TOP 5 BOOKS RECOMMENDATION SYSTEM

Books

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1. BUSINESS UNDERSTANDING

> PROJECT OVERVIEW
>
> - **Recommendation systems** are powerful tools that use machine learning algorithms to provide relevant suggestions to users based on behaviour patterns or user data.
> - **A Book Recommendation System** is a recommendation system where we recommend similar books to readers based on their interests.
> - Recommendation systems help drive engagement, increase sales, increases revenue and this in return brings in loyal clients as the customer experience is elevated promoting customer satisfaction.
> - We have 2 main recommendation system models:
>   - 1. Collaborative filtering
>   - 1. Content-based Filtering BUSINESS PROBLEM
> - Over the past years, there has been rise in huge ecommerce and online services leading clients facing difficulty when searching for the right products.
> - Clients looking to purchase books also face the same struggle when trying to match the right books with their taste and preferences.
> - **The Business Problem** is to develop a recommendation system that recommends books that are tailored to our users preferences inorder to improve customer experience and engagement. PROJECT OBJECTIVE
>
> 1. To build a book recommendation system that provides personalized suggestions to our users.
> 2. Improve sales by showcasing books a user is most likely to buy.
> 3. Offer relevant books to users inorder to improve customer retention.
> 4. Increase customer engagement

The analysis aims to achieve these objectives by considering the following analysis questions:

1.Which authors consistently receive higher ratings from users?

2.How does the year of publication affect the average ratings of books? Are newer books preferred over older ones?

3.How accurate are the recommendations generated by the collaborative filtering model especially in terms of precision?

4.How does class imbalance in ratings affect the performance of the recommendation model?

> DATA SOURCE
>
> - We used data obtained from Kaggle mined by Cai-Nicolas Ziegler
> - It contains 3 CSV Files:
>   1. Books.csv - contains information about books{ISBN;Title;Author;Year;Publisher}
>   2. Ratings.csv - contains book ratings provided by users that range from 0 to 10. {{User-ID;ISBN;Rating}}
>   3. Users.csv - contains information about the users {User-ID;Age} STAKEHOLDERS

> 1. Customers
>
> - As the end user, they expect accurate book suggestions based on personal interests.
>
> 1. Marketing team
>
> - They would want to do targeted advertising on specific books and also promote personalized offers.
>
> 1. Data scientist
>
> - Interested in ensuring the recommendation system models are accurate and scalable.
>
> 1. Book Authors
>
> - They would be interested in knowing how their books are recommended inorder to learn and understand their readers taste and preferences.
>
> 1. Executive {CEO}
>
> - They would want to understand how recommendation systems impact revenue and customer retention comparing it to the budget allocated to the project. METHODOLOGY
> - Our project will focus on the CRISP-DM:
>   1. Business Understanding
>   2. Data Understanding
>   3. Data Preparation
>   4. Modeling
>   5. Evaluation
>   6. Deployment

DATA UNDERSTANDING

The foundation of any machine learning project lies in a thorough understanding of the dataset. For the Book Recommendation System project, the data understanding phase involves the following key steps:

A. Dataset Overview

- Books Dataset: Contains information about the books, such as the ISBN (International Standard Book Number), title, author, year of publication, and publisher.

- Users Dataset: Provides demographic information about users, including their user IDs and age.

- Ratings Dataset: Includes user-provided ratings for books on a scale from 0 to 10. It connects users to the books they've rated via user IDs and ISBNs.

B. Data Merging

- We merged Ratings.csv and Users.csv on the User-ID column and then further merged the resulting dataframe with Books.csv on the ISBN column.
- This provides a comprehensive dataset including the ratings, user demographic data (age), and book details.

C. Key Insights from the Data

> **Outliers**
>
> - The Age column contains unrealistic values. These outliers will skew model results and should be handled by capping or removing.
>
> **Missing Values**

> - The Age column has approximately 27% missing data, which poses a significant challenge. For this analysis, we will impute the median to fill these missing values in order to preserve data integrity.
> - The Book-Author and Publisher columns have negligible missing data, which can be dropped without much impact.
> - The Image URLs columns will be dropped as they havve no significance in our data analysis.

D. Data Analysis

To have a better visualization of the data distribution, we conduct an extensive analysis through:

> **i) Univariate Analysis**

- **Book Ratings**: Visualizing the distribution of ratings helps to identify trends like how many users may tend to give mid-range or higher ratings.
- **User Ages**: The age distribution will not only show certain age clusters like young adult readers and middle-aged readers but also reveal outliers.

> **ii) Bivariate Analysis**

- **User Age vs. Book Ratings**: Investigating how user age affects their book ratings can uncover patterns like how younger users might prefer different genres than older users.
- **Book Author vs Average Rating**: This will help to identify which authors tend to get higher ratings.
- **Publisher vs. Average Book Rating**:This examines whether certain publishers consistently publish books that receive higher ratings.
- **Age vs. Publisher Preference**:This analysis helps to explore if users of certain age groups prefer books from specific publishers.
- **User vs. Book Rating**:This helps to understand if certain users tend to give consistently higher while others may be more critical.
- **Year of Publication vs. Average Book Rating**:This helps to investigate whether older books or more recent publications tend to receive higher ratings.

E. Modeling

For this project, we will build and evaluate two types of recommendation systems:

> 1. Collaborative Filtering
>
> - This approach recommends books based on user behavior and preferences of similar users that is user-user collaborative filtering or similar books rated highly by a user that is item-item collaborative filtering.
> - We will implement collaborative filtering using matrix factorization techniques like SVD and Cosine similarities to compute similar books based on ratings.

- **Drawback**: New users or items without sufficient interaction history may not receive accurate recommendations.

F. Model Evaluation

> ### Collaborative Filtering
>
> For evaluation, we will use Accuracy Test to evaluate using metrics like:

- **Precision** to measure how many of the top book recommendations made by the collaborative filtering model are relevant to the user
- **Recall** to measure how many relevant books are included in the top recommendations out of all the relevant books available. This metric ensures users have a wide variety of book recommendations without missing out on any relevant books that similar users have liked.
- **F1-score** that ensures the system provides accurate recommendations without excluding too many potential relevant books.
- **RSME & MAE** will also be used to give further evaluation of our model in understanding it's accuracy and performance in prediction.

G. Expected Outcome

> For our overall metric our analysis will mostly focus on **precision**. This is because we want to ensure that the recommendations provided are relevant meaning the suggested books is very likely to be relevant to the user. This helps meet the goal of user satisfaction by prioritizing highly relevant items to enhance the user experience.
>
> The overall expectation is to have a recommendation system with a high precision score of **atleast 75%** that ensures the model provides accurate, personalized book suggestions to users based on their ratings and preferences.

DATA PREPARATION

For this section of the project we will prepare our data for analysis by loading our data for inspection, visualizing it , cleaning it and performing feature engineering to better improve the dataset for analysis.

i) Loading the Datasets

In [1]:
```
#Import neccessary  libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#Load 'books.csv' dataset
Books = pd.read_csv(r'DATA\Books.csv',low_memory= False)
Books.head()
```

Out[2]:

	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	Image-URL-S	Image-URL-M	Image-URL-L
0	0195153448	Classical Mythology	Mark P. O. Morford	2002	Oxford University Press	http://images.amazon.com/images/P/0195153448.0...	http://images.amazon.com/images/P/0195153448.0...	http://images.amazon.com/images/P/0195153448.0...
1	0002005018	Clara Callan	Richard Bruce Wright	2001	HarperFlamingo Canada	http://images.amazon.com/images/P/0002005018.0...	http://images.amazon.com/images/P/0002005018.0...	http://images.amazon.com/images/P/0002005018.0...
2	0060973129	Decision in Normandy	Carlo D'Este	1991	HarperPerennial	http://images.amazon.com/images/P/0060973129.0...	http://images.amazon.com/images/P/0060973129.0...	http://images.amazon.com/images/P/0060973129.0...
3	0374157065	Flu: The Story of the Great Influenza Pandemic...	Gina Bari Kolata	1999	Farrar Straus Giroux	http://images.amazon.com/images/P/0374157065.0...	http://images.amazon.com/images/P/0374157065.0...	http://images.amazon.com/images/P/0374157065.0...
4	0393045218	The Mummies of Urumchi	E. J. W. Barber	1999	W. W. Norton & Company	http://images.amazon.com/images/P/0393045218.0...	http://images.amazon.com/images/P/0393045218.0...	http://images.amazon.com/images/P/0393045218.0...

In [3]:
```
#Load 'ratings.csv' dataset
Ratings = pd.read_csv(r'DATA\Ratings.csv',low_memory=False)
Ratings.head()
```

Out[3]:

	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 [4]:
```
#Load 'users.csv' dataset
Users = pd.read_csv(r'DATA\Users.csv',low_memory=False)
Users.head()
```

Out[4]:

	User-ID	Location	Age
0	1	nyc, new york, usa	NaN
1	2	stockton, california, usa	18.0
2	3	moscow, yukon territory, russia	NaN
3	4	porto, v.n.gaia, portugal	17.0
4	5	farnborough, hants, united kingdom	NaN

Merging the datasets

From our datasets above, there 3 files share some columns that can be used to merge them into one. The ratings and users dataset share a common column 'User-ID'.

In [5]:
```
#perform the merge based on 'User-ID'
merged_df = pd.merge(Ratings,Users[['User-ID','Age']],on='User-ID',how='inner')
#keep only the selected columns
merged_df = merged_df[['User-ID','Book-Rating','Age','ISBN']]
merged_df.head()
```

Out[5]:

	User-ID	Book-Rating	Age	ISBN
0	276725	0	NaN	034545104X
1	276726	5	NaN	0155061224
2	276727	0	16.0	0446520802
3	276729	3	16.0	052165615X
4	276729	6	16.0	0521795028

We the merge the third dataset to our merged data using the common column 'ISBN' to create the final combined dataframe.

In [6]:
```
#perform the merge based on 'ISBN'
merged_df1 = pd.merge(merged_df,Books,on='ISBN',how='inner')
merged_df1.head()
```

Out[6]:

	User-ID	Book-Rating	Age	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	Image-URL-S	Image-URL-M	Image-URL-L
0	276725	0	NaN	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...
1	2313	5	23.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...
2	6543	0	34.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...
3	8680	5	2.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...

	User-ID	Book-Rating	Age	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	Image-URL-S	Image-URL-M	Image-URL-L
4	10314	9	NaN	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...	http://images.amazon.com/images/P/034545104X.0...

From the data above we drop the irrelevant url columns as they will not be used for our analysis.

