

# INTRODUCTION TO DATA SCIENCE (CAP 5771) PROJECT REPORT

## Project Title: SMARTSHELF - BOOK RECOMMENDATION SYSTEM USING CONTENT-BASED AND COLLABORATIVE FILTERING TECHNIQUES

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### Project Objective

The objective of the project is to develop a recommendation system that suggests books to the users based on the reading preferences and historical ratings. The goal of the project is to apply content-based filtering and collaborative filtering techniques to provide personalized book recommendations. The project aims to analyze the user behavior and books metadata to improve the recommendation system's accuracy.

This project will be implemented as a web application developed using Streamlit. This enables users to input their preferences, ratings, and then the system will generate recommendations based on user's profile of historical ratings and book preferences.

### Tech Stack

The following are the tools, technologies and libraries required for this project:

**Python** – the core programming language for building this project.

**Pandas & Numpy** – Python libraries used for data manipulation and numerical computing.

**Matplotlib & Seaborn** – Python Library used for data visualization.

**Surprise** – a python scikit for building and analyzing recommender systems.

**Scikit-Learn** – used for feature engineering and model evaluation.

**SQLite** – Used for storing book and user data.

**Streamlit** – Python based web application development framework.

## **Project Timeline**

**Milestone 1: Data collection, Preprocessing and Exploratory Data Analysis.** (Feb 5 – Feb 21)

**Milestone 2: Feature Engineering, Feature Selection and Data Modeling** (Feb 22 – Apr 03)

**Milestone 3: Evaluation, Interpretation and Tool Development** (Apr 04 – Apr 22)

# MILESTONE 1: Data Collection, Preprocessing and Exploratory Data Analysis

(Feb 5, 2025 – Feb 21, 2025)

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## 1. Data Collection

Three datasets taken from Kaggle are used to build this recommendation engine.

### Books.csv:

It contains book metadata. Attributes are ISBN(Book-ID), Book-Title, Book-Author, Year-Of-Publication, Publisher, Image-URL-S, Image-URL-M, Image-URL-L. It has 271360 records in total.

```
Books.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271360 entries, 0 to 271359
Data columns (total 8 columns):
#   Column                Non-Null Count  Dtype
---  ---
0   ISBN                  271360 non-null object
1   Book-Title            271360 non-null object
2   Book-Author           271358 non-null object
3   Year-Of-Publication    271360 non-null object
4   Publisher              271358 non-null object
5   Image-URL-S            271360 non-null object
6   Image-URL-M            271360 non-null object
7   Image-URL-L            271357 non-null object
dtypes: object(8)
memory usage: 16.6+ MB
```

Fig 1.1 Books.csv

### Ratings.csv:

It includes book ratings given by the users on the scale of 0 to 10. Attributes are User-ID, ISBN, Book-Rating. It has 1149780 records in total.

```
Ratings.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1149780 entries, 0 to 1149779
Data columns (total 3 columns):
#   Column                Non-Null Count  Dtype
---  ---
0   User-ID               1149780 non-null int64
1   ISBN                  1149780 non-null object
2   Book-Rating           1149780 non-null int64
dtypes: int64(2), object(1)
memory usage: 26.3+ MB
```

Fig 1.2 Ratings.csv

## Users.csv:

It has the demographic information of the users, including User-ID, Location and Age. It has 278858 records.

```
Users.csv
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 278858 entries, 0 to 278857
Data columns (total 3 columns):
#   Column      Non-Null Count  Dtype
---  -
0   User-ID     278858 non-null  int64
1   Location    278858 non-null  object
2   Age         168096 non-null  float64
dtypes: float64(1), int64(1), object(1)
memory usage: 6.4+ MB
-----
```

Fig 1.3 Users.csv

## 2. Data Preprocessing

### 2.1 Data Preprocessing on Books.csv dataset

I dropped the image URL columns because they do not contribute to recommendation logic or machine learning models. These columns are considered irrelevant for analysis and were removed to simplify the dataset.

```
[14]: # dropping images columns from books.csv as they might not be useful
df_books.drop(columns = ["Image-URL-S", "Image-URL-M"], inplace = True)
```

This code checks if the Year-Of-Publication column contains any non-numeric values. Identifying such anomalies helps prevent data type issues during visualization or modeling.

```
[16]: # checking if we have non-numeric entries for "Year of publication"
non_numeric_years = df_books['Year-Of-Publication'].apply(lambda x: pd.to_numeric(x, errors='coerce')).isnull().sum()
```

I examined the dataset for missing values across all columns. This helps us decide whether to impute, drop, or treat missing data based on its impact.

```
[20]: # Checking for missing values in the dataset
df_books.isnull().sum()

[20]: ISBN                0
Book-Title              0
Book-Author            2
Year-Of-Publication     0
Publisher               2
Image-URL-L            0
dtype: int64
```

Missing entries in Book-Author and Publisher were filled with "Unknown" to maintain data completeness. This prevents errors in future steps like grouping or encoding without losing records.

```
[21]: # Handling missing values
      # Filling missing Book-Author and Publisher records with "Unknown"
      df_books["Book-Author"] = df_books["Book-Author"].fillna("Unknown")
      df_books["Publisher"] = df_books["Publisher"].fillna("Unknown")
```

I checked for duplicate rows to ensure data integrity. Fortunately, no duplicate entries were found in the dataset.

```
[23]: # checking for duplicates if any
      df_books.duplicated().sum()

[23]: 0
```

## 2.2 Data Preprocessing on Ratings.csv dataset

I checked for any missing values in the ratings dataset. Fortunately, no null entries were found, indicating the dataset is complete and ready for analysis.

```
[25]: # checking for any missing data
      df_ratings.isnull().sum()

[25]: User-ID      0
      ISBN        0
      Book-Rating  0
      dtype: int64
```

This line checks for duplicate rows in the ratings data. It ensures the dataset doesn't have repeated records that could skew the recommendation logic; in this case, none were found.

```
[26]: # checking for any duplicates
      df_ratings.duplicated().sum()

[26]: 0
```

I examined how many ratings each user has submitted. This is important for identifying active users versus inactive ones, which helps us later filter out users who haven't contributed enough data for collaborative filtering.

```
[27]: # number of ratings each user has given
df_ratings["User-ID"].value_counts()

[27]: User-ID
11676      13602
198711      7550
153662      6109
98391       5891
35859       5850
...
116180         1
116166         1
116154         1
116137         1
276723         1
Name: count, Length: 105283, dtype: int64
```

## 2.3 Data Preprocessing on Users.csv

I checked the Users.csv file for missing values and found that the "Age" column had a significant number of null entries. This indicated that further preprocessing was necessary to handle missing age data appropriately.

```
[29]: # checking for any missing values
df_users.isnull().sum()

[29]: User-ID      0
Location      0
Age      110762
dtype: int64
```

To deal with the missing age values, I calculated the median of the available ages and filled the null entries with it. I chose the median instead of the mean to reduce the impact of extreme outliers on the distribution.

```
[30]: # filling missing age values with median
median_age=df_users["Age"].median()
df_users["Age"]=df_users["Age"].fillna(median_age)
```

I decided to drop the "Location" column because it was not directly useful for building the recommendation system. Removing irrelevant features helps reduce dataset complexity and improves model efficiency.

```
[32]: # dropping "Location", as it is not a significant attribute
df_users.drop(columns = ["Location"], inplace = True)
```

