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GRiD 5.0

Problem Statement Title: Personalized Product Recommendations

Team members details

Team Name	Bit Wizards		
Institute Name/Names	Ahmedabad University , IIIT Vadodara, Charusat University		
Team Members >	**1 (Leader)**	**2**	**3**
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Batch	2020-2024	2020-2024	2020-2024

Use-cases

Novice Users: Popularity-based recommendations are useful for users who are new to a platform and have limited interaction history. These recommendations are based on the popularity of items, making them suitable for users without personalized data.

Diverse Content: They help introduce users to a wide variety of content since popular items typically have a broad appeal. This is especially beneficial in platforms like streaming services where users may be looking for trending or widely-liked content.

Cold-Start Problem: Popularity-based systems address the cold-start problem, which occurs when a new user or item has little to no interaction history. Such systems can provide initial recommendations until enough data is collected for personalized recommendations.

Data Sparsity handling: SVD helps address the sparsity problem by reducing the dimensionality of the user-item interaction matrix, enabling the system to infer user preferences even when there are missing data points.

Error Interpretation: RMSE provides a clear interpretation of the prediction errors in the same units as the original ratings. A lower RMSE indicates better model performance, with smaller errors between predicted and actual ratings.

Comparison Across Models: RMSE allows for direct comparison of different recommendation algorithms, enabling data scientists and researchers to choose the most effective approach for a given dataset.

Solution statement/ Proposed approach

SubProblem-1 Data Cleaning and Preprocessing

- Reading the dataset
- Removing NULL values
- Dropping unnecessary columns

SubProblem-2 Popularity-Based Recommendation

- Filtering users with sufficient interactions
- Finding popular products based on ratings
- Calculating average ratings and counts
- Defining a function for popularity-based recommendations
- Visualizing product popularity

Solution statement/ Proposed approach (Cont.)

SubProblem-3 Collaborative Filtering System - User-Based

- Creating a user-item interaction matrix
- Defining functions to find similar users and their scores
- Recommending products based on similar users

SubProblem-4 Model-Based Collaborative Filtering

- Transposing the user-item interaction matrix
- Performing Singular Value Decomposition (SVD)
- Calculating the correlation matrix
- Recommending products based on correlations

Solution statement/ Proposed approach (Cont.)

SubProblem-5 Model Evaluation

- Calculating average actual and predicted ratings
- Computing RMSE for model evaluation

Limitations

Changing Preferences: User preferences can evolve over time, and the system might struggle to adapt quickly to these changes, resulting in outdated recommendations.

Privacy Concerns: Collecting and utilizing user data for personalization could raise privacy concerns, leading to potential backlash if users feel their information is being misused.

Limited Context: The system might not fully capture the context of user preferences, leading to recommendations that are contextually irrelevant or inappropriate.

Scalability: As the user base and product catalog grow, the computational complexity of generating personalized recommendations could impact the system's scalability and responsiveness.

Results

1] Popularity Based Recommendation System:

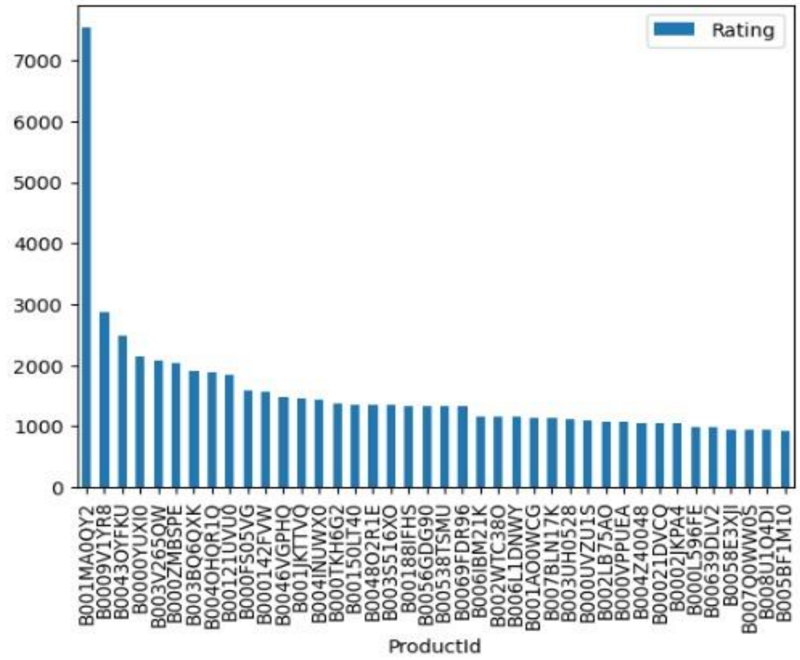

Fig 1.1 Ratings of Products

Results (Cont.)

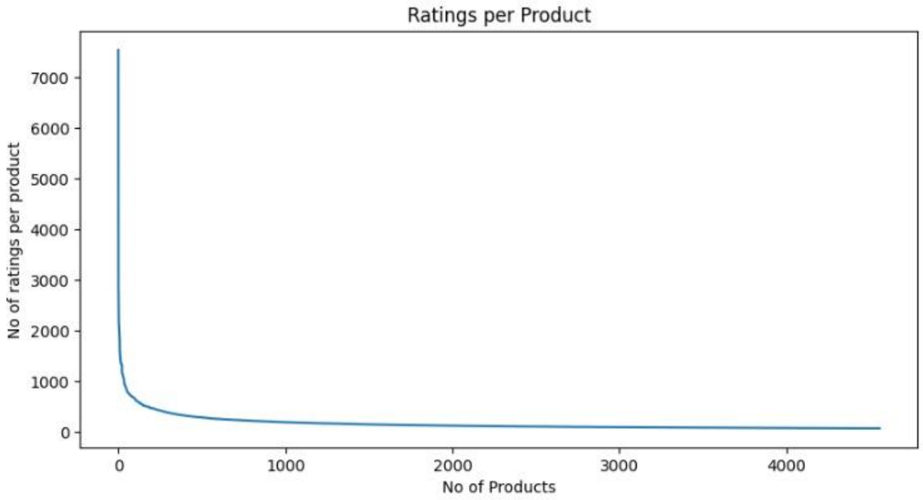

Fig1.2 Ratings per product

```
Top 10 products with 60 minimum interactions based on popularity are
['B000G686X6',
 'B000127UUA',
 'B000052YN7',
 'B0009R34JI',
 'B000127UVY',
 '9790790961',
 'B00004TMFE',
 'B00004TUBL',
 'B00004TUBV',
 'B00004U9UY']
```

Fig1.3 Top 10 Products recommended with more than minimum interactions set

Results

2] Collaborative Filtering:

2.1] User based Collaborative Filtering

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Top 10 similar users to the user index 3 are
[46, 81, 98, 101, 104, 180, 201, 282, 513, 517]
```

Fig 2.1.1 Similar Users are listed based on Similarity Score

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5 products recommended to user index 3 based on user similarity are
['B00005O0MZ', 'B0000YUXI0', 'B00008O2X5', 'B000141YHI', 'B00005B9FV']
```

Fig 2.1.2 Products Recommended to user based on user similarity

Results

2] Collaborative Filtering:

2.2] Model Based Collaborative Filtering

```
Top 10 products that a user might like the most are
['9790790961',
 'B000052WYN',
 'B000052YP6',
 'B000052ZTY',
 'B0000534VO',
 'B0000535CH',
 'B000056KK0',
 'B00005O0MZ',
 'B00006FDU6',
 'B00007M0CP']
```

Fig 2.2.1 Top 10 products that a user might like the most

Future Scope

Dynamic Weights: Experiment with different ways of calculating the weights for the correlation matrix in collaborative filtering to give more importance to recent user interactions.

Real-Time Updates: Implement mechanisms to update the recommendation models in real-time as new user interactions and product data become available.

A/B Testing: Implement A/B testing to validate the performance of different recommendation algorithms and models with real users.

Interactive Interface: Create an interactive user interface or integrate the recommendation system into an existing platform to provide a seamless and user-friendly experience.

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Thank You