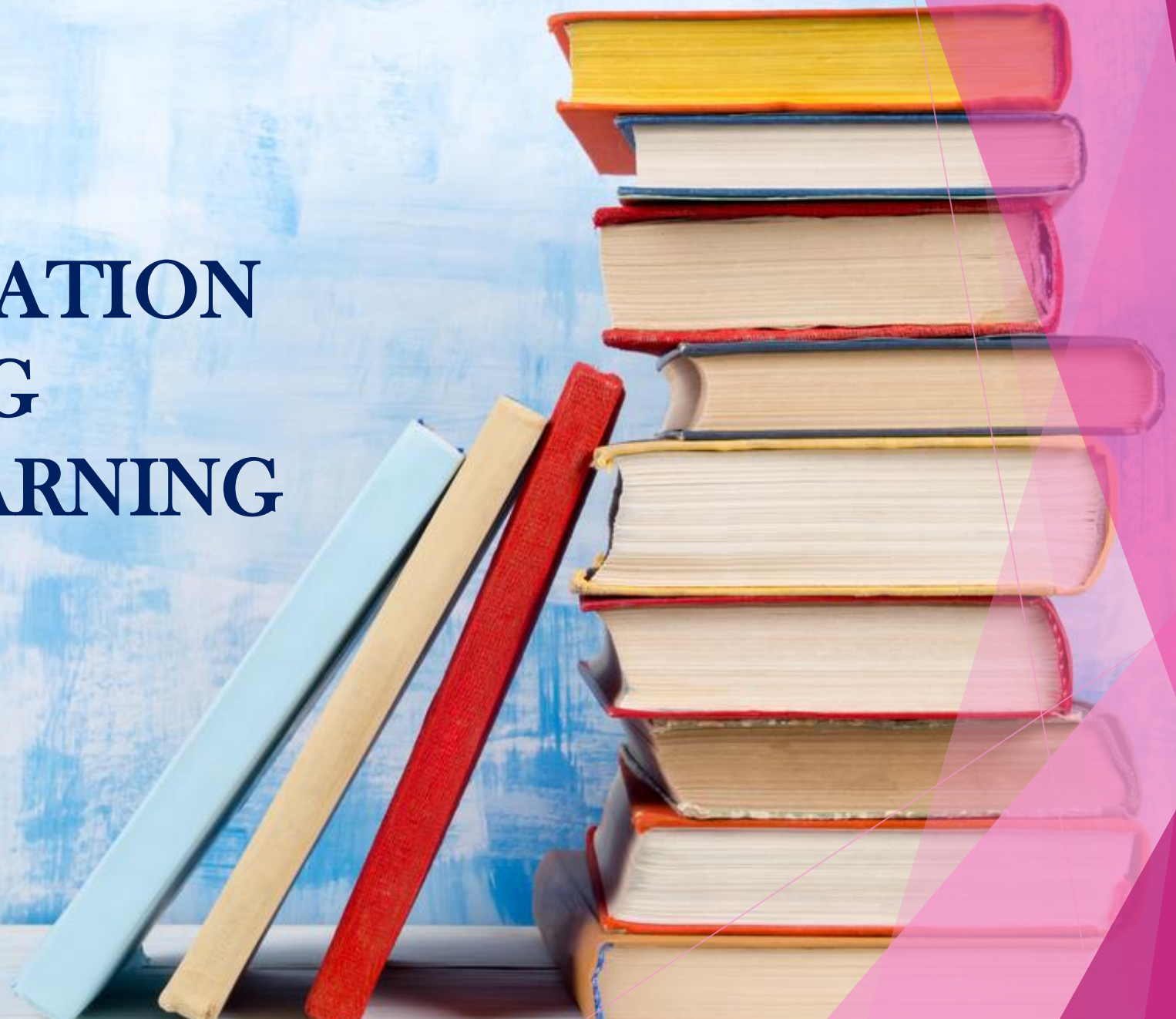


BOOK RECOMMENDATION SYSTEM USING MACHINE LEARNING



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INTRODUCTION:

A book recommendation system suggests books to users based on their interests. It uses data like user ratings, reviews, and book details to provide personalized recommendations. By analyzing this data, the system can predict which books a user might enjoy, enhancing their reading experience.

Why Book Recommendation Systems?

User Engagement: Encourages users to discover and read more books by suggesting titles that align with their interests.

Personalization: Tailors suggestions to individual user preferences, making the user experience more enjoyable and unique.

Increased Sales/Usage: Increases the likelihood of users purchasing or borrowing more books, thereby boosting sales or library usage.

Datasets:

Users_dataset:

- User-ID (unique for each user)
- Location (contains city, state and country separated by commas)

Books_dataset:

- ISBN (unique for each book)
- Book-Title
- Book-Author
- Year-Of-Publication

Ratings_dataset:

- User-ID
- ISBN
- Book ratings

PROJECT GOAL:

Explore and compare different approaches to recommending the most relevant books to users based on their interactions(ratings) with other books in the past or based on their similar users interactions with books