To build a complete dataset, I first merged Ratings.csv with Users.csv on "User-ID" to include user demographic details alongside their ratings. Then, I merged this result with Books.csv using "ISBN" to attach book information. I used inner joins in both steps to ensure only valid and complete records were retained. The final dataset now includes user, book, and rating information, which is essential for training the recommendation system.

```
[37]: # Merging Ratings.csv and Users.csv on "User-ID"
      df_ratings_users = pd.merge(df_ratings, df_users, on="User-ID", how="inner")

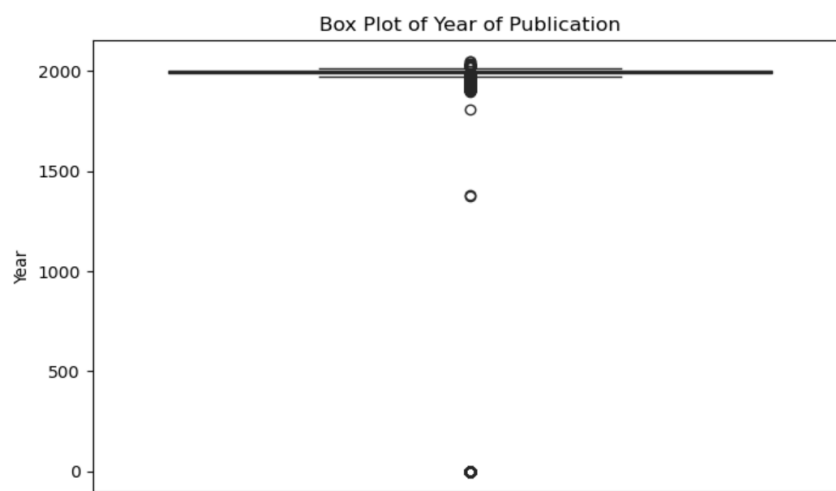
[39]: # The above ratings_users dataset can be merged with Books.csv on "ISBN"
      df = pd.merge(df_ratings_users, df_books, on="ISBN", how="inner")
```

### 3. Exploratory Data Analysis

EDA helps us in understanding the dataset structure, detect anomalies, and extracting valuable insights for predictive model development.

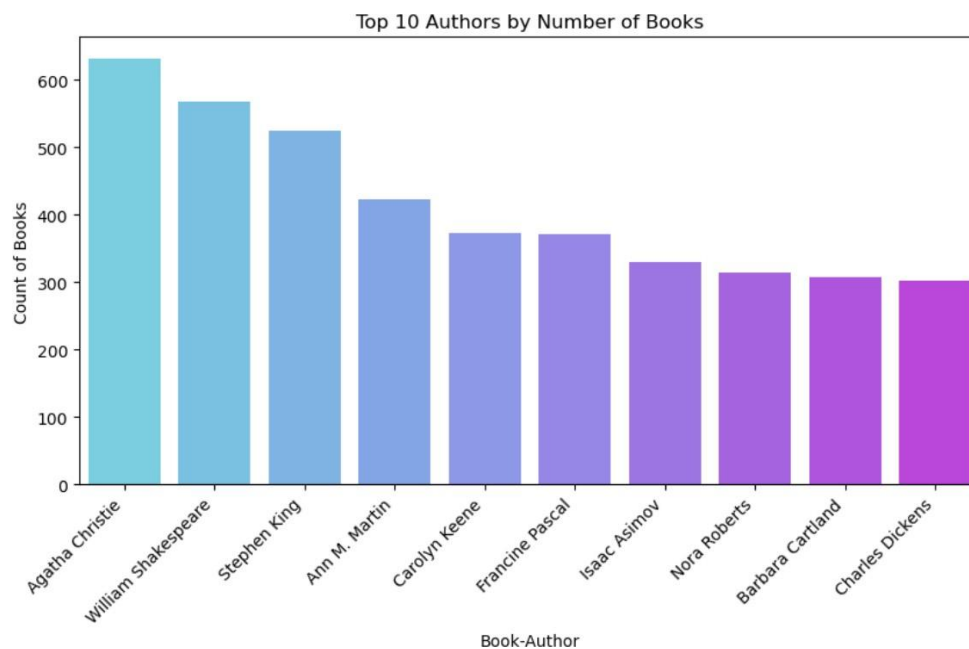
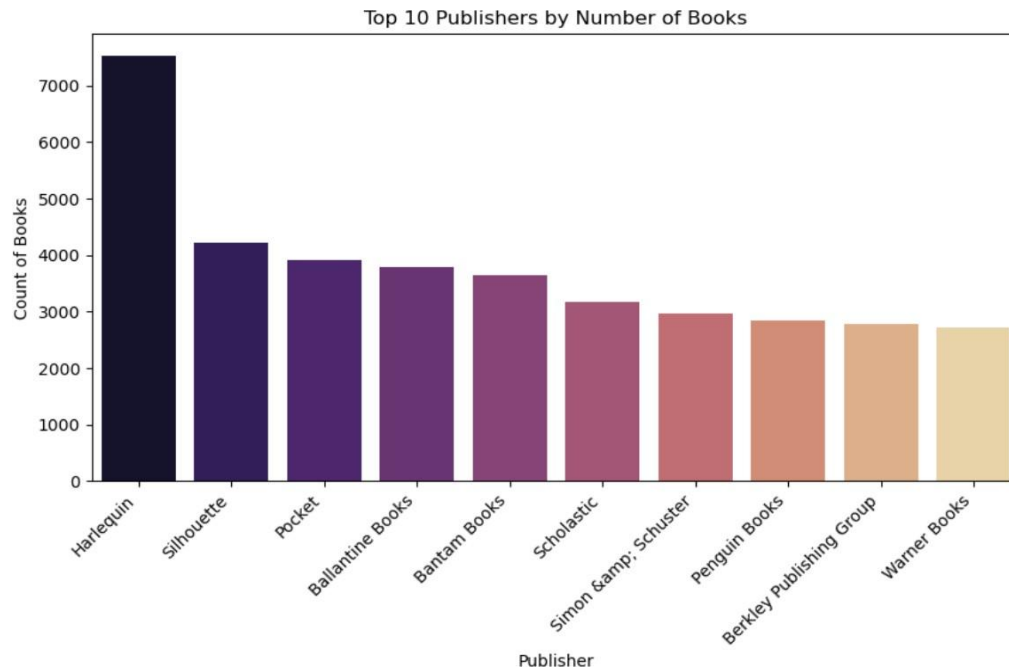
#### Books.csv Dataset

##### Boxplot for Year of Publication Distribution



We observe that there are some years which are unrealistic, example 0, and others <1800, which are not significant. These incorrect years can distort recommendations based on books age. So we can filter out the books that are published before 1800.

