Flipkart GRiD 5.0

Problem Statement Title: Personalized Product Recommendations
Team Name: Ginyu Force

Team members details

Team Name	GinyuForce		
Institute Name/Names	Graphic Era Deemed to be University		
Team Members >	**1(Leader)**	**2**	**3**
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Batch	2020-2024	2020-2024	2020-2024

IDEA + OVERVIEW

Personalized Product recommendations are used to enhance the scalability of an e-commerce website. We have combined different recommendation approaches to recommend the products based on user search history and similarity between users and items.

Gathered the data from multiple sources, which include skin care product data, book data, and clothing image data, using web mining.

We applied EDA (exploratory data analysis) to the textual data of books and skin care, which consists of rating products and user IDs associated with rating and CTR.

For the image dataset, we first preprocessed the data, and since we had enough data, we extracted the features from the images using the Resnet50 model.

Then created an item-user and item-item matrix for skin and book data, then used matrix factorization for SVD (Singular Value Decomposition) and the similarity calculation approach for calculating K nearest neighbors in N-dimensional space.

To display the recommended products based upon the user's search history and trending products based on CTR, we created a platform using MERN stack and Flask with homepages, user profiles, cart details, and the history of the user.

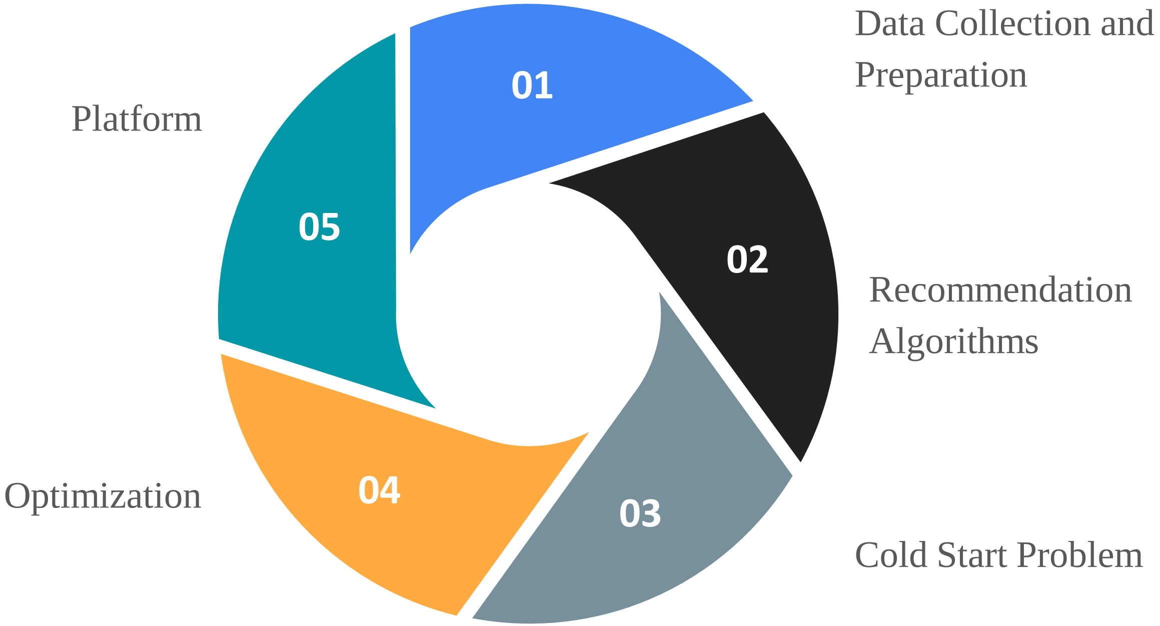
To improve application reliability, uptime and performance, we followed the microservice architecture with Node JS and Flask.

Glossary

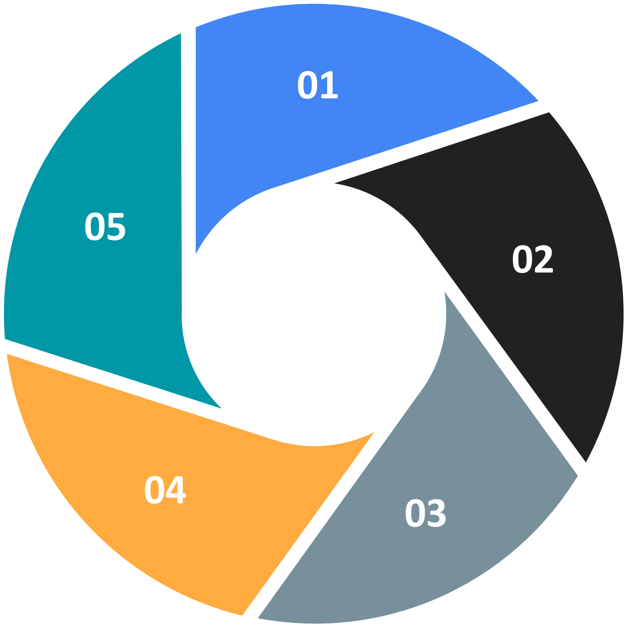
- **CTR : Click Through Rate (The number of clicks that product receives divided by the number of times it is shown)**
  Formula : CTR = Clicks/Impressions * 100

- **SVD : Singular Valued Decomposition (used in matrix factorization, a technique to decompose a matrix into three separate matrices that capture underlying latent factors)**

Sub Problems



Recommendation Algorithms



Collaborative filtering

Building models based on user-item interactions and leveraging similarities between users or items.