EDA

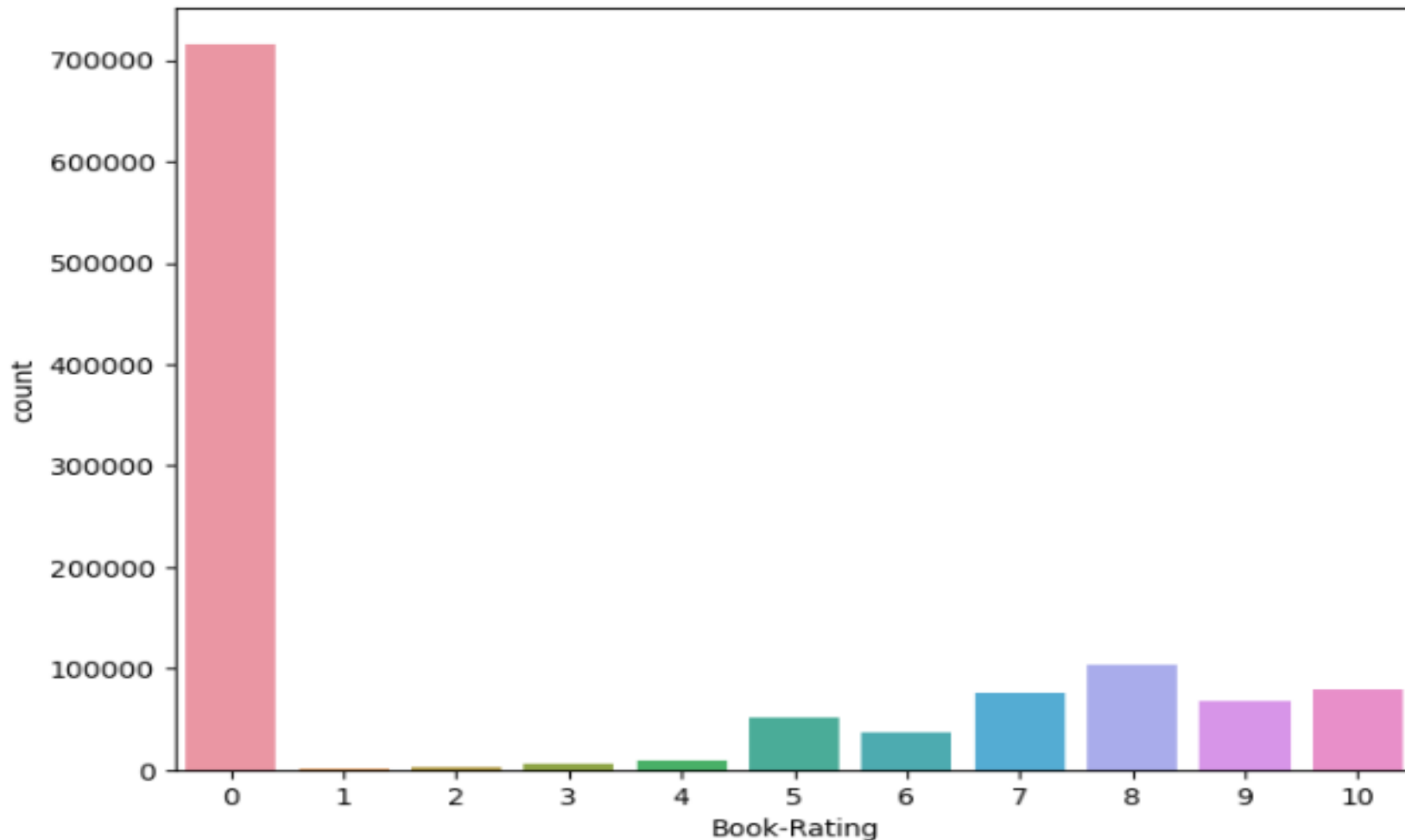
(Exploratory Data Analysis)

Visualising Rating Counts

Using Seaborn Library for plotting a countplot

```
] # countplot on Book Rating  
plt.figure(figsize=(8,6))  
sns.countplot(x="Book-Rating", data=ratings)
```

```
] <Axes: xlabel='Book-Rating', ylabel='count'>
```

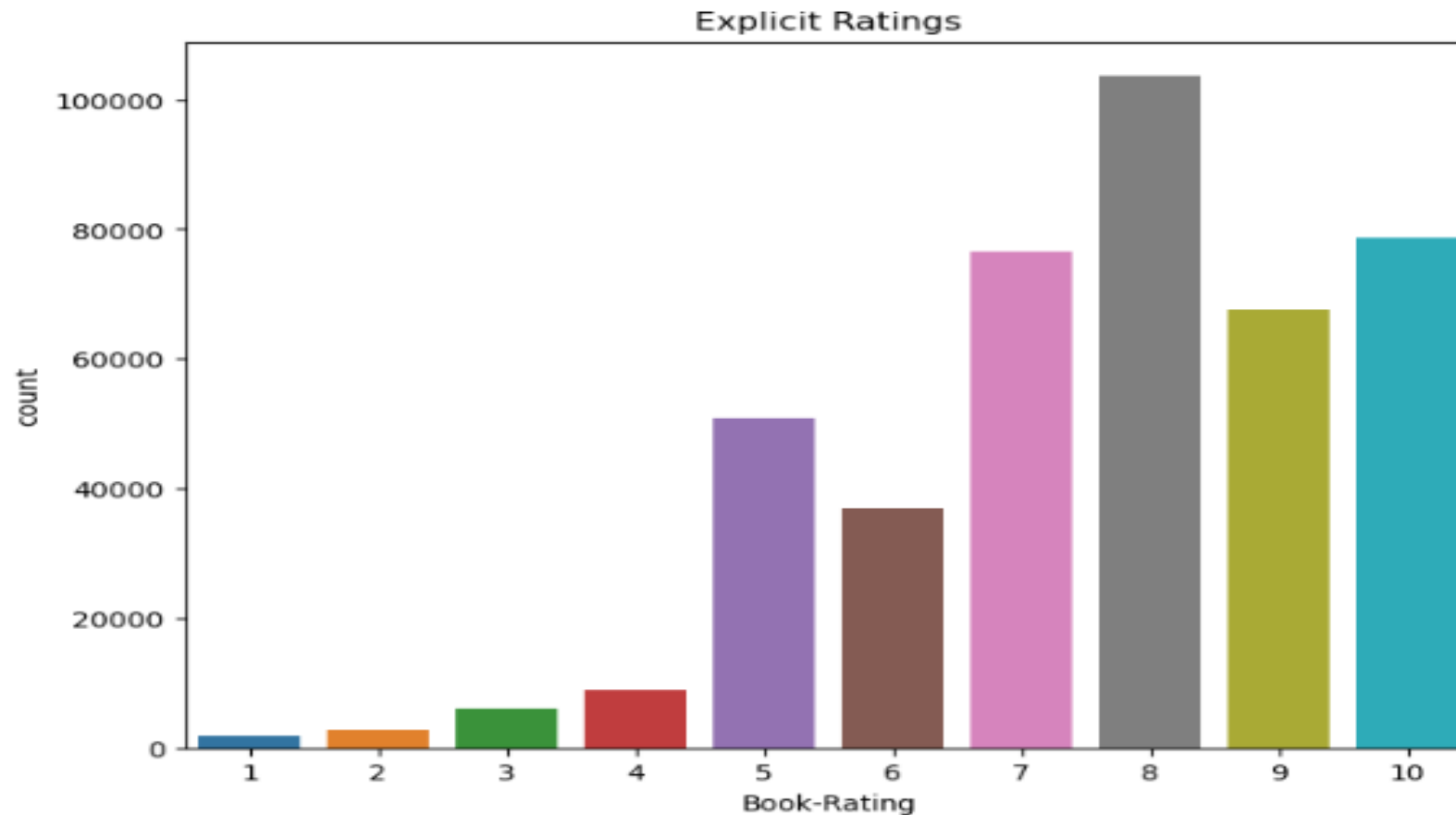


Visualising Explicit Rating Counts

Using Seaborn Library for plotting a countplot

```
plt.figure(figsize=(8,6))  
data = ratings[ratings['Book-Rating'] != 0]  
sns.countplot(x="Book-Rating", data=data)  
plt.title("Explicit Ratings")
```