##### Bar plots for Top Publishers and Authors

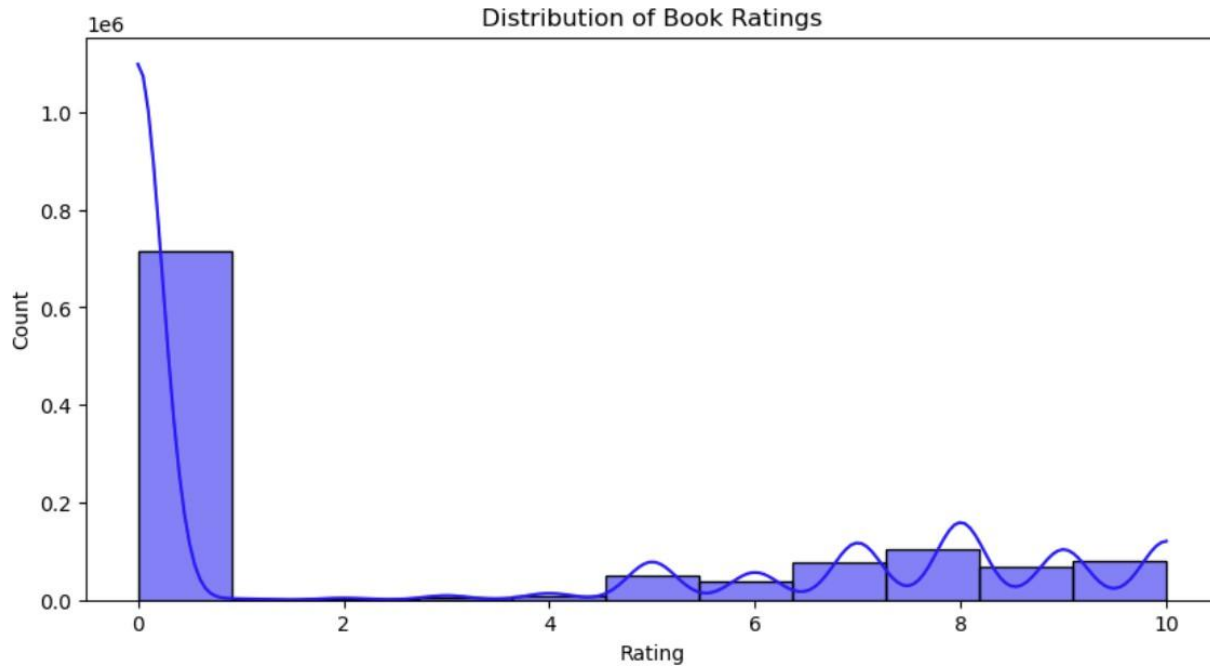


There are small number of publishers and authors responsible for a large portion of books. This visualization helps in identifying key contributors in the dataset, and understand the diversity of book sources available.

### **Ratings.csv Dataset**

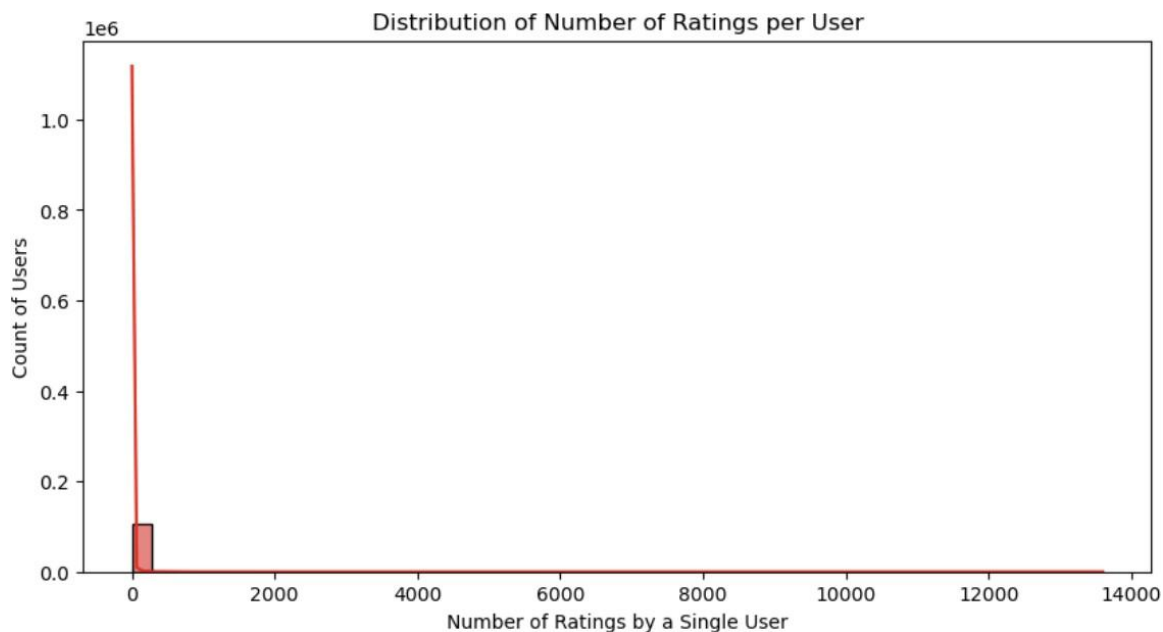
#### **Histogram for ratings distribution**





Ratings are highly skewed toward 0 or 10. This type of binary rating tendency might impact model performance. We can consider applying normalization or adjusting weighting to handle skewness.

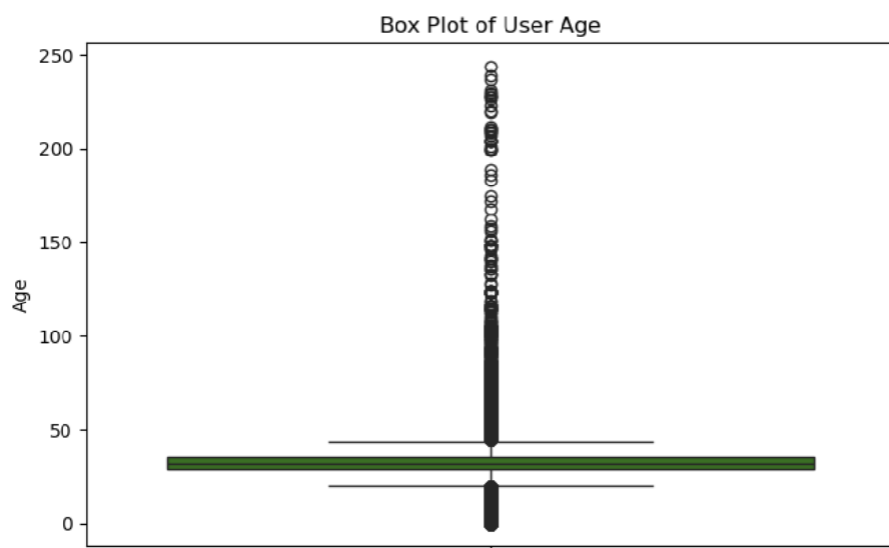
### Histogram for Number of Ratings per user



Most of the users have rated very few books, whereas a few users have rated thousands. This sparse data makes collaborative filtering less effective for users with minimal interactions. We consider filtering out the inactive users who rated  $<5$  books, so that model performance can be improved.

## Users.csv Dataset

### Box plot and Histogram for Age Distribution



Few users have unrealistic ages like 0 and 250. Such outliers can distort demographic based recommendations, and so we clip the age values to the range 5 to 100.

## MILESTONE 2: Feature Engineering, Feature Selection and Data Modeling

(Feb 23, 2025 – Apr 03, 2025)

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### 4. Data Cleaning and Filtering

Before proceeding with feature engineering, we perform data cleaning based on key insights discovered during exploratory data analysis. We observed anomalies such as unrealistic user ages, users with very few ratings, and books rated too few times to provide meaningful patterns. These cleaning steps help improve the quality of the dataset and ensure our recommendation models are trained on reliable data.