In [7]:
```
# Drop unnecessary image URL columns
merged_df1 = merged_df1.drop(columns=['Image-URL-L','Image-URL-M','Image-URL-S'],axis=1)
merged_df1.head()
```

Out[7]:

	User-ID	Book-Rating	Age	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher
0	276725	0	NaN	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
1	2313	5	23.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
2	6543	0	34.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
3	8680	5	2.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books
4	10314	9	NaN	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books

In [8]:
```
#Rename the columns
merged_df1.rename(columns={"User-ID": "UserID",
                   "Book-Rating":"Rating",
                   "Book-Title": "Book_title",
                    "Book-Author":"Author",
                   "Year-Of-Publication": "Publication_Year"}, inplace=True)
```

In [9]:
```
#Summary of our dataframe
merged_df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1031136 entries, 0 to 1031135
Data columns (total 8 columns):
 #   Column            Non-Null Count    Dtype  
---  ------            --------------    -----  
 0   UserID            1031136 non-null  int64  
 1   Rating            1031136 non-null  int64  
 2   Age               753301 non-null   float64
 3   ISBN              1031136 non-null  object 
 4   Book_title        1031136 non-null  object 
 5   Author            1031135 non-null  object 
 6   Publication_Year  1031136 non-null  object 
 7   Publisher         1031134 non-null  object 
dtypes: float64(1), int64(2), object(5)
memory usage: 70.8+ MB
```

In [10]:
```
#Get shape of the dataset
merged_df1.shape
```

Out[10]:
```
(1031136, 8)
```

ii) Exploratory Data Analysis (EDA)

1.Univariate Analysis

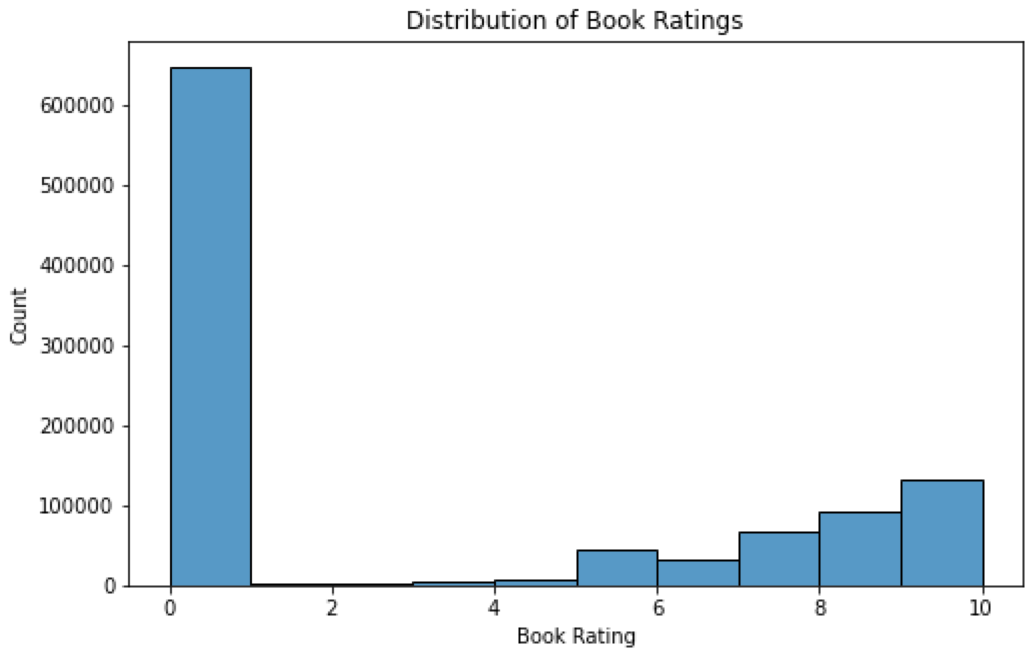
A. Distribution of Book Ratings

This helps to understand the general sentiment of users towards the books.

In [11]:
```
merged_df1['Rating'].value_counts()
```

Out[11]:
```
0     647294
8      91804
10     71225
7      66402
9      60778
5      45355
6      31687
4       7617
3       5118
2       2375
1       1481
Name: Rating, dtype: int64
```

In [14]:
```
#Plot the graph
plt.figure(figsize=(8, 5))
sns.histplot(merged_df1['Rating'], bins=10, kde=False)

plt.title('Distribution of Book Ratings')
plt.xlabel('Book Rating')
plt.ylabel('Count')
plt.show()
```



Interpretation

The rating of 0 is extremely frequent, which may indicate that many users haven't rated some books. This category dominates the distribution and may skew the data. In terms of Most Popular Ratings, apart from the large number of 0 ratings, the majority of ratings are concentrated in the higher range ratings of 7, 8, 9, and 10, indicating that users tend to give positive ratings. There's a gradual decline in counts as ratings decrease from 10 to 1. Ratings between 1 and 4 are significantly less frequent, suggesting that users are less likely to give very low ratings.

B. Distribution of User Age

In [12]:
```
#Top 20 most frequent user ages
merged_df1['Age'].value_counts().head(20)
```

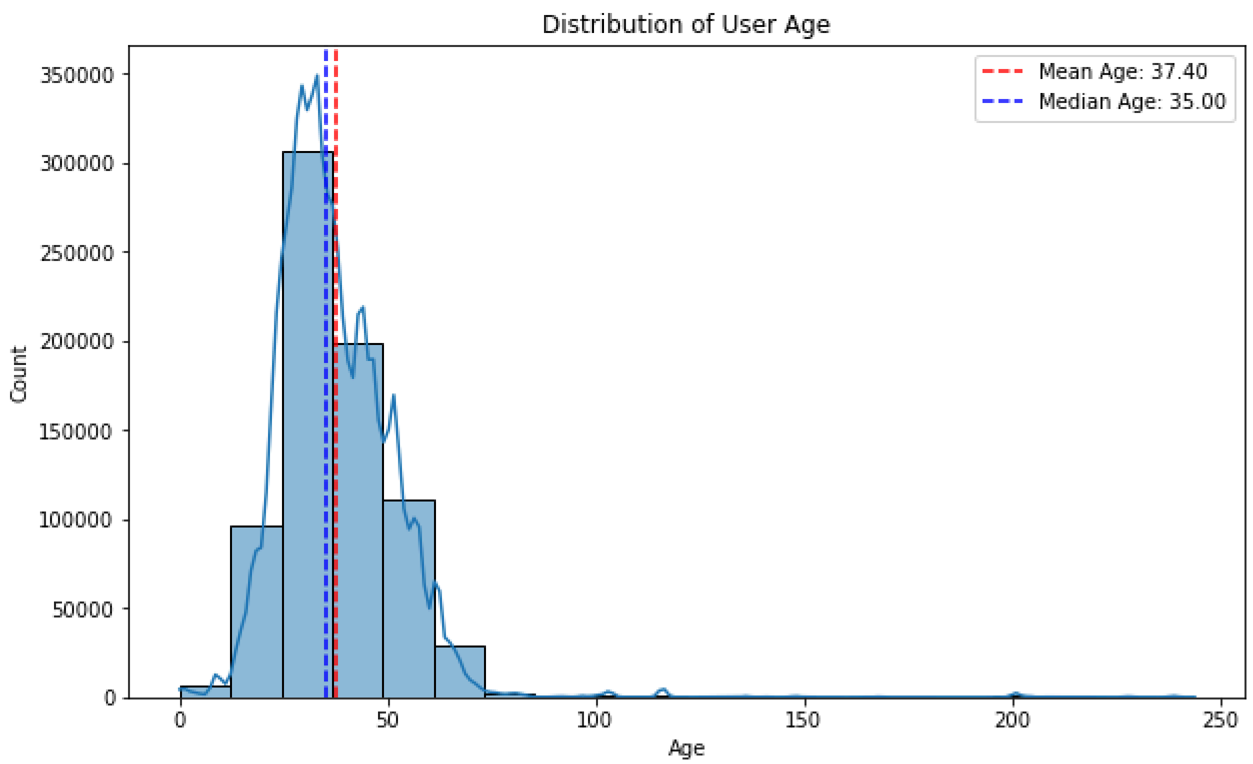
Out[12]:
```
33.0    32862
29.0    30646
30.0    27201
32.0    26490
36.0    26096
```

```
28.0    25966
31.0    25964
34.0    25893
38.0    22396
27.0    22280
26.0    22107
25.0    21768
44.0    21510
37.0    21116
43.0    20612
35.0    19573
23.0    18793
24.0    18572
47.0    18517
52.0    17637
Name: Age, dtype: int64
```

In [15]:
```
#Highest user age
merged_df1['Age'].max()
```

Out[15]:
```
244.0
```

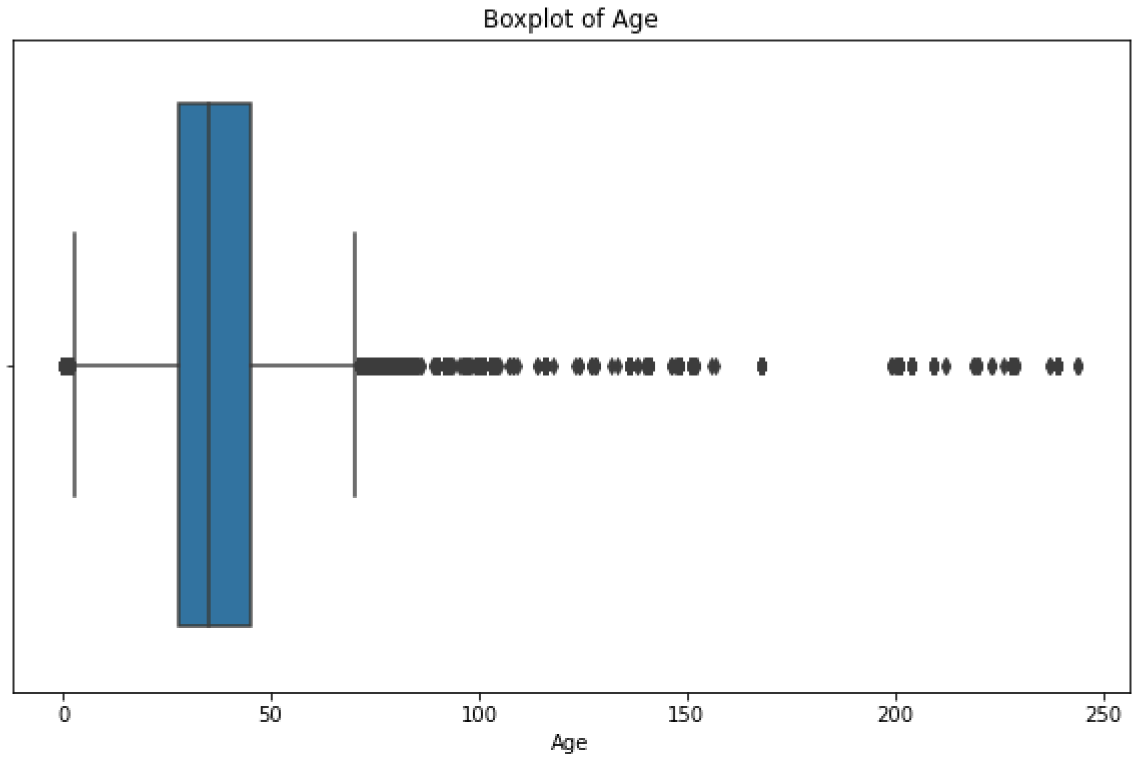
In [16]:
```
mean_age = merged_df1['Age'].mean()
median_age = merged_df1['Age'].median()

# Plot Distribution of User Age
plt.figure(figsize=(10, 6))
sns.histplot(merged_df1['Age'], bins=20, kde=True)
plt.axvline(mean_age, color='red', linestyle='--', label=f'Mean Age: {mean_age:.2f}')
plt.axvline(median_age, color='blue', linestyle='--', label=f'Median Age: {median_age:.2f}')
plt.title('Distribution of User Age')
plt.xlabel('Age')
plt.legend()
plt.show()
```



Interpretation

Based on the distribution above, majority of the users in the dataset lie between the age 18 to 60. The mean lies at 37 years while the median lies at 35 years suggesting majority of the users are near that age. The ages between 25 and 40 seem to dominate the dataset with the peak around ages 29-33, suggesting that most users are young to middle-aged adults. The age distribution covers a wide range from very low to very high values (up to 244 years). There's a long tail extending into the older age ranges, with small numbers of users listed as having ages greater than 100 indicating presence of outliers.