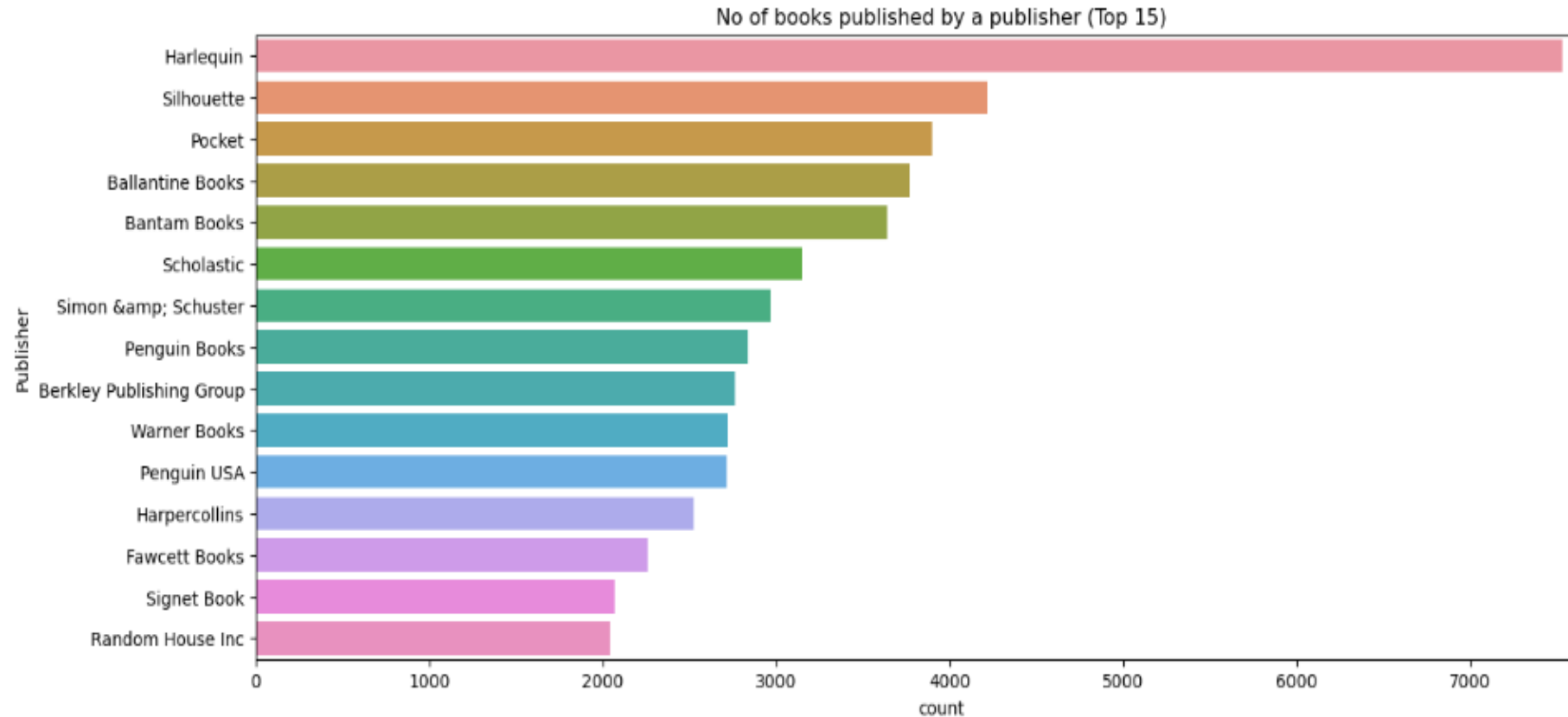
```
Text(0.5, 1.0, 'Explicit Ratings')
```



Visualizing (top 15) number of books published by publisher

```
plt.figure(figsize=(15,6))
sns.countplot(y="Publisher", data=books,order=books['Publisher'].value_counts().index[0:15])
plt.title("No of books published by a publisher (Top 15)")
```

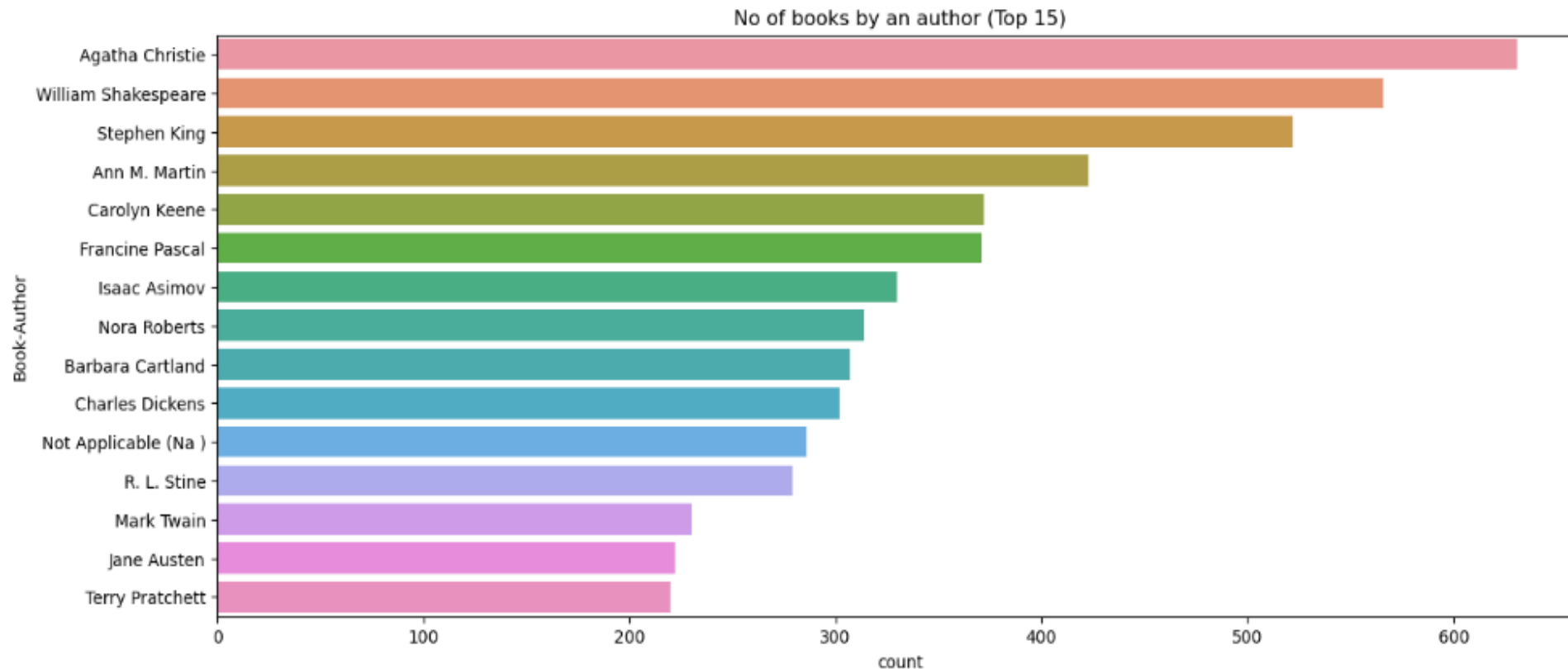
```
Text(0.5, 1.0, 'No of books published by a publisher (Top 15)')
```