To improve the quality of the dataset, I started by clipping the user ages to a sensible range between 5 and 100. This helped eliminate unrealistic values like 0 or 250, which could introduce noise in the analysis. I then filtered out users who had rated fewer than 5 books, as these users don't provide enough data to model their preferences effectively in collaborative filtering. Similarly, I excluded books that had received fewer than 10 ratings since such books lack sufficient feedback to be recommended reliably. These steps reduced noise and focused the data on active users and popular books, making the dataset more meaningful for training recommendation models.

```
[71]: # Clipping unrealistic ages to a sensible range (5 to 100). This helps us eliminate noisy outliers like 0 or 250 years old
cleaned_df['Age'] = cleaned_df['Age'].clip(lower=5, upper=100)
```

```
[72]: # Filtering out users who have rated fewer than 5 books. These users provide too little data to be useful for recommendations
user_rating_counts = cleaned_df['User-ID'].value_counts()
active_users = user_rating_counts[user_rating_counts >= 5].index
cleaned_df = cleaned_df[cleaned_df['User-ID'].isin(active_users)]
```

```
[73]: # Filtering out books that have been rated fewer than 10 times. These books don't have enough information for meaningful recommendations
book_rating_counts = cleaned_df['ISBN'].value_counts()
popular_books = book_rating_counts[book_rating_counts >= 10].index
cleaned_df = cleaned_df[cleaned_df['ISBN'].isin(popular_books)]
```

### 5. Feature Engineering

I performed feature engineering to enrich the dataset with additional information that could be useful for building more accurate and insightful recommendation models. I started by creating a copy of the cleaned dataset to avoid altering the original data. Then, I added four new features:

- **User-Rating-Count:** the number of ratings each user has given, which helps identify how active a user is.

- **User-Average-Rating:** the average score each user tends to give, which can be useful to normalize rating behavior.
- **Book-Rating-Count:** the number of times each book has been rated, helping assess a book's popularity.
- **Book-Average-Rating:** the overall perception of the book based on its average score.

These engineered features can be used for filtering, modeling, or providing weighted inputs in both collaborative and content-based filtering approaches to improve recommendation quality.

```
[77]: # Creating a new dataframe to store engineered features from the cleaned data
feature_df = cleaned_df.copy()

[78]: feature_df.shape

[78]: (445391, 9)

[79]: # Feature 1: Number of ratings given by each user
user_rating_count = feature_df.groupby('User-ID')['Book-Rating'].count().reset_index()
user_rating_count.columns = ['User-ID', 'User-Rating-Count']
feature_df = feature_df.merge(user_rating_count, on='User-ID', how='left')

[80]: # Feature 2: Average rating given by each user
user_avg_rating = feature_df.groupby('User-ID')['Book-Rating'].mean().reset_index()
user_avg_rating.columns = ['User-ID', 'User-Average-Rating']
feature_df = feature_df.merge(user_avg_rating, on='User-ID', how='left')

[81]: # Feature 3: Number of ratings received by each book
book_rating_count = feature_df.groupby('ISBN')['Book-Rating'].count().reset_index()
book_rating_count.columns = ['ISBN', 'Book-Rating-Count']
feature_df = feature_df.merge(book_rating_count, on='ISBN', how='left')

[82]: # Feature 4: Average rating received by each book
book_avg_rating = feature_df.groupby('ISBN')['Book-Rating'].mean().reset_index()
book_avg_rating.columns = ['ISBN', 'Book-Average-Rating']
feature_df = feature_df.merge(book_avg_rating, on='ISBN', how='left')

[83]: feature_df.shape

[83]: (445391, 13)
```

## 6. Model Building

This book recommendation system works in three different ways, depending on how a user interacts with it.

**6.1 Publisher-Based Classification from Title (Supervised ML Model).** We classify the Publisher of a book based on its title using machine learning, then recommend the top-rated books from the predicted publisher.

I dropped rows with missing titles or publisher data because these fields are essential for training a supervised model that predicts the publisher from a book title. Without both inputs and labels, the model wouldn't function properly.

```
[89]: # Drop rows with missing publisher or title
      publisher_df = cleaned_df.dropna(subset=['Book-Title', 'Publisher'])
```

I used **TfidfVectorizer** to convert book titles into numerical features based on term frequency-inverse document frequency. This helps the model focus on important words that distinguish titles, while reducing noise from common English words. Also, I split the data into training and testing sets to evaluate the model performance. I used a standard 80-20 split, ensuring reproducibility with a fixed random seed.

```
[91]: # Vectorizing titles
      vectorizer = TfidfVectorizer(stop_words='english')
      X = vectorizer.fit_transform(publisher_df['Book-Title'])
      y = publisher_df['Publisher']

[92]: # Splitting into train and test
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

I trained three classifiers—Naive Bayes, Logistic Regression, and Decision Tree—to compare their effectiveness in predicting the publisher. Logistic Regression ultimately performed best and was used in the final recommendation logic.

```
[94]: # (i): Multinomial Naive Bayes
      model_nb = MultinomialNB()
      model_nb.fit(X_train, y_train)
      preds_nb = model_nb.predict(X_test)
      print("MultinomialNB Accuracy:", accuracy_score(y_test, preds_nb))
      print(classification_report(y_test, preds_nb))
```

```
MultinomialNB Accuracy: 0.6650388980567811 ●●●
```

```
[187]: # (ii): Logistic Regression
      model_lr = LogisticRegression(max_iter=1000)
      model_lr.fit(X_train, y_train)
      preds_lr = model_lr.predict(X_test)
      print("Logistic Regression Accuracy:", accuracy_score(y_test, preds_lr))
      print(classification_report(y_test, preds_lr))
```

```
Logistic Regression Accuracy: 0.8360107320468348
```

```

: # (iii): Decision Tree
model_dt = DecisionTreeClassifier(random_state=42)
model_dt.fit(X_train, y_train)
preds_dt = model_dt.predict(X_test)
print("Decision Tree Accuracy:", accuracy_score(y_test, preds_dt))
print(classification_report(y_test, preds_dt))

```

Among all the three classifiers, Logistic Regression performed well with the accuracy of 83.6%.

## 6.2 Content-Based Filtering (Based on Book Features)

When a real-time user searches for a book, we recommend similar books using TF-IDF on features like title, author, and publisher.

```

[189]: from sklearn.feature_extraction.text import TfidfVectorizer
      from sklearn.metrics.pairwise import cosine_similarity

      # Combine relevant textual features into a single string for every book
      cleaned_df['Combined'] = (cleaned_df['Book-Title'].fillna('') + ' '
                               + cleaned_df['Book-Author'].fillna('') + ' '
                               + cleaned_df['Publisher'].fillna(''))
      cleaned_df = cleaned_df.reset_index(drop=True)

[191]: # creating the book_indices mapping
      book_indices = pd.Series(cleaned_df.index, index=cleaned_df['Book-Title']).drop_duplicates()
      # fitting the model
      vectorizer_cb = TfidfVectorizer(stop_words='english')
      tfidf_matrix = vectorizer_cb.fit_transform(cleaned_df['Combined'])
      from sklearn.neighbors import NearestNeighbors
      model_cb = NearestNeighbors(metric='cosine', algorithm='brute')
      model_cb.fit(tfidf_matrix)

[191]: NearestNeighbors
      NearestNeighbors(algorithm='brute', metric='cosine')

```

Here, I prepared the data for content-based book recommendations. First, I created a new column called Combined, which merges the book's title, author, publisher, and a custom label for the rating (like "Highly Rated", "Moderately Rated", or "Low Rated") to form a single descriptive string for each book. This helps capture more context when comparing books. Then, I removed duplicate entries based on book titles to ensure only unique books are used. Using this cleaned data, I applied a TF-IDF vectorizer to convert the combined text into numerical form. Finally, I used a K-Nearest Neighbors model with cosine similarity to find similar books based on their vectorized text features.



### 6.3 Collaborative Filtering (Based on User Ratings)

We recommend books to a user by identifying users with similar rating patterns using a K-Nearest Neighbors model. The system suggests books that those similar users have rated highly but the current user hasn't interacted with yet.