In [17]:
```
# Boxplot to visualize Age outliers
plt.figure(figsize=(10, 6))
sns.boxplot(x=merged_df1['Age'])
plt.title('Boxplot of Age')
plt.xlabel('Age')
plt.show()
```



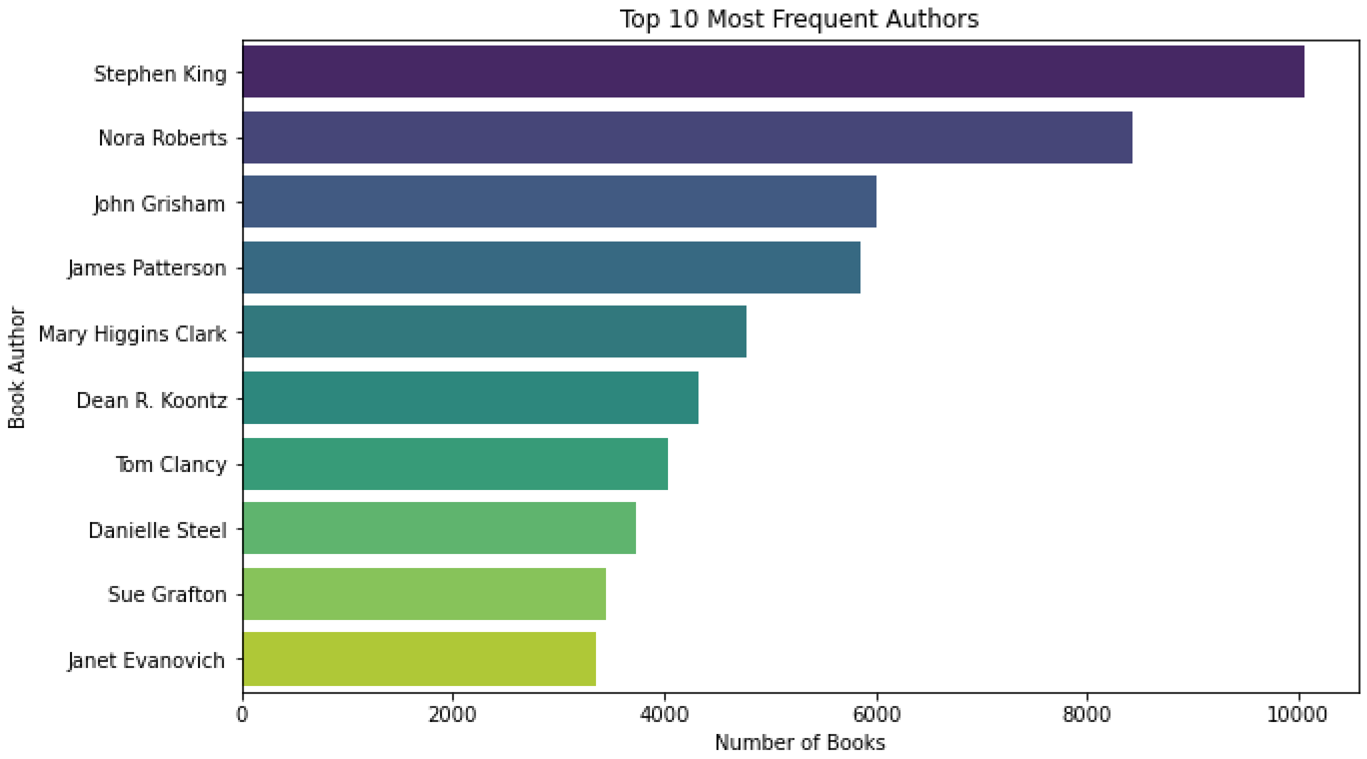
Interpretation

The boxplot highlights a significant number of outliers indicating the need for data cleaning. Users with ages exceeding approximately 75 are flagged as potential outliers, suggesting there are abnormally high age values in the dataset. Values much higher than the median (around 29-33) extend far beyond the normal range of typical users.

C. Most Frequent Authors

This shows the most common authors in the dataset based on the number of books they have authored which might reflect author's popularity.

In [18]:
```
# Top 10 most frequent Authors
top_authors = merged_df1['Author'].value_counts().head(10)

# Plot for Top 10 Authors
plt.figure(figsize=(10, 6))
sns.barplot(x=top_authors.values, y=top_authors.index, palette='viridis')
plt.title('Top 10 Most Frequent Authors')
plt.xlabel('Number of Books')
plt.ylabel('Book Author')
plt.show()
```



Interpretation

Based on the graph above, Stephen King is the most frequent author in the dataset, with over 10,000 books. The list continues with other well-known authors. It gives a clear visual of how much more frequent Stephen King's books are compared to the rest, showing him as a highly prolific author in this dataset.

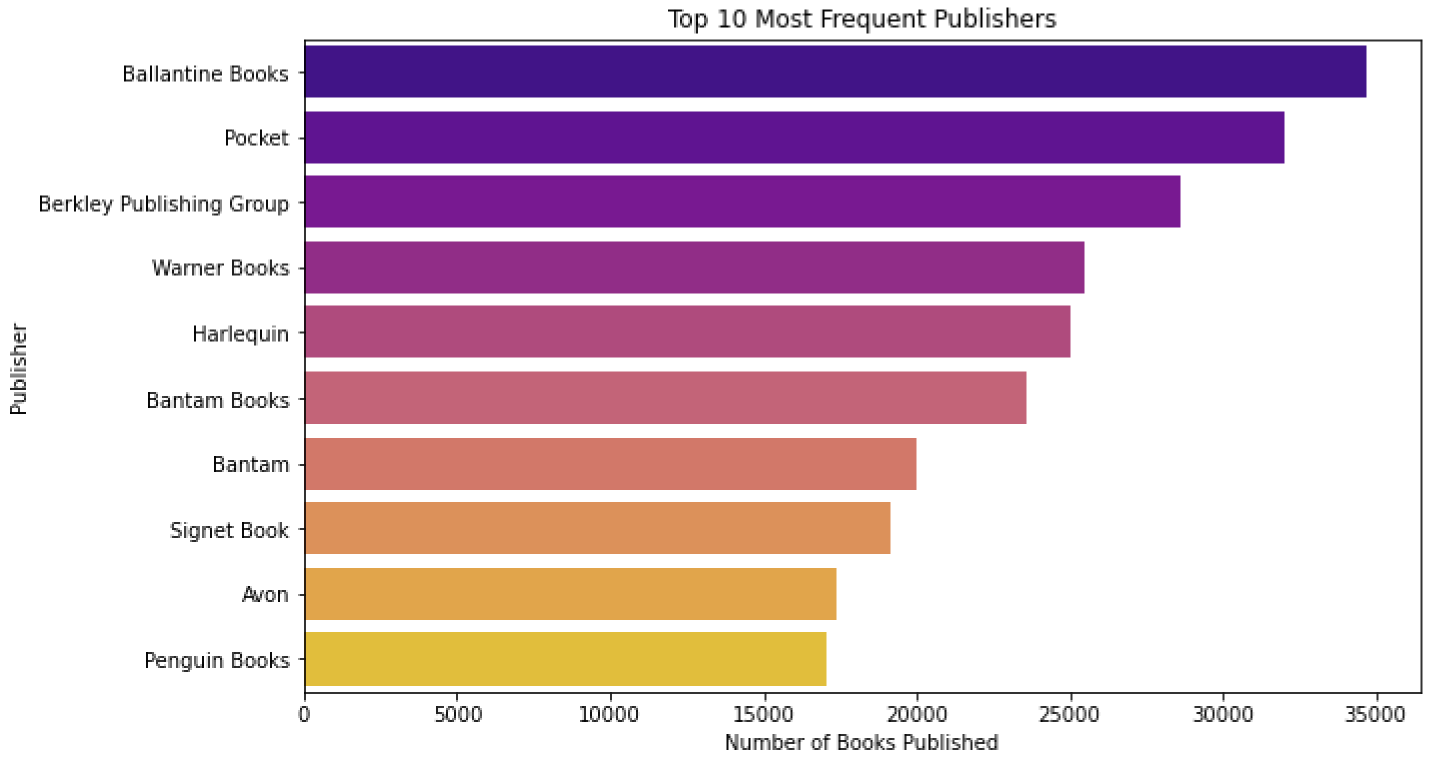
D. Most Frequent Publishers

This shows the publishers most frequent in the dataset which might reflect publisher popularity.

In [19]:
```
top_publishers = merged_df1['Publisher'].value_counts().head(10)
top_publishers
```

Out[19]:
```
Ballantine Books            34724
Pocket                      31989
Berkley Publishing Group    28614
Warner Books                25506
Harlequin                   25027
Bantam Books                23598
Bantam                      20007
Signet Book                 19155
Avon                        17352
Penguin Books               17033
Name: Publisher, dtype: int64
```

In [20]:
```
# Top 10 most frequent Publishers
top_publishers = merged_df1['Publisher'].value_counts().head(10)

# Plot for Top 10 Publishers
plt.figure(figsize=(10, 6))
sns.barplot(x=top_publishers.values, y=top_publishers.index, palette='plasma')
plt.title('Top 10 Most Frequent Publishers')
plt.xlabel('Number of Books Published')
plt.ylabel('Publisher')
plt.show()
```



Interpretation

Based on the graph above,Ballantine Books is the most frequent publisher, with over 34,000 books published, followed by Pocket. Other prominent publishers include Berkley Publishing Group, Warner Books, and Harlequin, with over 25,000 books each. Publishers like Signet Book, Avon, and Penguin Books complete the list, with Penguin Books publishing just over 17,000 books.

2. Bivariate Analysis

A. Book Rating vs User age

We'll explore the relationship between user age and the ratings they give to books.

In [21]:
```
# Group by 'Age' and calculate the average 'Book-Rating'
average_rating_by_age = merged_df1.groupby('Age')['Rating'].mean().reset_index()

# Rename the columns
average_rating_by_age.columns = ['Age', 'Average Book-Rating']
average_rating_by_age
```

Out[21]:

	Age	Average Book-Rating
0	0.0	2.859180
1	1.0	3.464953
2	2.0	4.214953
3	3.0	4.923077
4	4.0	4.630996
...	...	...
136	228.0	0.492063
137	229.0	2.000000
138	237.0	3.333333
139	239.0	2.206897

	Age	Average Book-Rating
140	244.0	3.142857

141 rows × 2 columns

In [22]:
```
#Plot a Scatter plot of Book-Rating vs Age
plt.figure(figsize=(8, 6))
sns.scatterplot(x=merged_df1['Age'], y=merged_df1['Rating'])
plt.title('Scatter Plot of Age vs Book-Rating')
plt.xlabel('Age')
plt.ylabel('Book-Rating')
plt.show()
```

Interpretation

The plot reveals the distribution of ratings based on user age. Users between 0 to about 90 years are densely distributed throughout the ratings. The presence of outliers may influence the observations made as the age is seen to range from 0 up to 244 years. Further analysis could include segmenting the age groups into specific ranges to assess these trends in more detail or exploring the specific genres or authors rated to understand what drives these differences in ratings.

Interpretation

B. Book Author vs. Average Book Rating

This helps determine which authors tend to receive higher or lower average ratings.

In [23]:
```
avg_ratings_author = merged_df1.groupby('Author')['Rating'].mean().sort_values(ascending=False).reset_index()
avg_ratings_author.head(20)
```

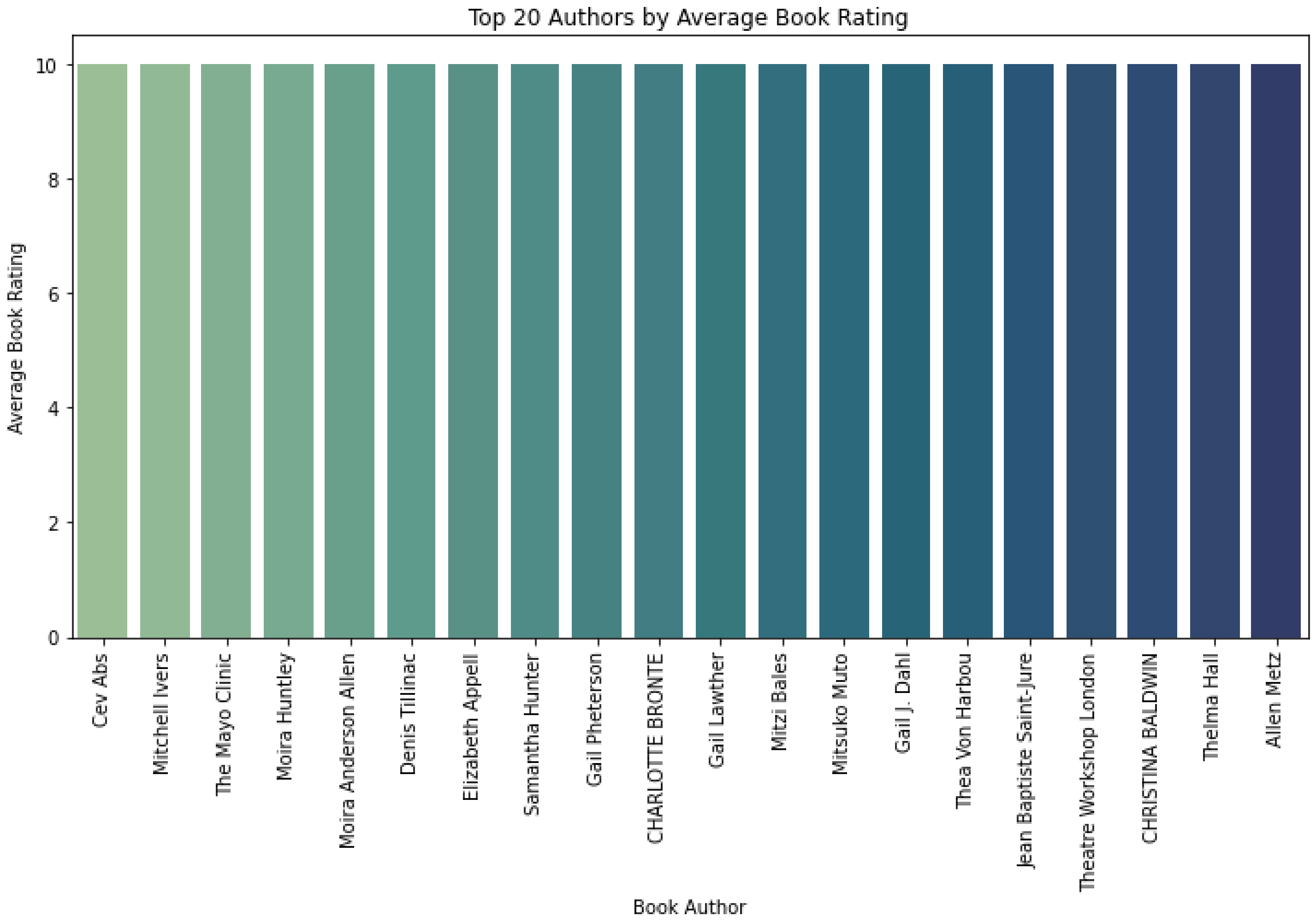
Out[23]:

	Author	Rating
0	Cev Abs	10.0
1	Mitchell Ivers	10.0
2	The Mayo Clinic	10.0

	Author	Rating
3	Moira Huntley	10.0
4	Moira Anderson Allen	10.0
5	Denis Tillinac	10.0
6	Elizabeth Appell	10.0
7	Samantha Hunter	10.0
8	Gail Pheterson	10.0
9	CHARLOTTE BRONTE	10.0
10	Gail Lawther	10.0
11	Mitzi Bales	10.0
12	Mitsuko Muto	10.0
13	Gail J. Dahl	10.0
14	Thea Von Harbou	10.0
15	Jean Baptiste Saint-Jure	10.0
16	Theatre Workshop London	10.0
17	CHRISTINA BALDWIN	10.0
18	Thelma Hall	10.0
19	Allen Metz	10.0

In [24]:

```
# Define a custom color palette
colors = sns.color_palette("crest", len(avg_ratings_author.head(20)))

#Plot the distribution
plt.figure(figsize=(12, 6))
sns.barplot(x='Author', y='Rating', data=avg_ratings_author.head(20), palette=colors)#Get top 20 authors
plt.xticks(rotation=90)
plt.title('Top 20 Authors by Average Book Rating')
plt.xlabel('Book Author')
plt.ylabel('Average Book Rating')
plt.show()
```



Interpretation

All of the listed authors have a perfect rating of 10.0, indicating that their books have been highly rated by users. Based on the plot we can assume that these authors are highly favored by their readers. The perfect ratings could be due to low rating count or a niche audience. Books from these highly-rated authors could be prioritized in recommendation systems, especially for users who enjoy similar types of content or genres.

C. Publisher vs. Average Book Rating

This examines whether certain publishers consistently publish books that receive higher ratings.

In [25]:
```
avg_ratings_publisher = merged_df1.groupby('Publisher')['Rating'].mean().sort_values(ascending=False).reset_index()
avg_ratings_publisher.head(20)
```

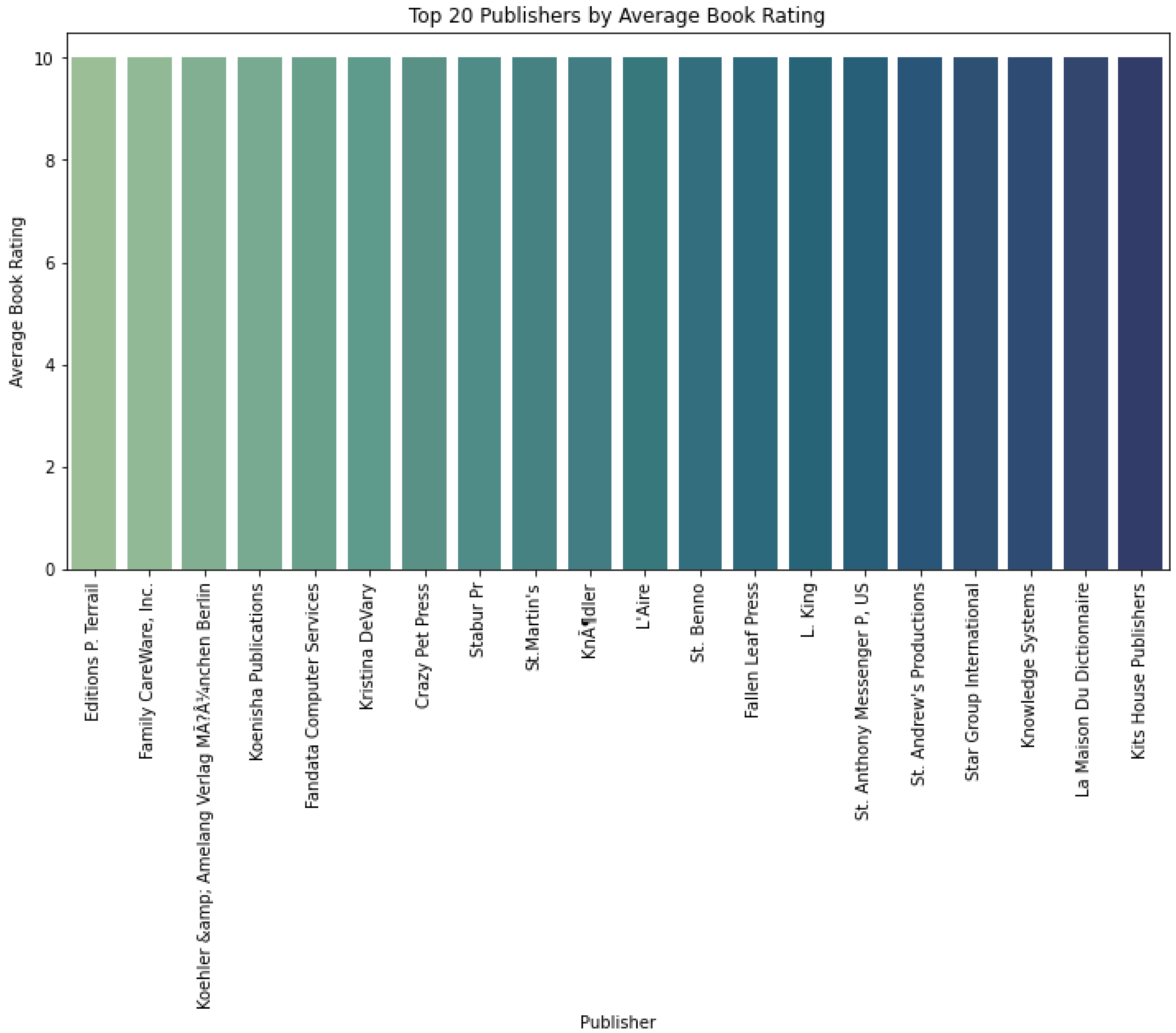
Out[25]:

	Publisher	Rating
0	Editions P. Terrail	10.0
1	Family CareWare, Inc.	10.0
2	Koehler & Amelang Verlag MÃ?Â¼nchen Berlin	10.0
3	Koenisha Publications	10.0
4	Fandata Computer Services	10.0
5	Kristina DeVary	10.0
6	Crazy Pet Press	10.0
7	Stabur Pr	10.0
8	St.Martin's	10.0

	Publisher	Rating
9	KnÃ¶dler	10.0
10	L'Aire	10.0
11	St. Benno	10.0
12	Fallen Leaf Press	10.0
13	L. King	10.0
14	St. Anthony Messenger P, US	10.0
15	St. Andrew's Productions	10.0
16	Star Group International	10.0
17	Knowledge Systems	10.0
18	La Maison Du Dictionnaire	10.0
19	Kits House Publishers	10.0

In [26]:

```
#Plot the graph
# Define a custom color palette
colors = sns.color_palette("crest", len(avg_ratings_publisher.head(20)))

plt.figure(figsize=(12, 6))
sns.barplot(x='Publisher', y='Rating', data=avg_ratings_publisher.head(20), palette=colors)
plt.xticks(rotation=90)
plt.title('Top 20 Publishers by Average Book Rating')
plt.xlabel('Publisher')
plt.ylabel('Average Book Rating')
plt.show()
```



Interpretation

The bar plot visually shows that all publishers in the top 20 have achieved a 10.0 average rating. The publishers could be from a diverse range of industries, from mainstream to niche publishing houses.In the analysis, books published by these top-rated publishers could be prominently featured in recommendation system for users who are likely to appreciate such content.Knowing which publishers consistently produce high-rated books allows for targeted advertising strategies, particularly for niche books that may attract specific types of readers. We might also conclude that publishers with few ratings may not be as influential.

D. Age vs. Publisher Preference

This analysis helps to explore if users of certain age groups prefer books from specific publishers.

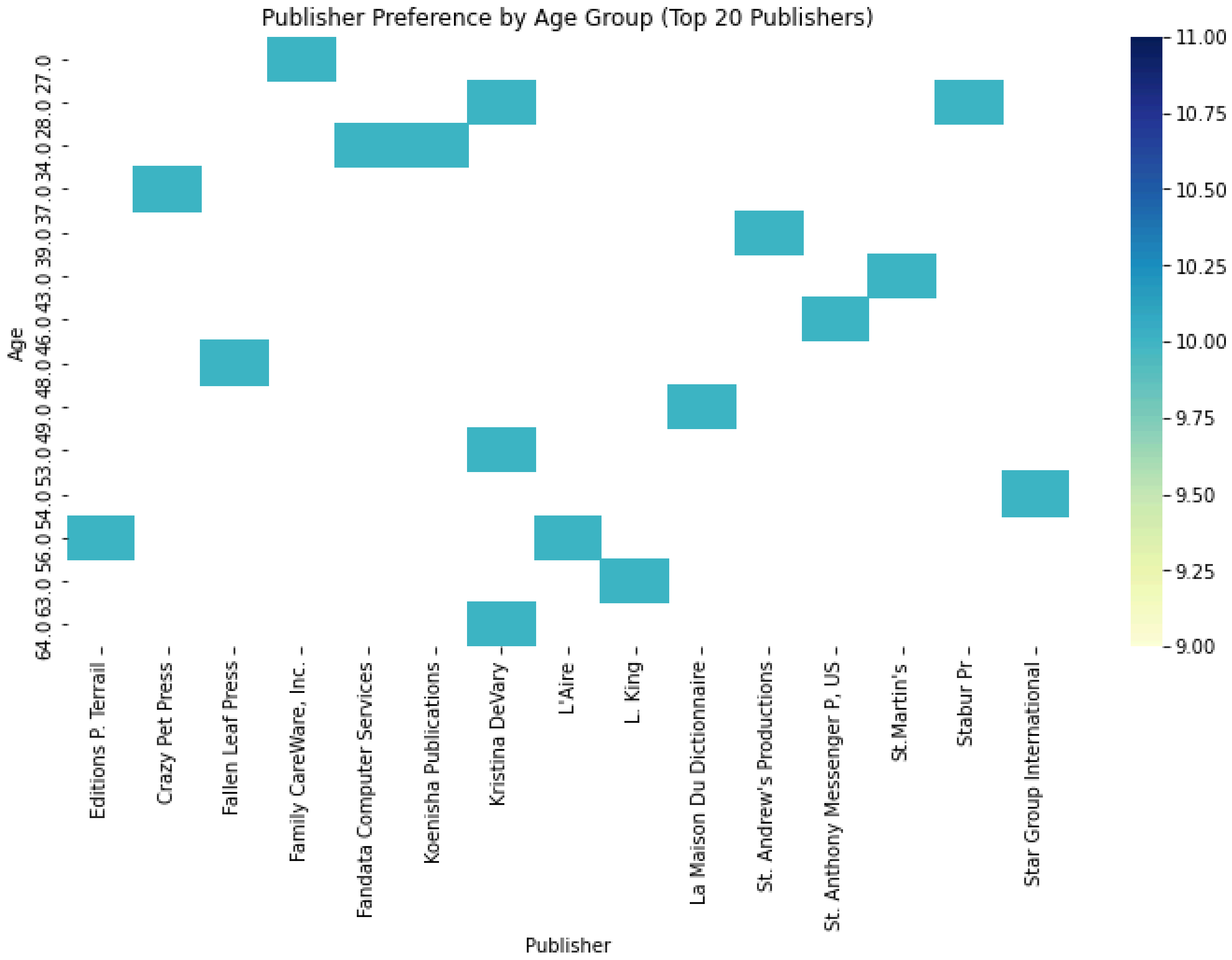
In [27]:
```
# Group by Publisher to get the average rating
avg_ratings_publisher = merged_df1.groupby('Publisher')['Rating'].mean().sort_values(ascending=False).reset_index()

# Select the top 20 publishers with the highest ratings
top_20_publishers = avg_ratings_publisher.head(20)

# Filter the merged_df1 dataset to only include the top 20 publishers
top_publishers_data = merged_df1[merged_df1['Publisher'].isin(top_20_publishers['Publisher'])]

# Group the data by Age and Publisher to calculate the average Book-Rating for each Age-Publisher combination
publisher_pref_by_age = top_publishers_data.groupby(['Age', 'Publisher'])['Rating'].mean().reset_index()
publisher_pref_by_age
```