Visualizing (top 15) number of books wrote by author

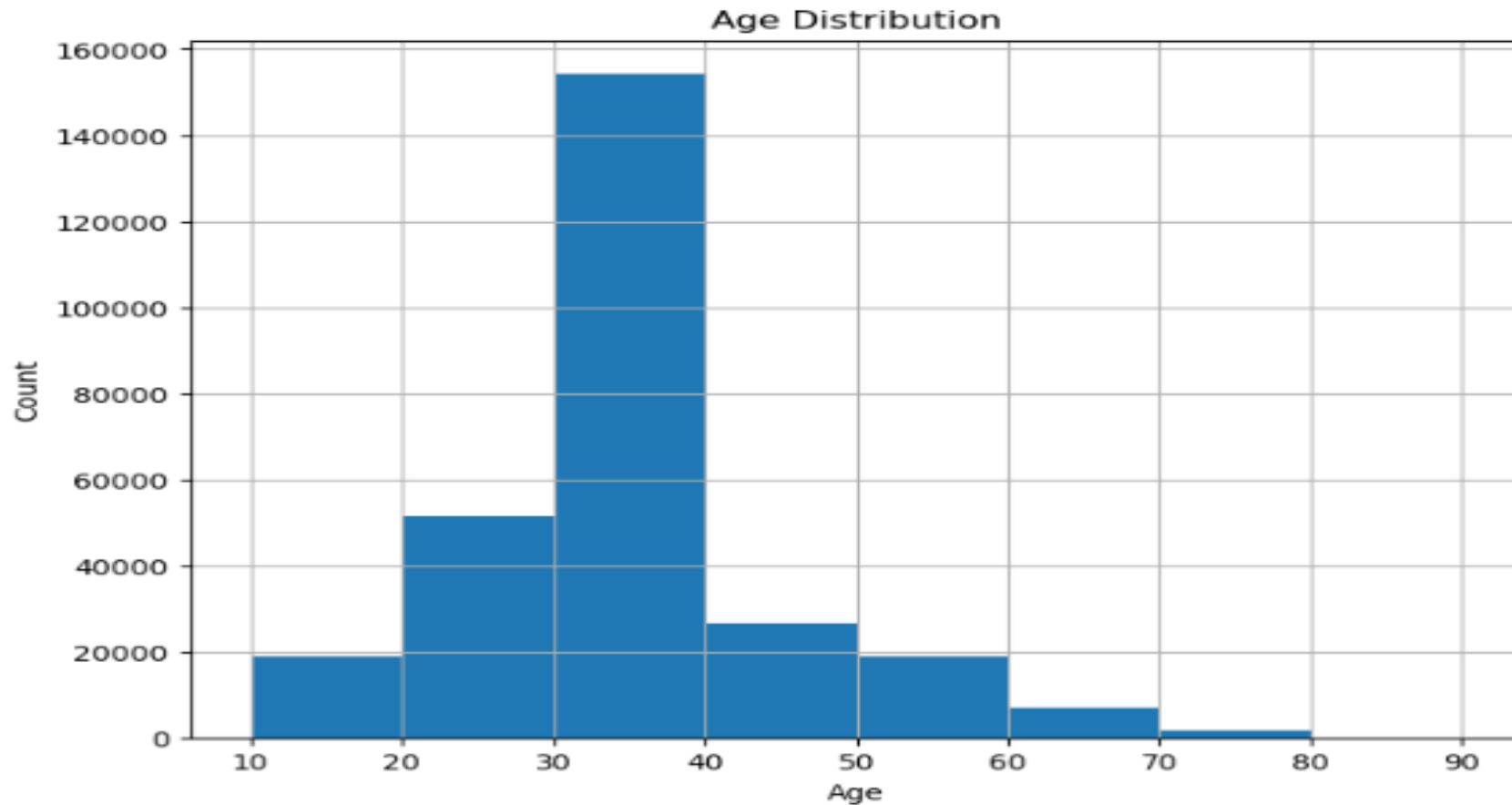
```
plt.figure(figsize=(15,6))
sns.countplot(y="Book-Author", data=books,order=books['Book-Author'].value_counts().index[0:15])
plt.title("No of books by an author (Top 15)")
```

```
Text(0.5, 1.0, 'No of books by an author (Top 15)')
```



Visualizing the age distribution of the users

```
plt.figure(figsize=(8,6))
users.Age.hist(bins=[10*i for i in range(1, 10)])
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



MODEL BUILDING

Model Building:

Popularity Based Recommender System:

In this model, we recommended the books according to their popularity score i.e. based on the average rating the book received. We considered only those books whose ratings are more than 250 and received the top 50 books accordingly.

- Considering those books whose book rating is more than 250

```
#filtering books with num_rating>250 and then sorting the books and displaying top 50 books
```

