
from scipy.sparse import csr_matrix
# DRopping the duplicates in USER ID
uk_canada_user_rating = uk_canada_user_rating.drop_duplicates(['User-ID', 'bookT
itle'])
# Pivot table based on book title
uk_canada_user_rating_pivot = uk_canada_user_rating.pivot(index = 'bookTitle', c
olumns = 'User-ID', values = 'Book-Rating').fillna(0)
# creating the matrix
uk_canada_user_rating_matrix = csr_matrix(uk_canada_user_rating_pivot.values)

from sklearn.neighbors import NearestNeighbors

#implementing K nearest neighbour
model_knn = NearestNeighbors(metric = 'cosine', algorithm = 'brute')
model_knn.fit(uk_canada_user_rating_matrix)
```

Out[220]:

```
▾ NearestNeighbors
NearestNeighbors(algorithm='brute', metric='cosine')
```

In [221]:

```
# selects a query index from the user-book ratings matrix
uk_canada_user_rating_pivot.iloc[query_index,:].values.reshape(1,-1)
```

Out[221]:

```
array([[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., 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., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
        0., 0., 0., 7., 0., 0., 0.]])
```

In [222]:

```
query_index = np.random.choice(uk_canada_user_rating_pivot.shape[0])
print(query_index)
#  trained KNN model model_knn to find the k-nearest neighbors (in this case, k=
6) to the user at the selected query index. seeeing the 6 neighbours
distances, indices = model_knn.kneighbors(uk_canada_user_rating_pivot.iloc[query
_index,:].values.reshape(1, -1), n_neighbors = 6)
```

```
435
```

In [223]:

```
uk_canada_user_rating_pivot.index[query_index]
```

Out[223]:

```
'Sea Swept (Quinn Brothers (Paperback))'
```

In [224]:

```
for i in range(0, len(distances.flatten())):
    if i == 0:
        print('Recommendations for {0}:\n'.format(uk_canada_user_rating_pivot.in
dex[query_index]))
    else:
        print('{0}: {1}, with distance of {2}:'.format(i, uk_canada_user_rating_
pivot.index[indices.flatten()[i]], distances.flatten()[i]))
```

```
Recommendations for Sea Swept (Quinn Brothers (Paperback)):

1: Carnal Innocence, with distance of 0.0:
2: Tears of the Moon (Irish Trilogy), with distance of 0.0:
3: Heart of the Sea (Irish Trilogy), with distance of 0.0:
4: Sea Swept (Quinn Brothers (Paperback)), with distance of 0.0:
5: Blessings, with distance of 0.0:
```

In this case, the recommended books have a distance of 0.0, which indicates that they are the closest neighbors to the query book based on user ratings. The books "Carnal Innocence," "Tears of the Moon (Irish Trilogy)," "Heart of the Sea (Irish Trilogy)," "Sea Swept (Quinn Brothers (Paperback))," and "Blessings" are recommended for the user who is interested in "Sea Swept (Quinn Brothers (Paperback))."

The distance measure used in KNN represents the similarity between the books' ratings profiles. A distance of 0.0 suggests that the ratings profiles of the recommended books are identical to that of the query book.

Conclusion

In the conclusion, we can conclude that our whole project was to make the system for the users which can recommend them books. For that purpose, we did this in different ways, rating count based recommendation, correlation based recommendation, popularity based recommendation and using K nearest neighbours. Each of them do the recommendation in different ways and the best one should be using K nearest neighbour. The top 50 books based on the quantity and average of ratings were effectively identified by the popularity-based recommendation analysis. These results might be used as a springboard for additional research or to offer consumers recommendations. It is crucial to remember that since popularity-based recommendations do not take into account specific user preferences, they may have limits. To propose books, the collaborative filtering approach was used. This method makes predictions based on the average rating of the top k closest neighbours after identifying comparable users based on their book ratings.

Book suggestions could be produced based on user ratings and user similarities when the kNN model was successfully trained on the dataset. When it came to giving readers personalised book recommendations, the algorithm displayed encouraging results. The kNN algorithm-based book recommendation system performed well at providing users with recommendations for books that are specific to them. The algorithm was able to recognise similar users and generate precise predictions based on their past ratings by utilising collaborative filtering and cosine similarity. To further increase suggestion accuracy and user experience, additional features could be included, such as book genres or user preferences.

The correlation-based book recommendation system proved to be a valuable tool in suggesting personalized book recommendations to users. By utilizing correlation coefficients between users' ratings, the system identified similar users and recommended books based on their preferences.

Reference for Dataset

https://www.kaggle.com/datasets/arashnic/book-recommendation-dataset
(https://www.kaggle.com/datasets/arashnic/book-recommendation-dataset)