Content-based filtering

Recommending items based on user profiles and item attributes.

Deep learning models

Used ResNet50 to extract multiple features from images and used for similarity computation.

Matrix factorization

use SVD algorithm for decomposing user-item interaction matrices to discover latent factors.

Hybrid approaches

Combining collaborative and content-based methods to improve recommendation quality.

Data Collection and Preparation

We used web scraping to gather the data. Our data initially includes the following categories: apparel, skin care products, and books.

Recommendation Algorithms

We tested every recommendation algorithm for several product categories before selecting the best one for each one.

- Books :Hybrid Approach (SVD and KNN Results Blended based on User Ratings)
- Skin Products : Content Filtering (Based on Attributes)
- Apparel : Recommendation based on features extracted from Product Image

Cold Start Problem

For new users, we have provided the trending products based on CTR(Click Through Rate) score

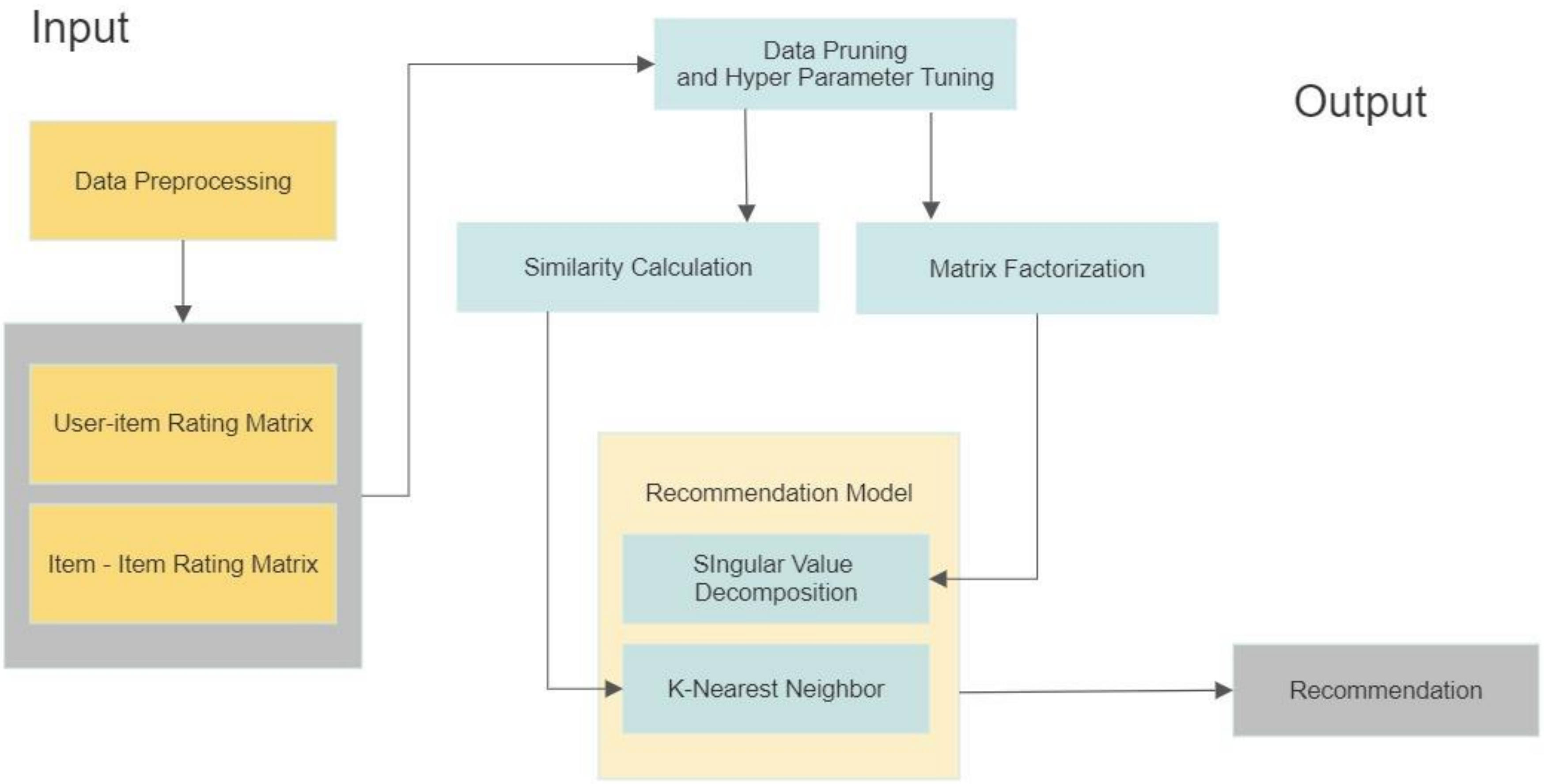
Optimization

Tuned model parameters and hyperparameters to optimize recommendation performance.