```
[175]: # Creating a user-item matrix (rows: users, columns: books, values: ratings)
user_item_matrix = feature_df.pivot_table(index='User-ID', columns='Book-Title', values='Book-Rating').fillna(0)
```

```
[177]: # Fitting the KNN model on user-item matrix using cosine similarity
knn_model = NearestNeighbors(metric='cosine', algorithm='brute')
knn_model.fit(user_item_matrix)
```

```
[177]: NearestNeighbors
NearestNeighbors(algorithm='brute', metric='cosine')
```

```
[179]: # fro instance, consider a real-time user who rated 3 books
real_user_ratings = {
    'The Hobbit': 8,
    'Harry Potter and the Philosopher\'s Stone': 9,
    '1984': 7
}
```

```
[181]: # Convert real-time user ratings to a DataFrame matching user-item matrix columns
real_user_df = pd.DataFrame([real_user_ratings])
real_user_df = real_user_df.reindex(columns=user_item_matrix.columns, fill_value=0)
```

```
[183]: # Find the 5 nearest users based on rating similarity
distances, indices = knn_model.kneighbors(real_user_df, n_neighbors=5)
# Get User-IDs of the nearest users
similar_users = user_item_matrix.iloc[indices[0]].index.tolist()
# Retrieve their ratings
similar_ratings = user_item_matrix.loc[similar_users]
# Calculate average rating for each book rated by similar users
avg_ratings = similar_ratings.mean().sort_values(ascending=False)
# Remove books already rated by the real-time user
already Rated = set(real_user_ratings.keys())
final_recommendations = avg_ratings[~avg_ratings.index.isin(already Rated)].head(10)
```

```
[185]: # Display final book recommendations
print("Recommended Books (Collaborative Filtering):")
print(final_recommendations)

Recommended Books (Collaborative Filtering):
Book-Title
Murder of a Sleeping Beauty (Scumble River Mysteries (Paperback))    0.0
Stolen Lives : Twenty Years in a Desert Jail (Oprah's Book Club (Paperback))  0.0
Still Pumped From Using The Mouse    0.0
Still Waters    0.0
Still life with Woodpecker    0.0
Still of the Night    0.0
Stillwatch    0.0
Stitch 'N Bitch: The Knitter's Handbook    0.0
Stitches in Time    0.0
Stolen    0.0
dtype: float64
```

```
[ ]:
```

I implemented a user-based collaborative filtering approach using the K-Nearest Neighbors (KNN) algorithm. First, I created a user-item matrix where each row represents a user and each column represents a book title, with the cell values indicating the rating a user gave to that book. I filled missing values with zero to maintain matrix integrity for similarity calculations. This matrix served as the foundation for identifying user-user relationships based on their rating behavior.

I then trained a KNN model using cosine similarity, which is effective for measuring how closely users' rating patterns align, regardless of the scale of ratings. To simulate a real-time scenario, I defined a mock user who rated three popular books. This user's input was converted into the same format as the user-item matrix to allow for similarity comparison.

Using the KNN model, I retrieved the top 5 users who had similar tastes to the mock user based on their ratings. I then aggregated these similar users' ratings and calculated the average rating for each book. Books that the mock user had already rated were excluded from the results to avoid redundancy. Finally, I displayed the top 10 highest-rated books (by similar users) that the real-time user hadn't rated yet. These recommendations are tailored to the user based on the preferences of like-minded readers, making this stage a core component of personalized suggestions in the system.



## MILESTONE 3: Evaluation, Interpretation and Tool Development

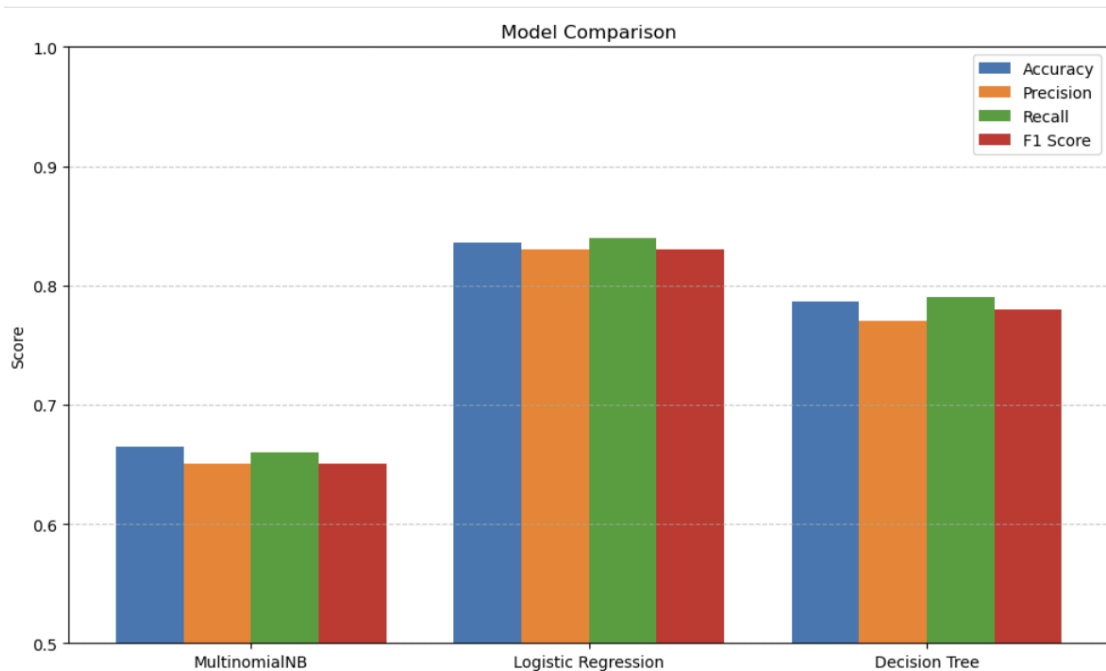
(Apr 04, 2025 – Apr 22, 2025)

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### 7. Evaluation and Interpretation

To evaluate the publisher-based classification model, I experimented with three algorithms: Multinomial Naive Bayes, Logistic Regression, and Decision Tree Classifier. The input to these models was TF-IDF vectorized book titles, and the goal was to predict the corresponding publisher. Among the three, Logistic Regression performed best with an accuracy of 83.6%, significantly higher than Decision Tree (78.6%) and Naive Bayes (66.5%). Given the high number of unique publishers, this level of accuracy was considered strong, especially since the model only used title text as input. Logistic Regression was selected as the final model and integrated into the recommendation system.

Logistic Regression outperformed the other models likely due to its ability to handle high-dimensional sparse data efficiently, which is characteristic of TF-IDF vectors. Naive Bayes, although fast, may have struggled with the overlapping vocabulary across publishers, while the Decision Tree tended to overfit on the training set due to the large number of classes.



For content-based filtering, the model uses TF-IDF vectorization on a combined feature column

consisting of the book's title, author, publisher, and a bucketed rating label (e.g., "Highly Rated", "Moderately Rated"). A K-Nearest Neighbors (KNN) model with cosine similarity is then used to identify books with similar patterns in this feature space. This approach helps recommend books that are similarly rated, even if they aren't by the same author or publisher.

In the collaborative filtering module, a user-item matrix was built based on historical ratings, where rows represent users and columns represent books. The KNN model again with cosine similarity is used to find similar users based on their rating behavior. Recommendations are then made by identifying books that these similar users have liked but the target user hasn't rated yet. This method allows the system to learn from shared user preferences, making it ideal for personalized suggestions.

## 8. Tool Development

I developed an interactive web application using Streamlit, allowing users to easily search for books, rate them, and receive personalized recommendations. The backend models including those for publisher classification, content-based filtering, and collaborative filtering were trained, optimized, and saved using Python's pickle library to ensure they could be loaded efficiently in the app without retraining.

The recommendation logic was modularized into functions, each handling a specific user interaction: predicting a book's publisher based on title input, recommending similar books using rating patterns, and finding books liked by users with similar preferences. These functions were integrated into a clean user interface where users can search, rate, and explore book suggestions in a single seamless experience. Additionally, user ratings are stored in a SQLite database, making the system dynamic and personalized for each login session.

This tool combines machine learning with a user-friendly interface to demonstrate how data science models can be translated into real-world applications.

### 8.1 Saving models

