Book Recommendation System Using Collaborative Filtering

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Course name: Python Lab

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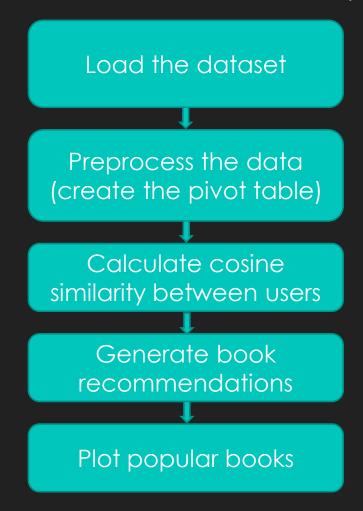


Introduction/Motivation

- 1. **Personalized Experience**: Helps users discover books based on preferences, saving time and improving user satisfaction.
- Overcome Information Overload: Recommends relevant books, reducing the overwhelm of choosing from a large catalog.
- Scalability: Grows with the dataset, adapting as more users rate books, offering dynamic recommendations.
- 4. Collaborative Filtering: Uses user similarity to recommend books, based on the idea that people with similar tastes like similar books.
- 5. Real-World Applications: Similar systems used by platforms like Amazon and Goodreads, demonstrating real-world value.
- **6. Challenges**: Solves problems like cold start (new users/books) and sparse data by leveraging collaborative filtering.
- 7. Potential for Improvement: Can be expanded with hybrid models, content-based filtering, and real-time feedback for better recommendations.

Approach Overview(Block Diagram)

Steps involved in the book recommendation system:





Pseudocode

Load book rating data from CSV.

```
def load_data(file_path):
```

Preprocess data into user-book rating matrix.

```
def preprocess_data(data):
```

•Calculate cosine similarity between users.

```
def calculate_similarity(pivot_table):
```

•Generate book recommendations based on similar users.

```
def get_recommendations(user_id, similarity_matrix, pivot_table, num_recommendations=5):
```

- Display top recommendations.
- Visualize the most popular books

```
def plot_popular_books(data):
```



Step 1: Loading Data

- The data is loaded from a CSV file using pandas:
- o data = pd.read_csv(file_path)

| UserID | BookTitle | Rating |
|--------|------------------------|--------|
| 1 | To Kill a Mockingbird | 5 |
| 1 | 1984 | 4 |
| 1 | The Great Gatsby | 3 |
| 1 | The Catcher in the Rye | 4 |
| 2 | To Kill a Mockingbird | 4 |
| 2 | 1984 | 5 |
| 2 | Pride and Prejudice | 4 |
| 2 | The Hobbit | 5 |
| 3 | To Kill a Mockingbird | 2 |
| 3 | The Great Gatsby | 5 |
| 3 | The Catcher in the Rye | 3 |
| 3 | The Hobbit | 4 |
| 4 | 1984 | 3 |
| 4 | The Great Gatsby | 4 |
| 4 | Pride and Prejudice | 5 |
| 4 | The Lord of the Rings | 5 |
| 5 | To Kill a Mockingbird | 5 |
| 5 | Pride and Prejudice | 3 |
| 5 | The Lord of the Rings | 4 |
| 5 | The Hobbit | 3 |
| 6 | 1984 | 5 |
| 6 | The Catcher in the Rye | 4 |
| 6 | The Great Gatsby | 4 |
| 6 | The Lord of the Rings | 3 |



Step 2: Data Preprocessing

Pivot the data to create a user-item matrix:

```
pivot_table = data.pivot_table(index='UserID', columns='BookTitle', values='Rating')
pivot_table.fillna(0, inplace=True) # Fill NaN values with 0
```

| UserID | 1984 | Pride and Prejudice | The Catcher in the Rye | The Great Gatsby | The Hobbit | The Lord of the Rings | To Kill a Mockingbird |
|--------|------|------------------------|------------------------|---------------------|---------------|-----------------------------|--------------------------|
| 1 | 4.0 | 0.0 | 4.0 | 3.0 | 0.0 | 0.0 | 5.0 |
| 2 | 5.0 | 4.0 | 0.0 | 0.0 | 5.0 | 0.0 | 4.0 |
| 3 | 0.0 | 0.0 | 3.0 | 5.0 | 4.0 | 0.0 | 2.0 |
| 4 | 3.0 | 5.0 | 0.0 | 4.0 | 0.0 | 5.0 | 0.0 |
| 5 | 0.0 | 3.0 | 0.0 | 0.0 | 3.0 | 4.0 | 5.0 |
| 6 | 5.0 | 0.0 | 4.0 | 4.0 | 0.0 | 3.0 | 0.0 |