Out[27]:

	Age	Publisher	Rating
0	27.0	Family CareWare, Inc.	10
1	28.0	Kristina DeVary	10
2	28.0	Stabur Pr	10
3	34.0	Fandata Computer Services	10
4	34.0	Koenisha Publications	10
5	37.0	Crazy Pet Press	10
6	39.0	St. Andrew's Productions	10
7	43.0	St.Martin's	10
8	46.0	St. Anthony Messenger P, US	10
9	48.0	Fallen Leaf Press	10
10	49.0	La Maison Du Dictionnaire	10
11	53.0	Kristina DeVary	10
12	54.0	Star Group International	10
13	56.0	Editions P. Terrail	10
14	56.0	L'Aire	10
15	63.0	L. King	10
16	64.0	Kristina DeVary	10

In [28]:

```
# Create the pivot table for the heatmap
pivot_table = publisher_pref_by_age.pivot(index='Age', columns='Publisher', values='Rating')

# Plot the heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(pivot_table, cmap='YlGnBu', annot=False)
plt.title('Publisher Preference by Age Group (Top 20 Publishers)')
plt.xlabel('Publisher')
plt.ylabel('Age')
plt.xticks(rotation=90)
plt.show()
```



Interpretation

The plot shows users ranging from 27 to 64 years. Some publishers may appeal more to younger readers, while others resonate with older audiences.Having a high concentration of ratings for certain publishers in specific age groups may indicate that those publishers focus on age-targeted content. All book ratings for the publishers listed in the heatmap are at the maximum value of 10. This indicates that the books published by these publishers are consistently rated highly across all age groups represented in the dataset. The consistent high ratings across various age groups suggest that the books from these publishers have a wide appeal and are well-received by readers of different ages. If some publishers have more ratings across different age groups, it can indicate they have a broader market reach or are more popular among various demographics.

E. User vs. Book Rating

This helps to understand if certain users tend to give consistently higher while others may be more critical.

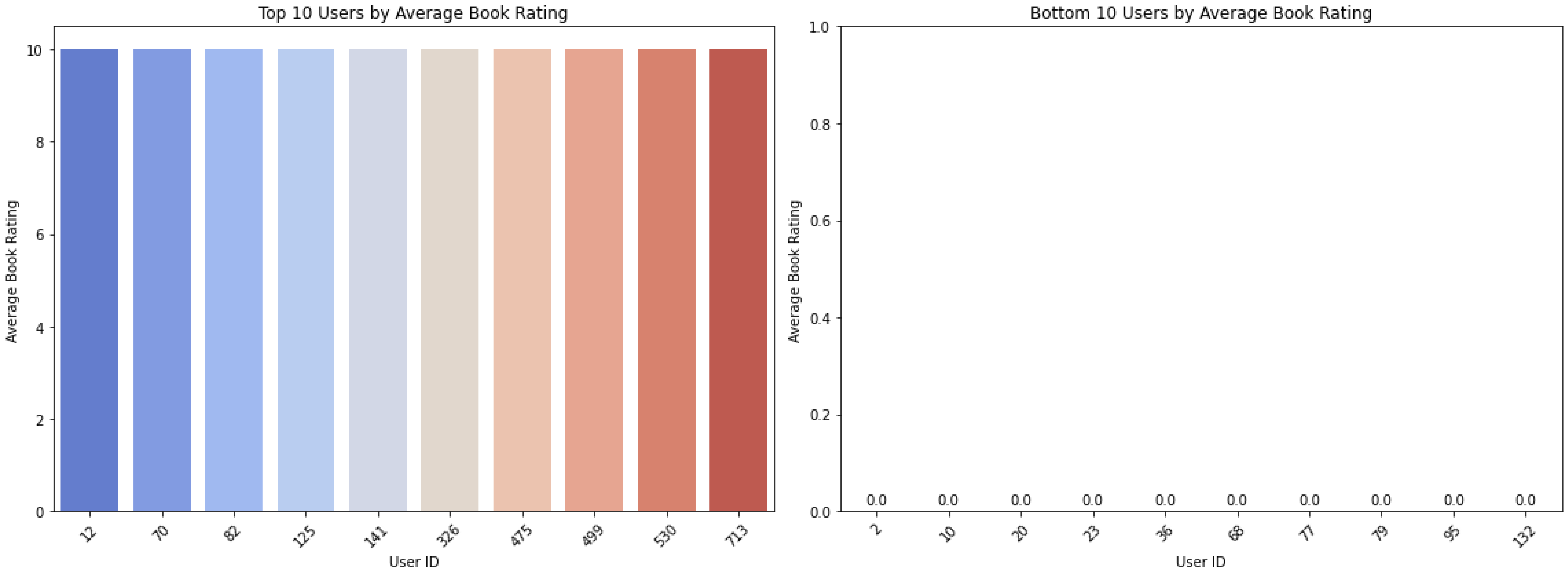
In [29]:
```
#Book rating by user
avg_ratings_user = merged_df1.groupby('UserID')['Rating'].mean().reset_index()

# Get the top 10 and bottom 10 users by average rating
top_10_users = avg_ratings_user.nlargest(10, 'Rating')
bottom_10_users = avg_ratings_user.nsmallest(10, 'Rating')
print(f"Top 10 users: {top_10_users}")
print(f"Bottom 10 users:{bottom_10_users}")
```

```
Top 10 users:      UserID  Rating
4        12    10.0
25       70    10.0
32       82    10.0
48      125    10.0
54      141    10.0
103     326    10.0
146     475    10.0
156     499    10.0
```

```
167     530    10.0
212     713    10.0
Bottom 10 users:    UserID  Rating
0        2     0.0
3       10     0.0
9       20     0.0
11      23     0.0
14      36     0.0
23      68     0.0
28      77     0.0
30      79     0.0
40      95     0.0
50     132     0.0
```

In [30]:

```
# Set up the figure and axes for side-by-side plots
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Define a custom color palette
colors = sns.color_palette("coolwarm", 10)

# Plot for Top 10 Users
sns.barplot(x='UserID', y='Rating', data=top_10_users, ax=axes[0], palette=colors)
axes[0].set_title('Top 10 Users by Average Book Rating')
axes[0].set_xlabel('User ID')
axes[0].set_ylabel('Average Book Rating')
axes[0].tick_params(axis='x', rotation=45)

# Plot for Bottom 10 Users
sns.barplot(x='UserID', y='Rating', data=bottom_10_users, ax=axes[1], palette=colors)
axes[1].set_title('Bottom 10 Users by Average Book Rating')
axes[1].set_xlabel('User ID')
axes[1].set_ylabel('Average Book Rating')
axes[1].tick_params(axis='x', rotation=45)

# Add labels to zero-rating bars
for bar in axes[1].patches:
    axes[1].annotate(
        format(bar.get_height(), '.1f'),  # Add text as '0.0' for zero ratings
        (bar.get_x() + bar.get_width() / 2, bar.get_height()),  # Position label in the middle
        ha='center', va='center', size=10, xytext=(0, 8), textcoords='offset points'
    )
# Adjusting y-axis limits to ensure visibility
axes[1].set_ylim(0, 1)

# Adjust layout
plt.tight_layout()
plt.show()
```



Interpretation

The top 10 users have an average book rating of 10.0 indicating that these users have only given perfect ratings to the books they have rated. Since all top users show the same maximum rating, it suggests that these users might have either a very favorable view of the books they rated, or they may have rated only a few select books that they felt deserved a perfect score which could point to a potential bias in their rating behavior.

The bottom 10 users have an average book rating of 0.0. This indicates that these users have not given any ratings above zero, implying they may not have engaged with the books in a way that they felt warranted a rating. These users might not have found any books satisfactory enough to rate positively, suggesting dissatisfaction with the content or quality of books available to them. It's also possible that these users are not active readers or have not rated enough books to form a comprehensive view. This lack of ratings might negatively affect the overall average ratings for books in the system if these users account for a substantial number of ratings.

The contrast between the top and bottom users highlights the variability in user engagement and satisfaction within the dataset. It suggests two extremes: highly engaged users with consistently positive feedback and users who do not engage meaningfully with the reading material.

F. Year of Publication vs. Average Book Rating

This helps to investigate whether older books or more recent publications tend to receive higher ratings.

In [31]:
```
avg_ratings_year = merged_df1.groupby('Publication_Year')['Rating'].mean().reset_index()
avg_ratings_year
```

Out[31]:

	Publication_Year	Rating
0	0	3.132415
1	1376	4.000000
2	1378	10.000000
3	1806	5.000000
4	1897	0.000000
...	...	...
113	2037	10.000000

	Publication_Year	Rating
114	2038	2.375000
115	2050	4.857143
116	DK Publishing Inc	2.333333
117	Gallimard	0.000000

118 rows × 2 columns

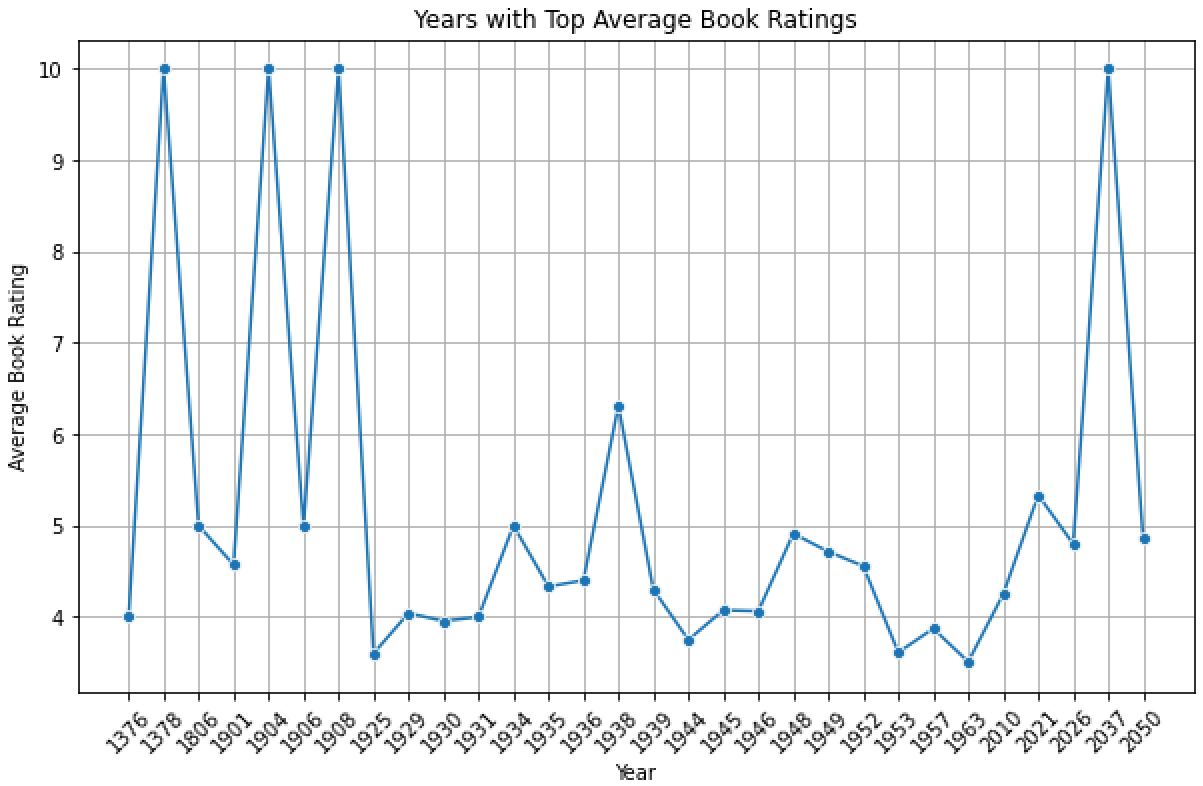
In [32]:
```
# Get the 75th percentile rating
top_ratings_threshold = avg_ratings_year['Rating'].quantile(0.75)
top_ratings_year = avg_ratings_year[avg_ratings_year['Rating'] >= top_ratings_threshold]#to get years with top ratings
top_ratings_year
```