```
popular_df = popular_df[popular_df['book_rating']>=250].sort_values('avg_rating',ascending=False).head(50)  
popular_df
```

TOP 10 POPULAR BOOKS :

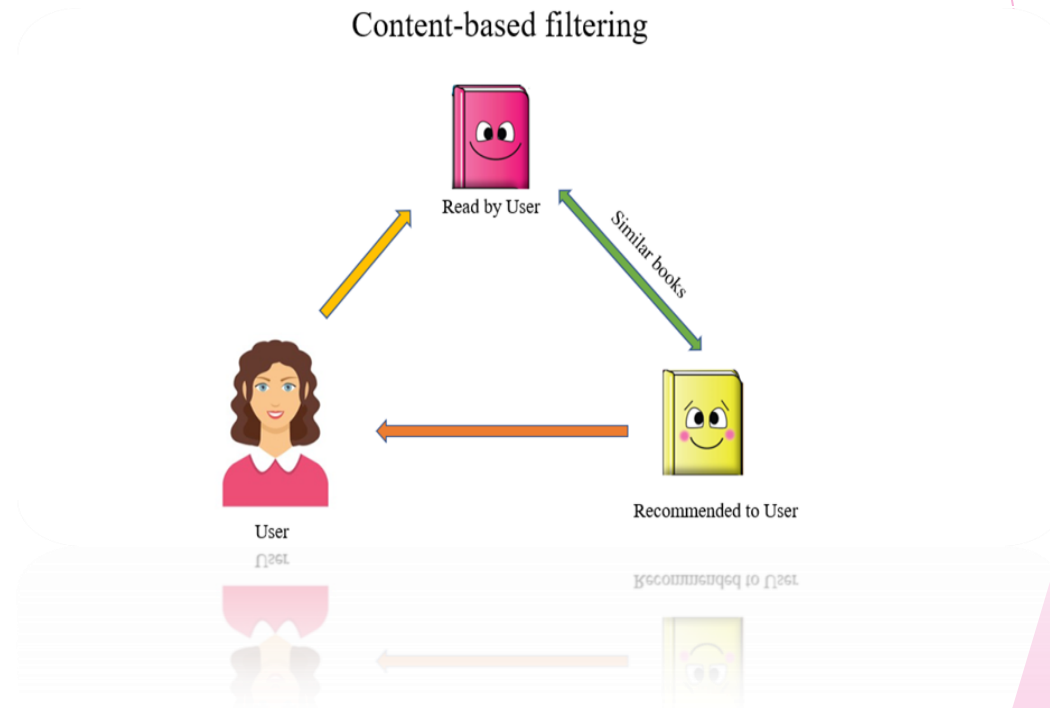
	Book-Title	Total-Ratings	Average Rating	score
1877	Harry Potter and the Chamber of Secrets Postcard Book	23	9.869565	9.450512
111	The Two Towers (The Lord of the Rings, Part 2)	136	9.330882	9.266768
3852	Dilbert: A Book of Postcards	13	9.923077	9.256352
1802	Calvin and Hobbes	24	9.583333	9.228080
4587	Postmarked Yesteryear: 30 Rare Holiday Postcards	11	10.000000	9.225896
2255	The Authoritative Calvin and Hobbes (Calvin and Hobbes)	20	9.600000	9.184573
1971	My Sister's Keeper : A Novel (Picoult, Jodi)	22	9.545455	9.170901
178	The Return of the King (The Lord of the Rings, Part 3)	103	9.213592	9.135318
3012	The Return of the King (The Lord of The Rings, Part 3)	16	9.625000	9.124492
1580	The Giving Tree	26	9.423077	9.116591

Different Filtering Techniques

Content-Based Filtering:

In Content-based recommender system, user provides data either explicitly (rating) or implicitly (By clicking on a link). The system captures this data and generates user profile for every user. By making use of user profile, recommendations are generate

In content-based filtering, recommendation is given by only watching single user's profile. System tries to recommend item similar to that item based on users past activity.



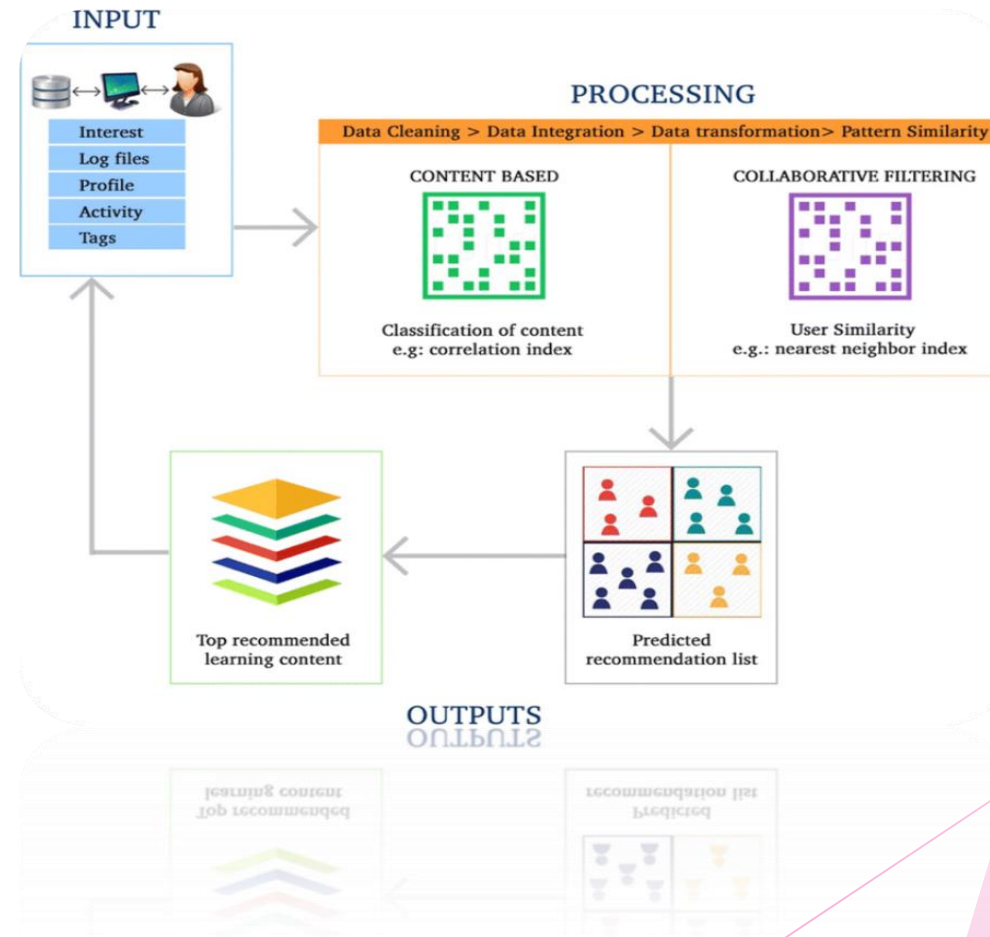
Collaborative Filtering:

Collaborative filtering is a technique that can filter out items that a user might like on the basis of reactions by similar users. It works by searching a large group of people and finding a smaller set of users with tastes similar to particular user



Hybrid Filtering:

A hybrid filtering approach is taken between context based filtering and collaborative filtering to implement the system. We can use content based filtering first and then pass those results to collaborative recommender (and vice-versa) or by integrating both the filter into one model to generate the results.



Collaborative Filtering Based Recommender System :

In this model, we used a Product-to-Product Based recommendation system. Here we recommended the books according to their similarity score. For that, we used a **cosine-based similarity score**.