Step 3: Calculating Cosine Similarity

Cosine Similarity is calculated as:

similarity(A, B) = (A . B) / (||A|| |||B||) Where A and B are the rating vectors for two users. Example calculation below: user1=[4,0,4,3,0,0,5] user2=[5,4,0,0,5,0,4] similarity(user1,user2)=40/(8.12*9.05)=0.544

similarity_matrix = cosine_similarity(pivot_table)

| UserID | 1 | 2 | 3 | 4 | 5 | 6 |
|--------|----------|----------|----------|----------|----------|----------|
| 1 | 1.000000 | 0.543727 | 0.619773 | 0.341121 | 0.400629 | 0.727273 |
| 2 | 0.543727 | 1.000000 | 0.420779 | 0.446304 | 0.675717 | 0.339830 |
| 3 | 0.619773 | 0.420779 | 1.000000 | 0.314270 | 0.389762 | 0.536020 |
| 4 | 0.341121 | 0.446304 | 0.314270 | 1.000000 | 0.526152 | 0.653816 |
| 5 | 0.400629 | 0.675717 | 0.389762 | 0.526152 | 1.000000 | 0.192302 |
| 6 | 0.727273 | 0.339830 | 0.536020 | 0.653816 | 0.192302 | 1.000000 |



Step 4: Generating Recommendations

- Recommendations are generated based on the ratings of similar users.
- For similar users, we take the weighted average of their ratings for unseen books.
- O For user 1:

$$\label{eq:Recommendation Score} \begin{aligned} \text{Recommendation Score} &= \frac{\sum (\text{Similarity of User 1 with other users} \times \text{Rating by other users})}{\sum \text{Similarities of User 1 with other users}} \end{aligned}$$

Recommendation scores:

1984=2.80

The Great Gatsby=2.80

Pride and Prejudice=2.45

The hobbit= 2.43

The Lord of Rings=2.08

The catcher in the Rye=1.81

To kill a mockingbird=1.06

Top book recommendations for user 1:

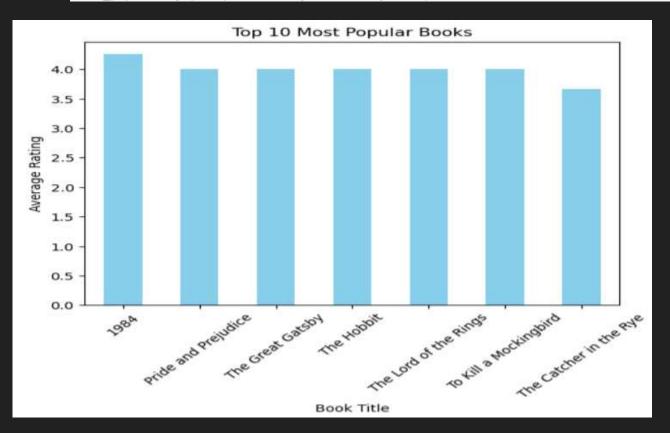
- 1. 1984
- 2. The Great Gatsby
- Pride and Prejudice
- 4. The Hobbit
- 5. The Lord of the Rings



Step 5: Plotting Popular Books

Plot the most popular books based on average ratings of each book

book_popularity = data.groupby('BookTitle')['Rating'].mean().sort_values(ascending=False).head(10)
book_popularity.plot(kind='bar', color='skyblue')



Total Run Time=5.757 4secs



Conclusion & Future Work

- Collaborative Filtering: Implemented user-based collaborative filtering using cosine similarity.
- Data Preprocessing: Cleaned and transformed data for use in recommendation algorithms.
- Python Libraries: Gained experience using Pandas, Numpy, and Scikit-learn.
- Recommendation System Design: Built a personalized recommendation system.
- Visualization: Created visual insights using Matplotlib (bar charts for popular books).