Out[32]:

	Publication_Year	Rating
1	1376	4.000000
2	1378	10.000000
3	1806	5.000000
6	1901	4.571429
8	1904	10.000000
9	1906	5.000000
10	1908	10.000000
22	1925	3.600000
26	1929	4.041667
27	1930	3.955224
28	1931	4.000000
31	1934	5.000000
32	1935	4.333333
33	1936	4.400000
35	1938	6.312500
36	1939	4.300000
41	1944	3.750000
42	1945	4.074074
43	1946	4.063830
45	1948	4.913043
46	1949	4.714286
49	1952	4.556962
50	1953	3.611830
54	1957	3.872587
60	1963	3.509434
105	2010	4.250000

	Publication_Year	Rating
109	2021	5.333333
111	2026	4.800000
113	2037	10.000000
115	2050	4.857143

In [44]:
```
# Plot the graph for top ratings
plt.figure(figsize=(10, 6))
sns.lineplot(x='Publication_Year', y='Rating', data=top_ratings_year, marker='o')  # Adding markers for clarity
plt.title('Years with Top Average Book Ratings')
plt.xlabel('Year')
plt.ylabel('Average Book Rating')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.grid(True)  # Optional: add a grid for better visual clarity
plt.show()
```



Interpretation

The ratings across different years show variability, indicating that some years produced books with significantly higher average ratings than others. By examining the overall trend across the years, you might observe if there are patterns in book quality over time. For instance, ratings seem relatively stable with some peaks, but there is also a drop in ratings in certain periods. This could suggest fluctuations in publishing quality, reader preferences, or the impact of historical events on literature. The average ratings for more recent years indicates a potential resurgence in quality, or perhaps the influence of modern publishing trends and accessibility through various platforms. Based on the graph we can see presence of outliers, particularly in future years from 2026-2050 that will need to be removed.

Data Cleaning

For this section we will clean the dataset of any duplicates, missing values and outliers.

i. Duplicates

In [34]:
```
#Checking for duplicates
merged_df1.duplicated().any()
```

Out[34]:
```
False
```

In [35]:
```
print("""From the above, we can conclude that our dataset has no duplicated values""")
```

```
From the above, we can conclude that our dataset has no duplicated values
```

ii. Outliers

There are some outliers in the 'Age' column that may affect our analysis and thus best to be removed.

In [36]:
```
#Capping the age column to a reasonable range of 5 < x <100
merged_df1['Age'] = merged_df1['Age'].apply(lambda x: 5 if x < 5 else (70 if x > 70 else x))
```

The 'Year-Of-Publication' column also had some outliers years exceeding the normal range that need to be removed. We will also convert the column into the right data type which is an interger column.

In [37]:
```
#Filter out non-integer values in the Year-Of-Publication column
merged_df1 = merged_df1[pd.to_numeric(merged_df1['Publication_Year'], errors='coerce').notnull()]

#Convert the Year-Of-Publication column to integers
merged_df1['Publication_Year'] = merged_df1['Publication_Year'].astype('int64')

#Remove rows where Year-Of-Publication is 2023 or later
merged_df1 = merged_df1[merged_df1['Publication_Year'] < 2024]
```

In [38]:
```
#Assert that all values in 'Year-Of-Publication' are integers
assert merged_df1['Publication_Year'].dtype == 'int64', "Year-Of-Publication is not of type int"

#Assert that all values are less than 2024
assert (merged_df1['Publication_Year'] < 2024).all(), "There are values in Year-Of-Publication that are not less than 2023"

#Assert that there are no missing values
assert merged_df1['Publication_Year'].notnull().all(), "There are missing values in Year-Of-Publication"
```

iii. Missing values

In [38]:
```
# Check for missing values
merged_df1.isnull().sum()
```

Out[38]:
```
UserID                   0
Rating                   0
Age                 277815
ISBN                     0
Book_title               0
Author                   1
Publication_Year         0
Publisher                2
dtype: int64
```

In [39]:
```
#Percentage of missing values
merged_df1.isnull().mean()*100
```

Out[39]:
```
UserID               0.000000
Rating               0.000000
Age                 26.944130
ISBN                 0.000000
Book_title           0.000000
Author               0.000097
Publication_Year     0.000000
Publisher            0.000194
dtype: float64
```

Dropping rows

For columns like 'Book-Author' and 'Publisher' with very few missing values, it's best to drop the rows with the null values.

In [40]:
```
# Drop rows with missing values in the two columns
merged_df1 = merged_df1.dropna(subset=['Author', 'Publisher'])
#Checking for remaining missing values
merged_df1.isnull().mean()*100
```

Out[40]:
```
UserID               0.000000
Rating               0.000000
Age                 26.944209
ISBN                 0.000000
Book_title           0.000000
Author               0.000000
Publication_Year     0.000000
Publisher            0.000000
dtype: float64
```

Replacing missing values

From the above, we can observe that the 'Age' column has a large number of null values as it has approximately 27% missing data. As this column is crucial, dropping it might affect our analysis thus we replace the missing values with the median using SimpleImputer.

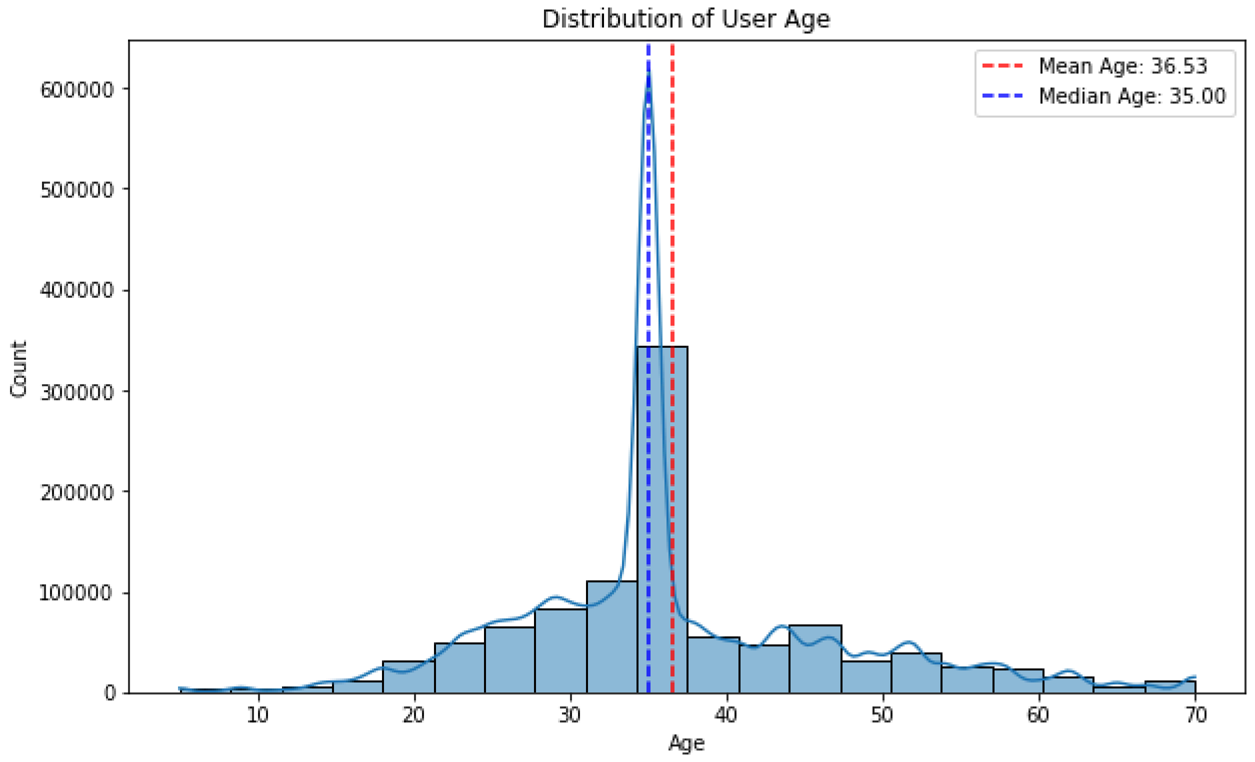
In [41]:
```
#import necessary libraries
from sklearn.impute import SimpleImputer
#filling missing in Age column with median
imputer = SimpleImputer(strategy='median')
merged_df1['Age'] = imputer.fit_transform(merged_df1[['Age']])
```

In [42]:
```
#Checking for any remaining missing values
merged_df1.isnull().sum()
```

Out[42]:
```
UserID              0
Rating              0
Age                 0
ISBN                0
Book_title          0
Author              0
Publication_Year    0
Publisher           0
dtype: int64
```

Rechecking Age Distribution

In [43]:
```
mean_age = merged_df1['Age'].mean()
median_age = merged_df1['Age'].median()

# Plot Distribution of User Age
plt.figure(figsize=(10, 6))
sns.histplot(merged_df1['Age'], bins=20, kde=True)
plt.axvline(mean_age, color='red', linestyle='--', label=f'Mean Age: {mean_age:.2f}')
plt.axvline(median_age, color='blue', linestyle='--', label=f'Median Age: {median_age:.2f}')
plt.title('Distribution of User Age')
plt.xlabel('Age')
plt.legend()
plt.show()
```



In [44]:
```
print("""There was a very slight decrease in mean to 36.53 with the median remaining at 35.
The distribution is improved with outliers being removed.""")
```

```
There was a very slight decrease in mean to 36.53 with the median remaining at 35.
The distribution is improved with outliers being removed.
```

Feature Engineering

From our dataset, a new column with age groups is created for better understanding of book preference based on certain age groups.