```
# saving the publisher model
import pickle
publisher_model = model_lr
with open('models/publisher_model.pkl', 'wb') as f:
    pickle.dump(publisher_model, f)
import pickle
with open("models/vectorizer.pkl", "wb") as f:
    pickle.dump(vectorizer, f)
```

This code snippet shows how the trained Logistic Regression publisher classification model and its associated TF-IDF vectorizer are saved using Python's pickle module. By storing them as .pkl files, the models can be quickly loaded into the web app later without needing to retrain, improving efficiency and responsiveness.

```
# Save TF-IDF vectorizer
with open('models/vectorizer_cb.pkl', 'wb') as f:
    pickle.dump(vectorizer_cb, f)

# Save Nearest Neighbors model
with open('models/model_cb.pkl', 'wb') as f:
    pickle.dump(model_cb, f)

# Save book-level dataframe
book_level_df.to_pickle('models/book_level_df_cb.pkl')

# Save the book_indices mapping
with open('models/book_indices_cb.pkl', 'wb') as f:
    pickle.dump(book_indices, f)
```

Similarly, this above code snippet demonstrates how all essential components of the content-based recommendation system are saved for deployment. It includes pickling the TF-IDF vectorizer and the trained KNN model, as well as storing the cleaned and deduplicated book\_level\_df and book\_indices mapping. These assets are crucial for efficiently retrieving similar books during runtime based on user input.

```
# Save KNN model
with open('models/knn_collaborative_model.pkl', 'wb') as f:
    pickle.dump(knn_model, f)

# Save column names (book titles)
with open('models/user_item_columns.pkl', 'wb') as f:
    pickle.dump(user_item_matrix.columns.tolist(), f)

# (Optional) Save full user-item matrix for re-indexing
user_item_matrix.to_pickle('models/user_item_matrix.pkl')
```

This snippet shows how the collaborative filtering system is prepared for deployment. The trained KNN model is saved, along with the column names (representing book titles) of the user-item matrix, which are essential for aligning real-time user input. The full user-item matrix is also saved for efficient re-indexing and similarity calculations when identifying books liked by similar users.

## 8.2 Recommendation Functions

I would like to explain the core functions that enable the three different recommendation strategies

implemented in this project. Each function plays a key role in translating user input into meaningful book suggestions by leveraging the trained models and preprocessed data stored during development.

### 8.2.1 Publisher based recommendation

```
def publisher_recommendation(book_title, models):
    pub_model = models['publisher_model']
    vectorizer = models['vectorizer']
    book_df = models['book_level_df_cb']

    vec = vectorizer.transform([book_title])
    pred_publisher = pub_model.predict(vec)[0]

    recs = book_df[book_df['Publisher'] == pred_publisher]
    recs = recs.drop_duplicates(subset="Book-Title").head(6)
    return recs
```

This function `publisher_recommendation()` is used to recommend books from the same publisher as the input book. It first uses the trained publisher classification model to predict the publisher of the given title based on TF-IDF features. Then, it filters the dataset to return a few other books from that predicted publisher, ensuring no duplicates based on the book title. This is useful when the system doesn't find the exact book but still wants to suggest similar ones from the same publishing source.

### 8.2.2 Content based recommendation

```
def content_recommendation(book_title, models, top_n=5):
    book_indices = models['book_indices_cb']
    book_df = models['book_level_df_cb']
    model = models['model_cb']
    tfidf_matrix = model._fit_X

    if book_title not in book_indices:
        return []
    idx = book_indices[book_title]
    distances, indices = model.kneighbors(tfidf_matrix[idx], n_neighbors=top_n+5)
    recommendations = []
    for i in indices[0]:
        candidate = book_df.iloc[i]
        if candidate['Book-Title'] != book_title and candidate['Book-Title'] not in [r['Book-Title'] for r in recommendations]:
            recommendations.append(candidate)
        if len(recommendations) == top_n:
            break
    return pd.DataFrame(recommendations)[['Book-Title', 'Book-Author', 'Publisher', 'Image-URL-L']]
```

The `content_recommendation()` function recommends books that are similar to the given title based on content features. It uses a KNN model trained on a TF-IDF matrix created from a combined feature column (title, author, publisher, and rating category). After finding the nearest neighbors of the input book, it filters out the input title and any duplicates, then returns a DataFrame of distinct, similar books with their titles, authors, publishers, and cover images. This helps users find books

that are contextually and stylistically related.

### 8.2.3 Collaborative based recommendation

```
def collaborative_recommendation(username, models, top_n=5):
    user_item_matrix = models['user_item_matrix']
    knn_model = models['knn_collaborative_model']
    user_ratings = get_user_ratings(username)

    if user_ratings.empty():
        return pd.DataFrame()

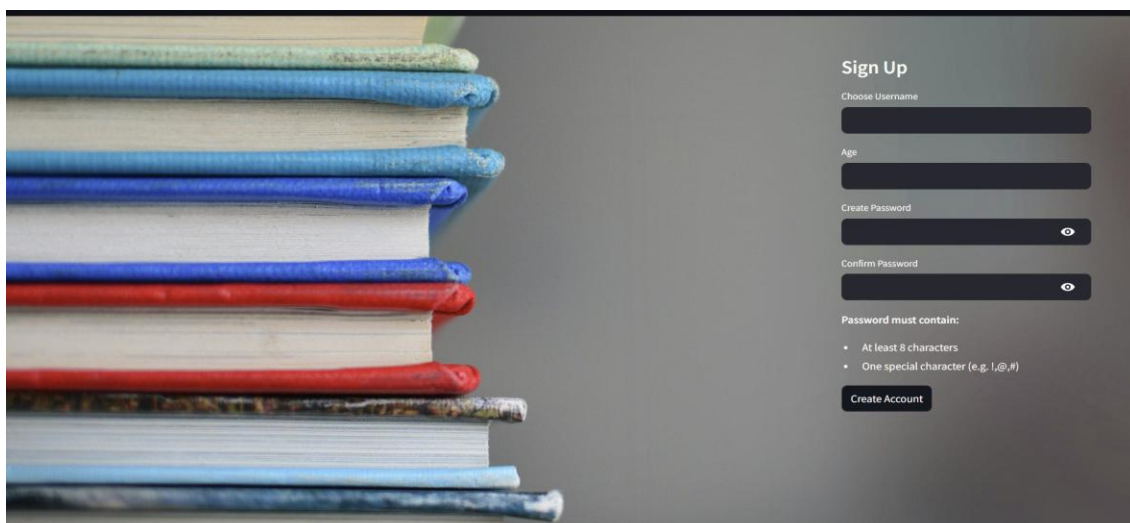
    real_user_ratings = dict(zip(user_ratings['book_title'], user_ratings['rating']))
    real_user_df = pd.DataFrame([real_user_ratings])
    real_user_df = real_user_df.reindex(columns=user_item_matrix.columns, fill_value=0)
    distances, indices = knn_model.kneighbors(real_user_df, n_neighbors=5)
    similar_users = user_item_matrix.iloc[indices[0]].index.tolist()
    similar_ratings = user_item_matrix.loc[similar_users]
    avg_ratings = similar_ratings.mean().sort_values(ascending=False)
    already_rated = set(real_user_ratings.keys())
    final_recommendations = avg_ratings[~avg_ratings.index.isin(already_rated)].head(top_n)