```
from sklearn.metrics.pairwise import cosine_similarity
```

```
similarity_score = cosine_similarity(pt)  
similarity_score
```

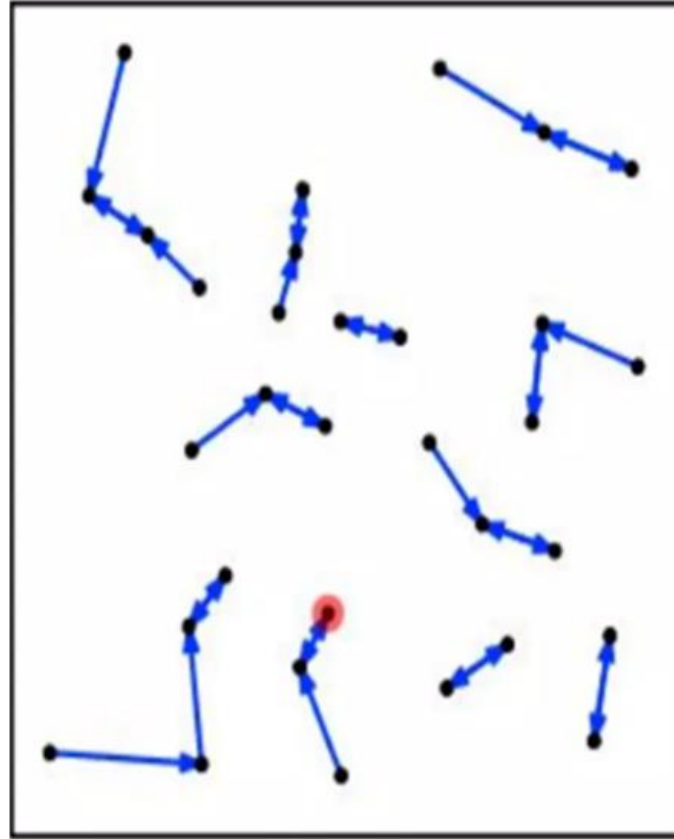
```
array([[1.          , 0.10255025, 0.01220856, ..., 0.12110367, 0.07347567,  
        0.04316046],  
       [0.10255025, 1.          , 0.2364573 , ..., 0.07446129, 0.16773875,  
        0.14263397],  
       [0.01220856, 0.2364573 , 1.          , ..., 0.04558758, 0.04938579,  
        0.10796119],
```

K Nearest neighbors

The K-nearest neighbors(KNN) algorithm is a data classification method for estimating the likelihood that a data point will become a member of one group or another based on what group the data points nearest to it belong to.

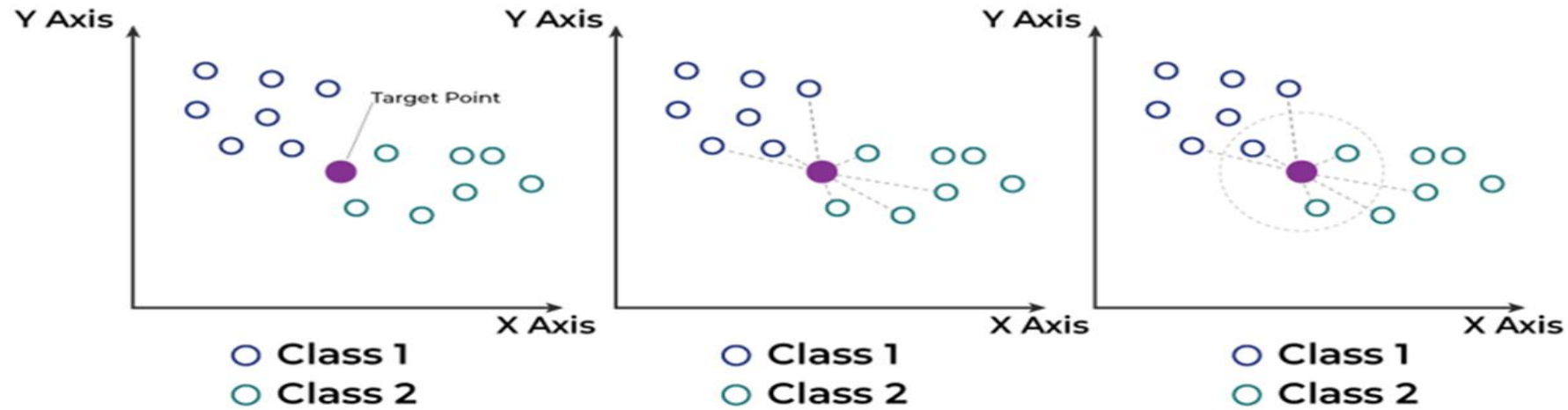
The principle behind nearest neighbor methods is to find a predefined number of samples closest in distance to the new point and predict labels from these.

The number of samples (K) can be a user-defined constant, or vary based on the local density of points(radius-based neighbor learning)



Working of KNN algorithm

The K-Nearest Neighbors (KNN) algorithm operates on the principle of similarity, where it predicts the label or value of a new data point by considering the labels or values of its K nearest neighbors in the training dataset.