In [48]:
```
#Define function for feature engineering
def age_group(age):
    if age < 18:
        return 'Child'
    elif age < 35:
        return 'Young Adult'
    elif age < 55:
        return 'Adult'
    else:
        return 'Senior'

# Apply the age_group function only on known ages
merged_df1['Age_Group'] = merged_df1['Age'].apply(lambda x: age_group(x) if pd.notnull(x) else np.nan)
merged_df1.head(5)
```

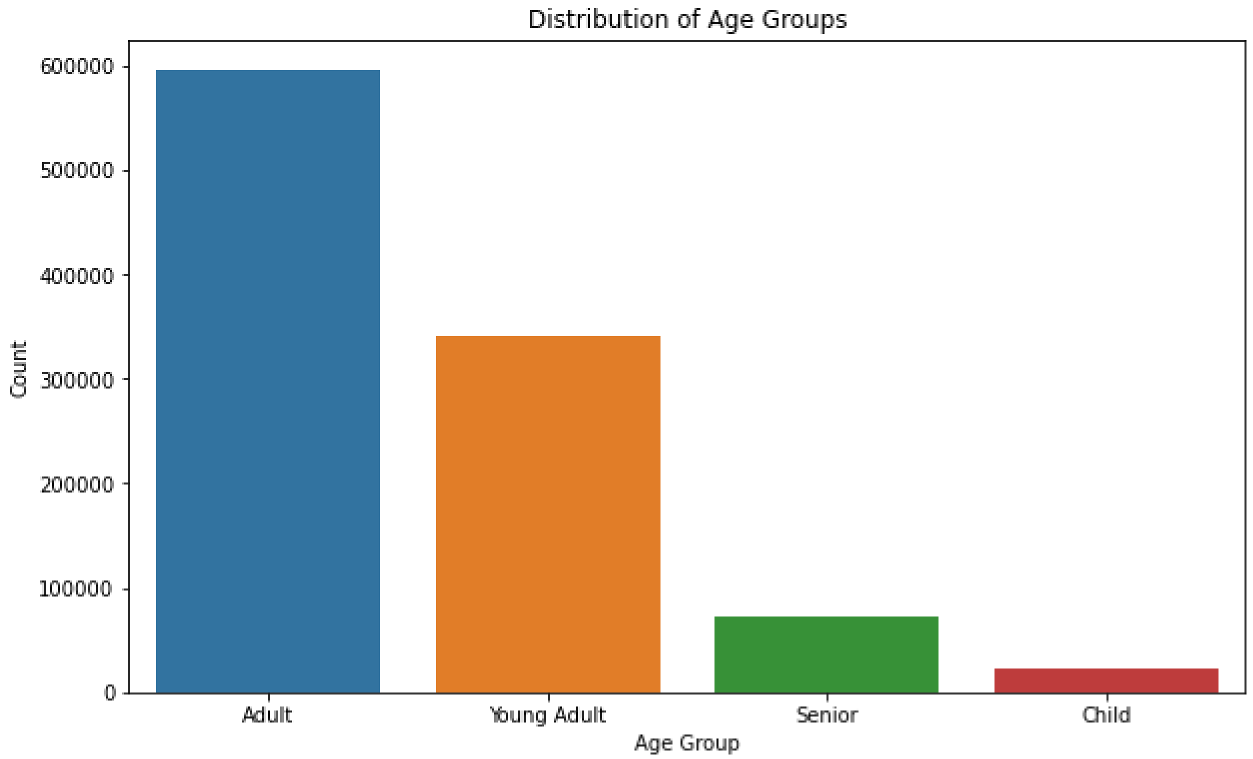
Out[48]:

	UserID	Rating	Age	ISBN	Book_title	Author	Publication_Year	Publisher	Age_Group
0	276725	0	35.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	Adult
1	2313	5	23.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	Young Adult
2	6543	0	34.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	Young Adult
3	8680	5	5.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	Child
4	10314	9	35.0	034545104X	Flesh Tones: A Novel	M. J. Rose	2002	Ballantine Books	Adult

In [49]:
```
#Count of each age group
merged_df1['Age_Group'].value_counts()
```

Out[49]:
```
Adult          595053
Young Adult    341169
Senior          72530
Child           22323
Name: Age_Group, dtype: int64
```

In [50]:
```
# Set the figure size
plt.figure(figsize=(10, 6))

# Create a count plot for Age Groups
sns.countplot(x='Age_Group', data=merged_df1, order=merged_df1['Age_Group'].value_counts().index)

# Set the title and labels
plt.title('Distribution of Age Groups')
plt.xlabel('Age Group')
plt.ylabel('Count')

# Display the plot
plt.show()
```



Interpretation

Based on the plot, the adult category significantly outnumbers the other age groups with a count of over 500,000, indicating that the dataset primarily consists of adult users. Young Adult group has a substantial representation but is almost half the size of the adult group. The smaller representation is of the Seniors and Children. The child group with less than 30,00 users, in particular, is quite small compared to the others.These findings may suggest that marketing strategies should primarily focus on adults and young adults, as they represent the majority of your user base.

MODELLING

In our analysis we will use collaborative based filtering to build our recommendation system.

Collaborative Filtering

We can use matrix factorization, such as Singular Value Decomposition (SVD), for collaborative filtering.

Loading from surprise library

In [51]:
```
from surprise import Dataset, Reader, SVD
from surprise.model_selection import train_test_split
from surprise import accuracy

# Prepare data for Surprise
reader = Reader(rating_scale=(0, 10))
data = Dataset.load_from_df(merged_df1[['UserID', 'ISBN', 'Rating']], reader)
```

Hyperparameter Tuning

We will use GridSearchCV from the surprise library to optimize hyperparameters.

In [52]:
```
#Import necessary libraries:Takes about 10 minutes to run
from surprise.model_selection import GridSearchCV

# Define the parameter grid for tuning
param_grid = {
    'n_factors': [30, 50],
    'reg_pu': [0.1, 0.2],
    'reg_qi': [0.1, 0.2]
}

# Perform GridSearchCV
grid_search = GridSearchCV(SVD, param_grid, measures=['rmse'], cv=2)
grid_search.fit(data)

# Get the best parameters
best_params = grid_search.best_params['rmse']
print("Best Parameters: ", best_params)
```

```
Best Parameters:  {'n_factors': 50, 'reg_pu': 0.2, 'reg_qi': 0.2}
```

Train/Test split and Model Training with tuned parameters

On our analysis we use Singular Value Decomposition for collaborative filtering. It factorizes the user-item interaction matrix into lower-dimensional matrices which helps in capturing latent features that explain the user-book relationship.

In [53]:
```
# Model Training: Using SVD for collaborative filtering
#Set best parameters
best_model = SVD(n_factors=best_params['n_factors'],
                  reg_pu=best_params['reg_pu'],
                  reg_qi=best_params['reg_qi'])

# Fit the model
trainset, testset = train_test_split(data, test_size=0.2, random_state=42)
best_model.fit(trainset)

# Evaluate on the test set
predictions = best_model.test(testset)

# Extract true and predicted ratings
true_ratings = [pred.r_ui for pred in predictions]  # Actual ratings
predicted_ratings = [pred.est for pred in predictions]  # Predicted ratings

# Evaluate model performance on the test set
accuracy.rmse(predictions)  # Root Mean Square Error
accuracy.mae(predictions)   # Mean Absolute Error
```

```
RMSE: 3.4212
MAE:  2.7467
```

Out[53]:
```
2.746746018767204
```

In [59]:
```
print("""Based on the above, an RMSE of 3.4212 suggests that on average,
the predicted ratings deviate from the true ratings by approximately 3.42 units.

An MAE of 2.7467 indicates that on average,
the predicted ratings differ from the true ratings by about 2.75 units.

A lower RMSE and MAE indicates better performance.""")
```

```
Based on the above, an RMSE of 3.4212 suggests that on average,
the predicted ratings deviate from the true ratings by approximately 3.42 units.

An MAE of 2.7467 indicates that on average,
the predicted ratings differ from the true ratings by about 2.75 units.

A lower RMSE and MAE indicates better performance.
```

Model Evaluation

For this model's evaluation we will use the accuracy metrics mainly foucusing on **precision score**. For this metrics we first need to class the recommendations into 'Relevant' and 'Non relevant', with 1 and 0 respectfully, given a particular threshold thus to evaluate our model"s accuracy.

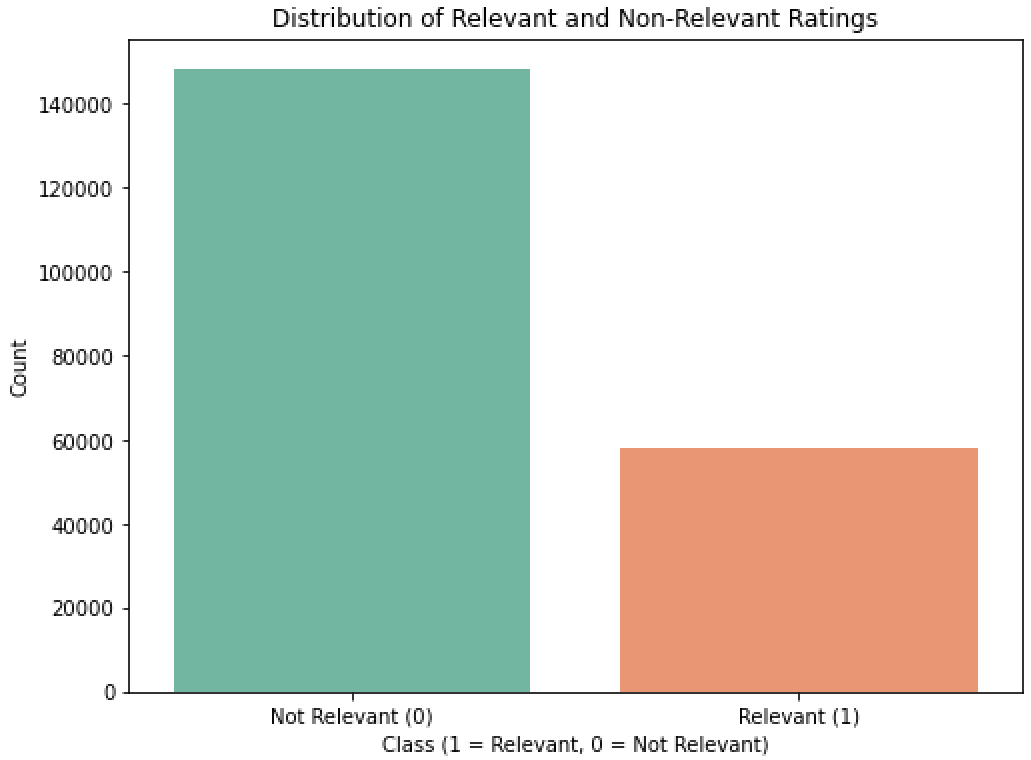
In [55]:
```
#Convert Ratings to Binary (1 if relevant, 0 if not)
# Define the threshold for relevance
threshold = 7

binary_true = [1 if rating >= threshold else 0 for rating in true_ratings]
binary_predicted = [1 if rating >= threshold else 0 for rating in predicted_ratings]
```

Class Imbalance

In [56]:
```
#Check the distribution of classes
class_distribution = pd.Series(binary_true).value_counts()

# Display the distribution
print("Class Distribution:")
print(class_distribution)
```

```
Class Distribution:
0    148242
1     57973
dtype: int64
```

In [57]:
```
#Check distribution of classes for class imbalance

# Create a count plot
plt.figure(figsize=(8, 6))
sns.countplot(x=binary_true, palette='Set2')

# Labeling the plot
plt.xlabel('Class (1 = Relevant, 0 = Not Relevant)')
plt.ylabel('Count')
plt.title('Distribution of Relevant and Non-Relevant Ratings')
plt.xticks(ticks=[0, 1], labels=['Not Relevant (0)', 'Relevant (1)'])
plt.show()
```



Handling class imbalance

There is a class imbalance as 'Non Relevant' class has a larger count compared to 'Relevant' class. We handle the class imbalance by applying Random under sampling where we reduce the the majority class thus balancing the dataset to avoid tampering with integrity of the data.

In [60]:
```
from imblearn.under_sampling import RandomUnderSampler

# Initialize the under-sampler
under_sampler = RandomUnderSampler(random_state=42)

# Create a DataFrame from binary ratings for resampling
data = pd.DataFrame({'True': binary_true, 'Predicted': binary_predicted})

# Apply under-sampling
X_under, y_under = under_sampler.fit_resample(data[['Predicted']], data['True'])

# Check new class distribution
new_class_distribution = pd.Series(y_under).value_counts()
print("New Class Distribution after Under-Sampling:")
print(new_class_distribution)
```

```
New Class Distribution after Under-Sampling:
1    57973
0    57973
Name: True, dtype: int64
```

Evaluation Metrics

We then apply the evaluation metrics to evaluate the performance of our model.

In [61]:
```
#import library
from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

#Calculate Precision, Recall, and F1-Score
precision = precision_score(binary_true, binary_predicted)
recall = recall_score(binary_true, binary_predicted)
f1 = f1_score(binary_true, binary_predicted)
accuracy = accuracy_score(binary_true, binary_predicted)
```

```
# Print the evaluation metrics
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"Accuracy: {accuracy:.4f}")
```

```
Precision: 0.7942
Recall: 0.0814
F1-Score: 0.1477
Accuracy: 0.7358
```

Interpretation

Precision of 79% measures the proportion of relevant recommendations that were actually correct i.e how many of the recommended books were truly relevant. It means that about 79.42% of the books recommended by your model were relevant (rated above the threshold of 7). This indicates that when our model recommends a book, there is a high chance that the recommendation is indeed a good fit for the user.