    df = models['book_level_df_cb']
    return df[df['Book-Title'].isin(final_recommendations.index)][['Book-Title', 'Book-Author', 'Publisher', 'Image-URL-L']]
```

The `collaborative_recommendation()` function generates personalized book recommendations by analyzing user similarity. It first retrieves the current user's ratings and builds a sparse vector aligned with a pre-built user-item matrix. Using a KNN model with cosine similarity, it finds users with similar rating patterns and computes the average ratings for books they've enjoyed. It then filters out books already rated by the current user and recommends new books that like-minded users rated highly. This method helps suggest books based on shared preferences among readers.

## 8.3 User Interface Layout/Design

### 8.3.1 Sign Up Page



The image displays a 'Sign Up' form overlaid on a background of stacked books. The form is titled 'Sign Up' and contains the following elements:

- Choose Username:** A text input field.
- Age:** A text input field.
- Create Password:** A text input field with a toggle icon (an eye) to the right.
- Confirm Password:** A text input field with a toggle icon (an eye) to the right.
- Password must contain:** A list of requirements:
  - At least 8 characters
  - One special character (e.g., !, @, #)
- Create Account:** A button at the bottom of the form.

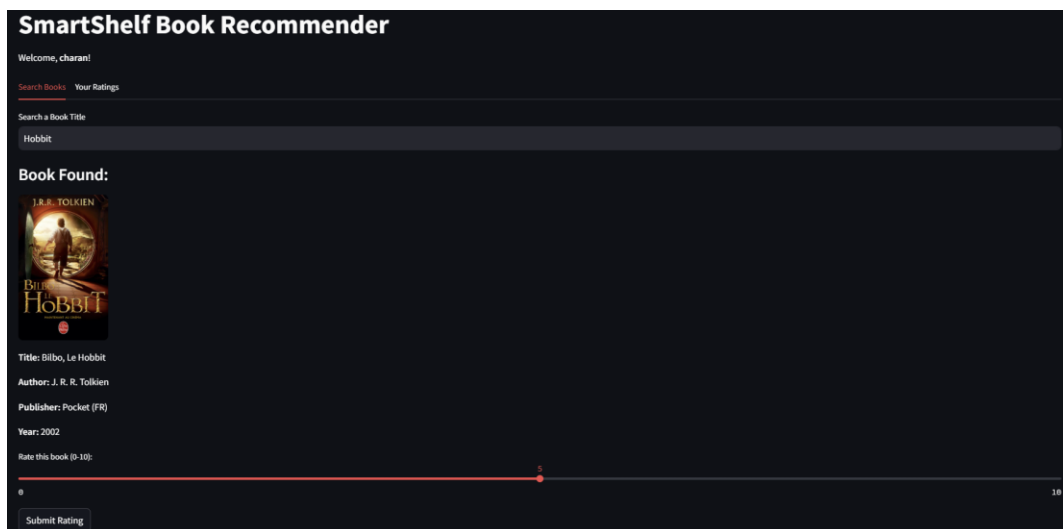
This screenshot shows the **Sign Up** page of the application. Users can register by providing a username, age, and a secure password that meets clearly stated complexity requirements. The form is designed to be intuitive and user-friendly, with real-time validation support for password criteria.

### 8.3.2 Login Page

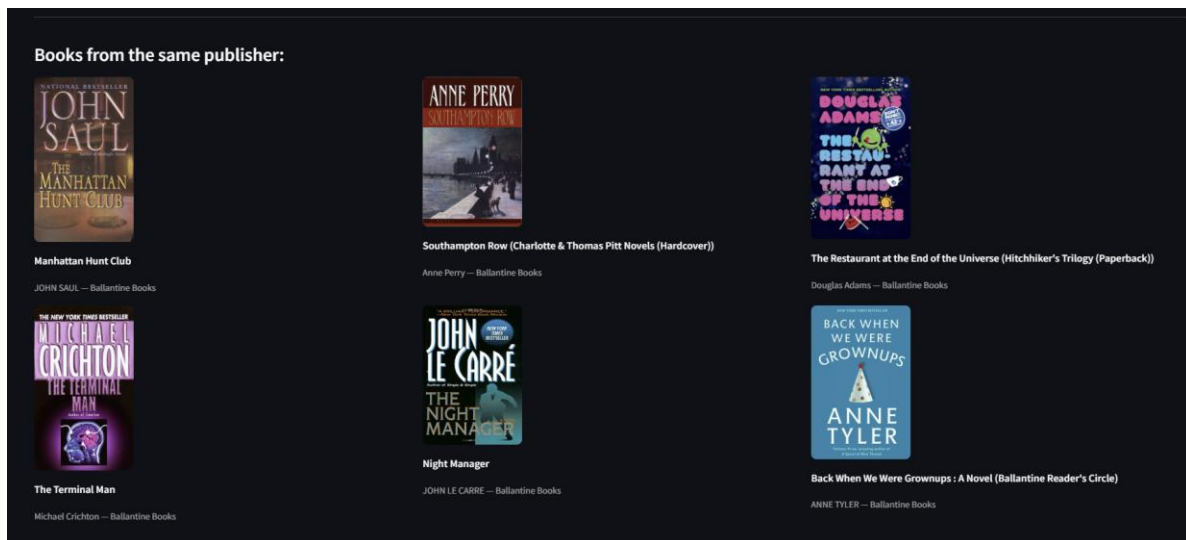


This screenshot displays the **Login** page of the application. It offers a minimalistic design for users to enter their credentials. In case of invalid input, clear feedback like "Invalid credentials" is shown, ensuring an intuitive user experience.

### 8.3.3 Publisher Based recommendation function

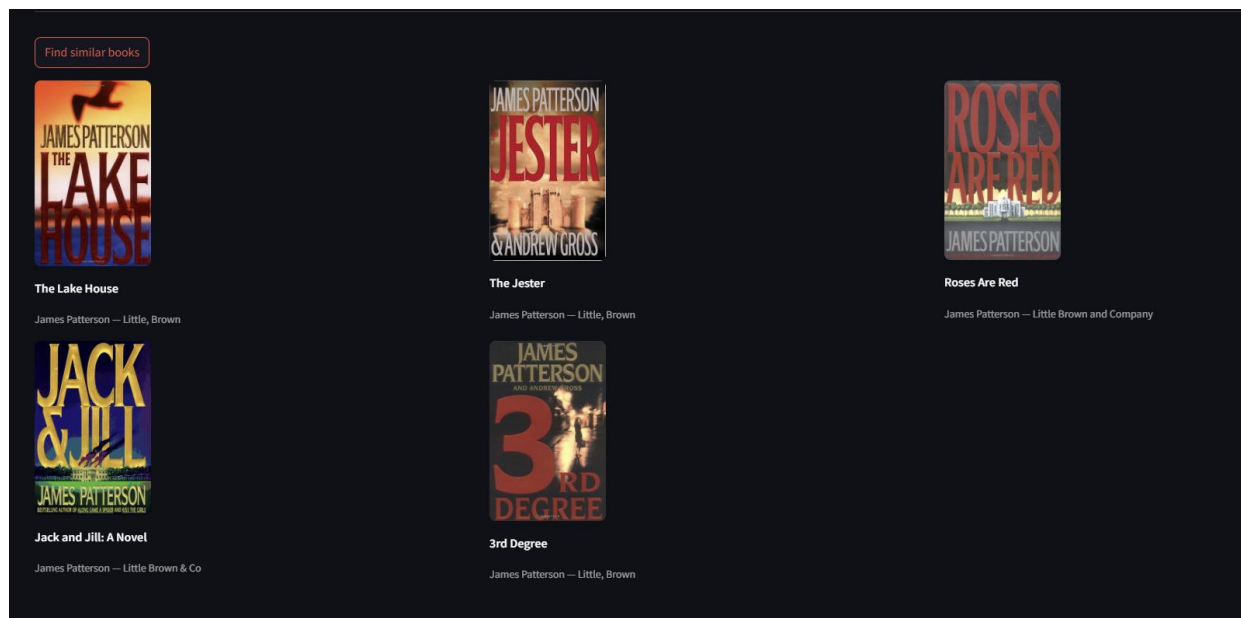


This screenshot captures the Search Books functionality. Once a user enters a title, the system displays the matched book along with its cover, title, author, publisher, and publication year. It also allows the user to rate the book using a slider, which helps build their personalized recommendation profile.