```
def recommend_book(book_name):  
    book_id = np.where(book_pivot.index == book_name)[0][0]  
    distance , suggestion = model.kneighbors(book_pivot.iloc[book_id,:].values.reshape(1,-1),n_neighbors=9)  
    for i in range(len(suggestion)):  
        books = book_pivot.index[suggestion[i]]  
        for j in books:  
            print(j)
```

```
np.where(book_pivot.index == "Harry Potter and the Goblet of Fire (Book 4)") [0][0]
```

473

```
book_name = 'Harry Potter and the Goblet of Fire (Book 4)'  
recommend_book(book_name)
```

```
Harry Potter and the Goblet of Fire (Book 4)  
Harry Potter and the Prisoner of Azkaban (Book 3)  
Harry Potter and the Chamber of Secrets (Book 2)  
Harry Potter and the Order of the Phoenix (Book 5)  
Harry Potter and the Sorcerer's Stone (Book 1)  
Special Delivery: A Novel  
Once in a Lifetime  
Star  
Monster Blood (Goosebumps, No 3)
```

MODEL DEPLOYMENT

MODEL DEPLOYMENT

Model Deployment Using Streamlit:

We created the necessary pickle files to deploy our model on Streamlit.

```
import pickle
import os

os.makedirs("artifacts",exist_ok=True)
pickle.dump(model , open('artifacts/model.pkl','wb'))
pickle.dump(books_name, open('artifacts/books_name.pkl','wb'))
pickle.dump(df,open('artifacts/final_rating.pkl','wb'))
pickle.dump(book_pivot,open('artifacts/book_pivot.pkl','wb'))
```


Code using stream lit Library:

We used Spyder IDE for the deployment code.

Two Sections :

1. Similar books

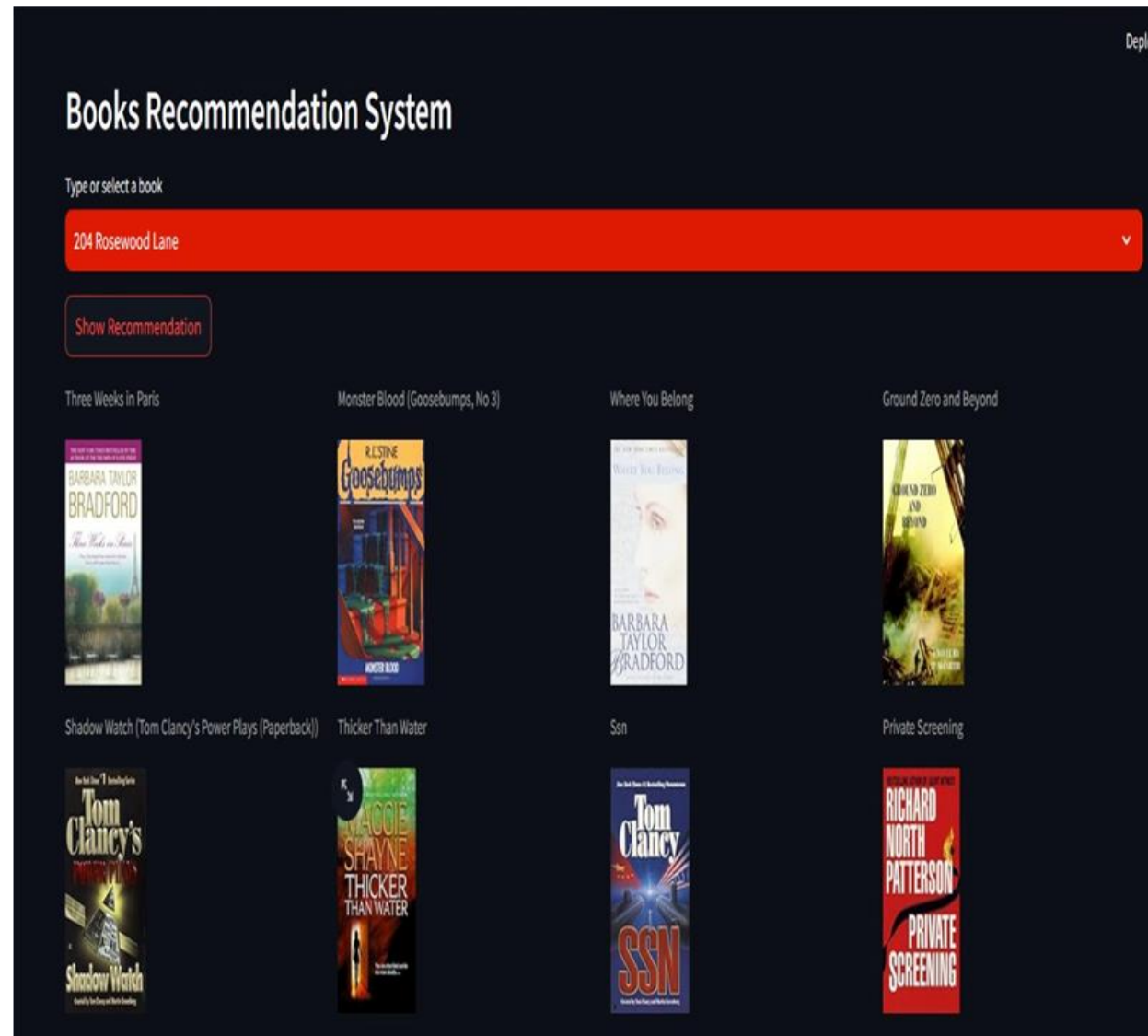
2. Book Recommender - Collaborative Filtering-Based Recommendation System

CODE:

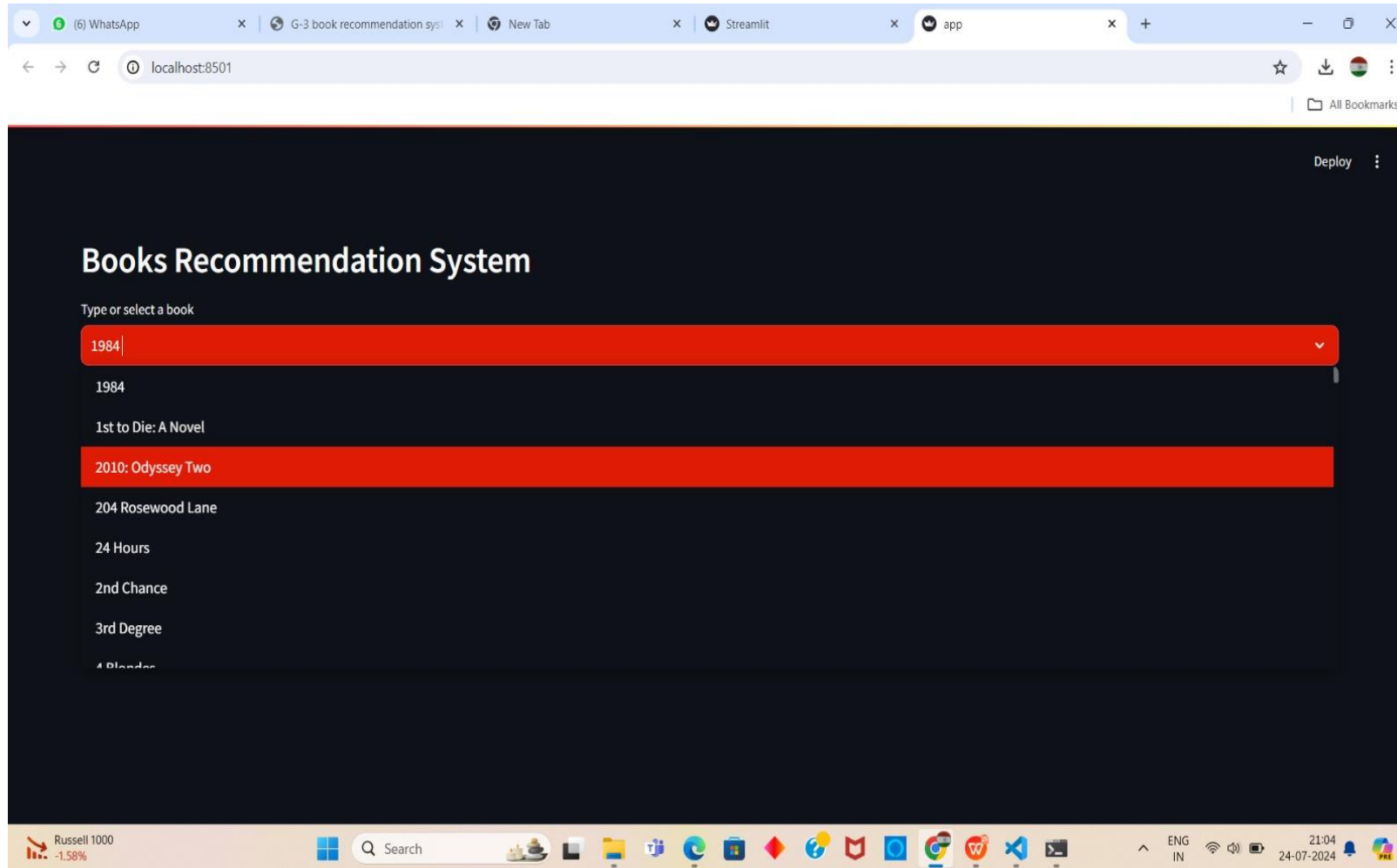
```
1 import pickle
2 import streamlit as st
3 from utils import recommend_books
4
5
6 st.header("Books Recommendation System")
7
8 model = pickle.load(open('artifacts/model.pkl', 'rb'))
9 books_name = pickle.load(open('artifacts/books_name.pkl', 'rb'))
10 final_rating = pickle.load(open('artifacts/final_rating.pkl', 'rb'))
11 book_pivot = pickle.load(open('artifacts/book_pivot.pkl', 'rb'))
12
13
14 selected_book = st.selectbox("Type or select a book", books_name)
15
16 if st.button("Show Recommendation"):
17     recommendation_books, poster_url = recommend_books(selected_book, model, books_name, final_rating, book_pivot)
18
19     col1, col2, col3, col4 = st.columns(4)
20     col5, col6, col7, col8 = st.columns(4)
21
22     with col1:
23         st.caption(recommendation_books[1])
24         st.image(poster_url[1])
25
26     with col2:
27         st.caption(recommendation_books[2])
28         st.image(poster_url[2])
29
30     with col3:
31         st.caption(recommendation_books[3])
32         st.image(poster_url[3])
33
34     with col4:
35         st.caption(recommendation_books[4])
36         st.image(poster_url[4])
37
38     with col5:
39         st.caption(recommendation_books[5])
40         st.image(poster_url[5])
41
42     with col6:
43         st.caption(recommendation_books[6])
44         st.image(poster_url[6])
45
46     with col7:
47         st.caption(recommendation_books[7])
48         st.image(poster_url[7])
49
50     with col8:
51         st.caption(recommendation_books[8])
52         st.image(poster_url[8])
```

Top 8 similar books:

Books are Recommended according to the user input book name it will recommend the similar books according to the user book name



Book Recommender:



(6) WhatsAppG-3 book recommendation sysNew TabStreamlitapp

localhost:8501

All Bookmarks

Deploy

Books Recommendation System

Type or select a book

204 Rosewood Lane

Show Recommendation

Three Weeks in Paris

Monster Blood (Goosebumps, No 3)

Where You Belong

Ground Zero and Beyond

Shadow Watch (Tom Clancy's Power Plays (Paperback))

Thicker Than Water

Ssn

Private Screening

Russell 1000
-1.58%

Search

ENG IN

21:05
24-07-2024

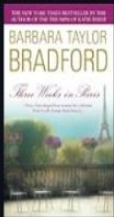
Books Recommendation System

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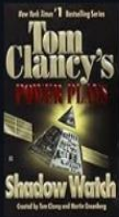
Where You Belong



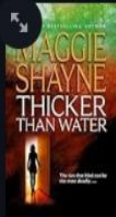
Ground Zero and Beyond



Shadow Watch (Tom Clancy's Power Plays (Paperback))



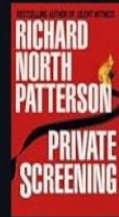
Thicker Than Water



Ssn



Private Screening



CONCLUSION:

Book Recommendation Project successfully demonstrates the capability to enhance user experience by providing personalized book suggestions. By leveraging collaborative filtering and content-based algorithms, we created a robust system that analyzes user preferences and book features to recommend titles that align with individual tastes. Overall, this project lays a strong foundation for creating a dynamic and user-centric book recommendation system that can continuously evolve and improve. Thank you for your attention.