A recall score of 0.0814 suggests that your model only identified 8.14% of all the relevant books that were actually present meaning many relevant books are being missed.

An F1-score of 0.1477 suggests that while the model is good at recommending relevant items, it fails to recommend most of the relevant items available.

An accuracy score of 0.7358 indicates that the model is correct about 73.58% of the time.

In [63]:
```
print("""Based on the results above,
our model meets our goal of having a precision score above 75% as it had a score of  0.7942
showing that about 79.42% of the books recommended by your model were relevant.""")
```

```
Based on the results above,
our model meets our goal of having a precision score above 75% as it had a score of  0.7942
showing that about 79.42% of the books recommended by your model were relevant.
```

Recommendation Quality Assessment

Calculating Cosine Similarity

We will use cosine similarity on the item-user matrix to find similar books based on ratings.

In [64]:
```
from scipy.sparse import csr_matrix
from sklearn.metrics.pairwise import cosine_similarity

# Keep only the top N users and items
top_n_users = merged_df1['UserID'].value_counts().head(5000).index
top_n_items = merged_df1['ISBN'].value_counts().head(5000).index

# Filter the original DataFrame
filtered_df = merged_df1[merged_df1['UserID'].isin(top_n_users) & merged_df1['ISBN'].isin(top_n_items)]

# Create the user-item rating matrix
user_item_matrix = filtered_df.pivot_table(index='UserID', columns='ISBN', values='Rating', aggfunc='mean').fillna(0)

# Calculate cosine similarity matrix
cosine_sim = cosine_similarity(user_item_matrix)

# Create a DataFrame for easier access
cosine_sim_df = pd.DataFrame(cosine_sim, index=user_item_matrix.index, columns=user_item_matrix.index)
cosine_sim_df.head()
```

Out[64]:

UserID	243	254	383	503	507	638	643	651	741	805	...	278144	278188	278194	278221	278356	278418	278535	278582	278633	278843
UserID																					
243	1.0	0.000000	0.0	0.0	0.000000	0.057844	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.042416	0.000000
254	0.0	1.000000	0.0	0.0	0.066145	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.166335	0.0	0.0	0.0	0.000000	0.076146

UserID	243	254	383	503	507	638	643	651	741	805	...	278144	278188	278194	278221	278356	278418	278535	278582	278633	278843
UserID																					
383	0.0	0.000000	1.0	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.000000
503	0.0	0.000000	0.0	1.0	0.000000	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.000000
507	0.0	0.066145	0.0	0.0	1.000000	0.000000	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.000000	0.000000

5 rows × 4938 columns

i) User-User Collaborative Filtering

This emphasizes on user-user collaborative filtering, leveraging similarities in user behavior.

In [73]:
```
def get_similar_users(user_id, n=5):
    # Get similar users based on cosine similarity
    similar_user_ids = cosine_sim_df[user_id].sort_values(ascending=False)[1:n+1].index

    # Prepare a list to hold the results
    results = []

    # Iterate through each similar user
    for sim_user_id in similar_user_ids:
        # Get the books rated by the similar user
        user_books = merged_df1[merged_df1['UserID'] == sim_user_id]

        # Add the book ratings and titles to the results
        for _, row in user_books.iterrows():
            results.append({
                'UserID': sim_user_id,
                'Rating': row['Rating'],
                'Book_title': row['Book_title'],
                'Author':row['Author'],
                'Age_Group':row['Age_Group']# Replace with the correct column name for book title
            })

    # Convert results to a DataFrame
    results_df = pd.DataFrame(results)

    return results_df
```

In [74]:
```
#Recommend 5 books for user with User-ID
user_id=11676
books_recommended = get_similar_users(user_id, n=5)
books_recommended.head()
```

Out[74]:

	UserID	Rating	Book_title	Author	Age_Group
0	16795	8	Lightning	Dean R. Koontz	Adult
1	16795	7	Manhattan Hunt Club	JOHN SAUL	Adult
2	16795	0	Night Sins	TAMI HOAG	Adult
3	16795	0	Make Them Cry	Kevin O'Brien	Adult
4	16795	0	The Pillars of the Earth	Ken Follett	Adult

In [75]:
```
user_id=merged_df1['UserID'][50]
books_recommended = get_similar_users(user_id, n=5)
books_recommended.head()
```

Out[75]:

	UserID	Rating	Book_title	Author	Age_Group
0	231081	10	Harry Potter and the Order of the Phoenix (Boo...	J. K. Rowling	Child
1	231081	9	Harry Potter and the Chamber of Secrets (Book 2)	J. K. Rowling	Child
2	231081	10	Memnoch, the Devil (Vampire Chronicles)	ANNE RICE	Child
3	231081	0	Interview with the Vampire	Anne Rice	Child
4	231081	4	The Fellowship of the Ring (The Lord of the Ri...	J.R.R. TOLKIEN	Child

Interpretation

The output of the function lists the books rated by the similar users along with their ratings highlighting the books that these similar users found appealing. The inclusion of books with varying ratings indicates that the function captures a range of preferences. This approach does not seem to depend on rating as the books all vary in ratings with some having high ratings while others have zero.

Overall conclusion is that, the user-user collaborative filtering approach effectively identifies relevant books based on the behavior of similar users.

ii)Item-based collaborative filtering

Building a recommendation function based on Item rating

This method is based on a predictive model (SVD) that estimates ratings for unseen books concentrating on providing personalized recommendations based on predicted ratings for specific books.

In [76]:

```
# Function to recommend books based on collaborative filtering
def recommend_books(user_id, best_model, merged_df, num_recommendations=5):
    """
    Recommends books for a given user based on collaborative filtering using the trained SVD model.
    Returns:
     A DataFrame with the top N book recommendations for the user
    """
    # Get all book ISBNs
    all_books = merged_df['ISBN'].unique()

    # Get books already rated by the user
    rated_books = merged_df[merged_df['UserID'] == user_id]['ISBN'].unique()

    # Find books that the user hasn't rated yet
    unrated_books = [isbn for isbn in all_books if isbn not in rated_books]

    # Predict ratings for all unrated books
    predictions = []
    for isbn in unrated_books:
        pred = best_model.predict(user_id, isbn)
        predictions.append((isbn, round(pred.est)))  # ISBN and predicted rating

    # Sort by predicted rating in descending order and select the top recommendations
    recommendations = sorted(predictions, key=lambda x: x[1], reverse=True)[:num_recommendations]

    # Create a DataFrame with recommended books and their predicted ratings
    recommendations_df = pd.DataFrame(recommendations, columns=['ISBN', 'Predicted Rating'])

    # Merge with the original dataset to get additional book details (Book title, Author, etc.)
    recommendations_df = recommendations_df.merge(
        merged_df[['ISBN', 'Book_title', 'Author', 'Publisher']].drop_duplicates(),
        on='ISBN',
        how='left'
    )
   # Calculate the average age for each book based on users who rated it
    age_group_df = merged_df.groupby('ISBN')['Age_Group'].agg(lambda x: x.mode()[0] if not x.mode().empty else None).reset_index()
```

```
    # Merge average age group back into recommendations DataFrame
    recommendations_df = recommendations_df.merge(age_group_df, on='ISBN', how='left', suffixes=('', '_Avg'))

    # Rename the average age group column for clarity
    recommendations_df.rename(columns={'Age_Group_Avg': 'Average_Age_Group'}, inplace=True)

    return recommendations_df
```

In [77]:
```
#Recommend 5 books for user with User-ID '11676': Takes a few minutes to run
user_id = 11676
recommended_books = recommend_books(user_id, best_model, merged_df1, num_recommendations=5)
recommended_books
```

Out[77]:

	ISBN	Predicted Rating	Book_title	Author	Publisher	Age_Group
0	0689714335	10.0	The Cat Who Went to Heaven	Elizabeth Coatsworth	Aladdin	Adult
1	0615116426	9.0	Marching Through Culpeper : A Novel of Culpepe...	Virginia Beard Morton	Edgehill Books	Adult
2	0385498802	9.0	Bee Season: A Novel	Myla Goldberg	Anchor Books/Doubleday	Adult
3	0066238501	9.0	Complete Chronicles of Narnia	C. S. Lewis	Harpercollins Juvenile Books	Adult
4	0312950586	9.0	Every Living Thing	James Herriot	St. Martin's Press	Adult

In [78]:
```
#Recommend 5 books for user
user_id = user_id = merged_df1['UserID'][50]
recommended_books = recommend_books(user_id, best_model, merged_df1, num_recommendations=5)
recommended_books
```

Out[78]:

	ISBN	Predicted Rating	Book_title	Author	Publisher	Age_Group
0	0446310786	8.0	To Kill a Mockingbird	Harper Lee	Little Brown & Company	Adult
1	0743418204	8.0	In Her Shoes : A Novel	Jennifer Weiner	Washington Square Press	Adult
2	0440498058	7.0	A Wrinkle In Time	MADELEINE L'ENGLE	Yearling	Adult
3	0385729340	7.0	The Second Summer of the Sisterhood	ANN BRASHARES	Delacorte Books for Young Readers	Adult
4	0439064864	7.0	Harry Potter and the Chamber of Secrets (Book 2)	J. K. Rowling	Scholastic	Young Adult

Interpretation

For both examples, the recommendations shows high predicted ratings, with some of the books receiving a perfect score of 10.0 while others are rated 8.0 and 9.0. This indicates a strong expectation that the user will enjoy these titles based on the preferences of similar users.

The recommended books caters to different interests with majority in the "Adult" age group and a few in the 'Young Adult' age group which could translate to the users in the examples likely being in the Adult age group.

The successful generation of relevant recommendations indicates that the SVD model effectively captures the nuances of user preferences and behaviors.

Saving are storing the data & model

In [81]:
```
#import library
import pickle

# Save the trained model
with open('Data/svd_model.pkl', 'wb') as f:
    pickle.dump(best_model, f)

# Save the cosine similarity matrix as a CSV file
cosine_sim_df.to_csv('Data/cosine_similarity.csv', index=True)
```

```python
#Save the 'merged_df1' to a csv file
merged_df1.to_csv('Data/CleanMerged_df.csv', index=False)
```

CONCLUSION

Based on our analysis we came to the following conclusions:

1. Effectiveness of Collaborative Filtering: The analysis demonstrated that collaborative filtering using Singular Value Decomposition (SVD) can effectively predict book ratings for users based on their historical preferences and those of similar users. The model achieved a precision score of 0.7977, indicating a high percentage of relevant recommendations. This suggests that users are likely to find the recommended books appealing.

2. Model Performance Evaluation: The RMSE of 3.4219 and MAE of 2.7470 indicate that the model has a reasonable predictive accuracy, with the errors being manageable for the recommendation context. However, the low recall score of 0.0817 indicates that many relevant books are not being captured by the model, which may require further attention to enhance the recommendation quality.

3. User and Item-Based Collaborative Filtering: The user-user method effectively identified similar users and their preferences as majority lie it the same age group, while the item-based approach using SVD provided personalized recommendations based on predicted ratings for unseen books. Based on our analysis, the same user has different recommendations based on the two different approaches. This shows that different factors are considered for each approach in recommending.

4. Based on the item-based approach, highly rated books are preferred by most users.

RECOMMENDATIONS

1. Enhance Personalization and Feedback Mechanisms: Implementation of user profiles and feedback options like encourage users to rate books to gather preferences,thus improving the accuracy of book recommendations.
2. Utilize Data for Targeted Marketing: Leveraging insights from the recommendation system, focusing on a certain age group can be quite beneficial as majority are drawn to the same type of books.
3. The business should feature highly rated books prominently on the homepage and recommendation carousels, especially for new users to ensure a high user engagement and providing discounts based on individual reading preferences can also promote customer satisfaction thus boosting revenue.
4. Use “Top-rated” or “Trending” labels to highlight highly rated books in marketing campaigns, making it easier for users to discover these books.

FURTHER STUDIES

Based on our analysis there are areas that may need further analysis.

1. Explore Alternative Algorithms: Investigate the performance of other recommendation algorithms, such as neural collaborative filtering or hybrid approaches, to compare their effectiveness against the current SVD model.

2. Content-Based Recommendations: Explore the potential for a content-based recommendation system that utilizes book attributes, such as author, to complement collaborative filtering methods and provide more holistic recommendations.