This screenshot displays the **Publisher-Based Recommendations** feature. After predicting the publisher from the user's searched title, the system recommends a curated list of other books from the same publisher. Each recommendation is visually presented with the book cover, title, author, and publisher in a clean grid layout.

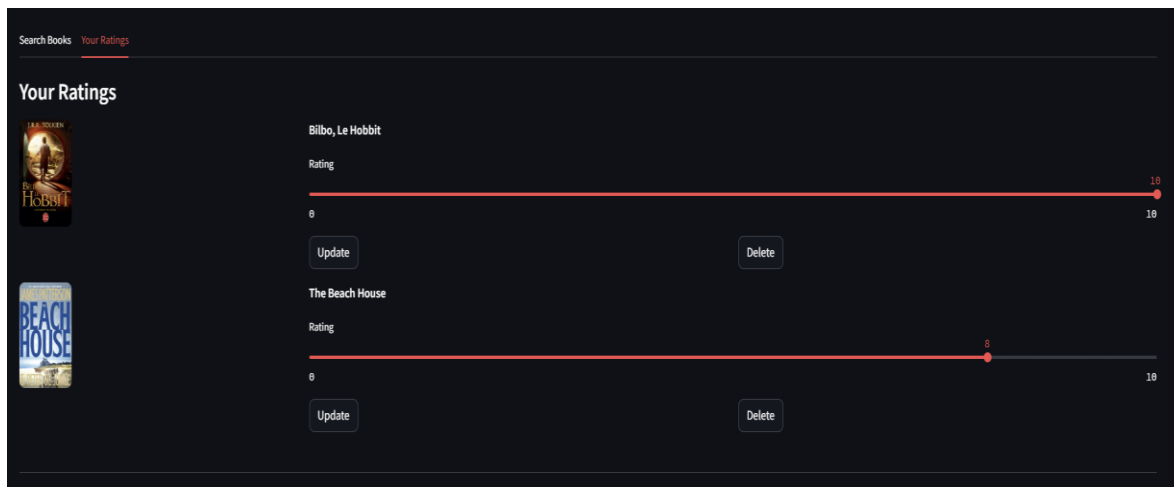
### 8.3.4 Content Based Recommendation



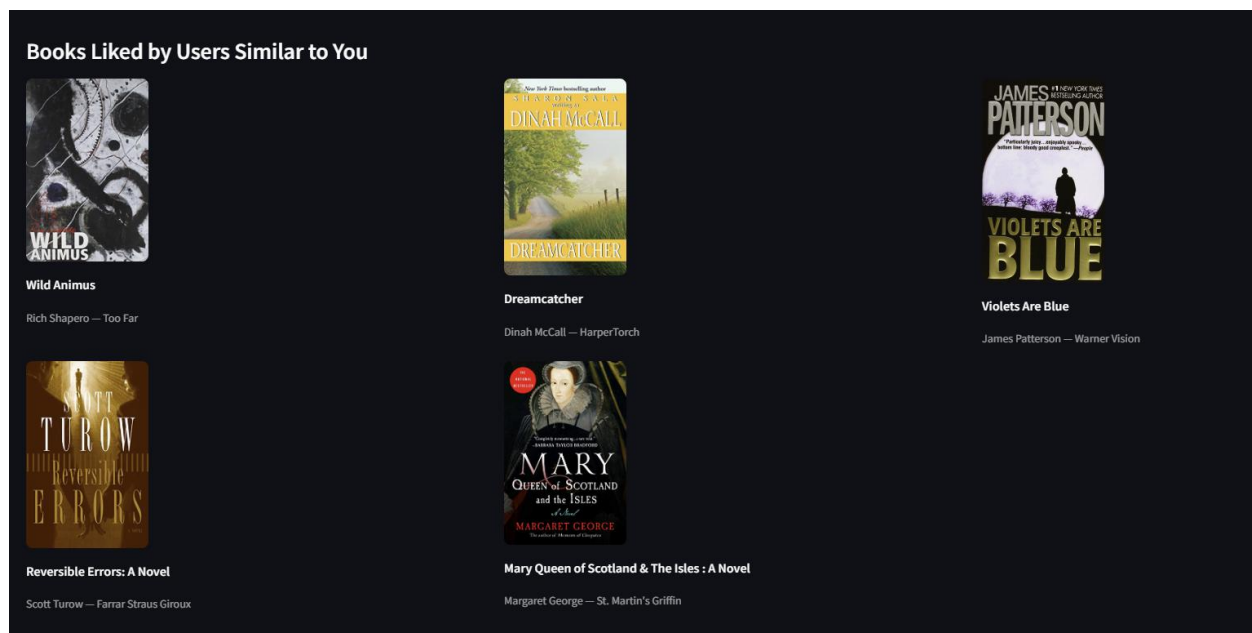
This screenshot illustrates the Content-Based Filtering feature. After a user marks a book as "read," they can click "Find similar books" to trigger recommendations based on combined features like title, author, publisher, and rating category. The displayed results are visually organized and highlight books that share content similarities with the selected title.



### 8.3.5 Collaborative Filtering Recommendation



This page shows the user's personalized ratings history. Each rated book is displayed with its cover image, and users can update or delete their ratings directly from this interface using sliders and buttons. These stored ratings are essential for generating collaborative filtering recommendations based on similar user preferences.



This section showcases **collaborative filtering recommendations**, where the system identifies books enjoyed by users who have similar rating patterns. These suggestions are generated based on aggregated ratings from similar users, offering personalized book options the current user hasn't rated yet.



## CONCLUSION

In conclusion, this project successfully delivers a comprehensive book recommendation system that combines three powerful approaches: publisher-based classification, content-based filtering, and collaborative filtering—to generate meaningful and personalized suggestions for users. By integrating TF-IDF vectorization, machine learning classifiers, and KNN-based similarity searches into an interactive Streamlit web app with user authentication and real-time rating updates, the tool demonstrates both technical depth and practical usability. It highlights the value of combining structured metadata with user behavior to enhance recommendation accuracy and user engagement, ultimately offering a smart, scalable platform for discovering new reads.