Platform

Built an E-commerce website to help users in getting personalized recommendations based on their search history and product similarities

Workflow Diagrams


Input
Data Preprocessing
User-item Rating Matrix
Item - Item Rating Matrix
Data Pruning
and Hyper Parameter Tuning
Similarity Calculation
Matrix Factorization
Recommendation Model
SIngular Value
Decomposition
K-Nearest Neighbor
Output
Recommendation

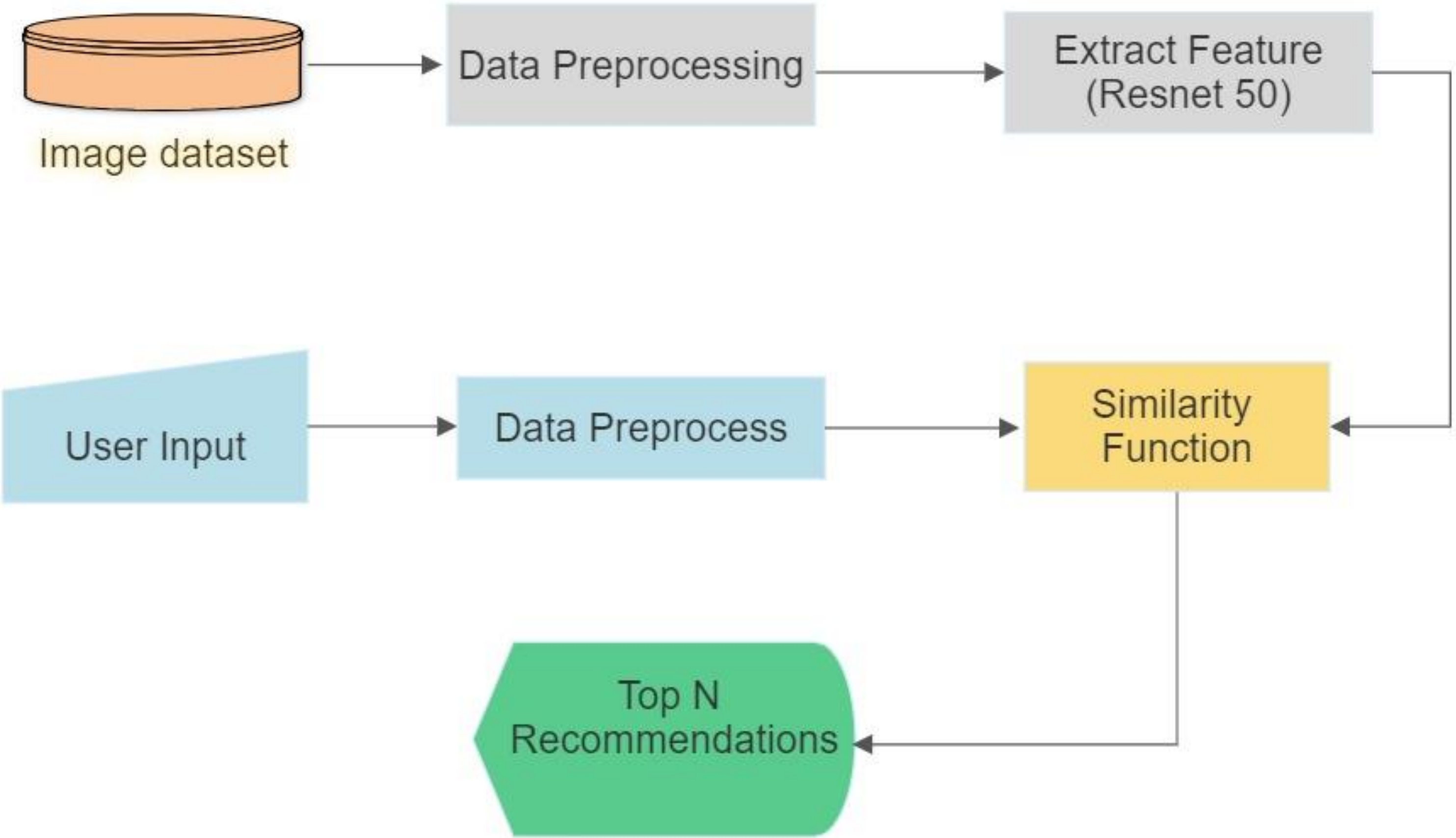
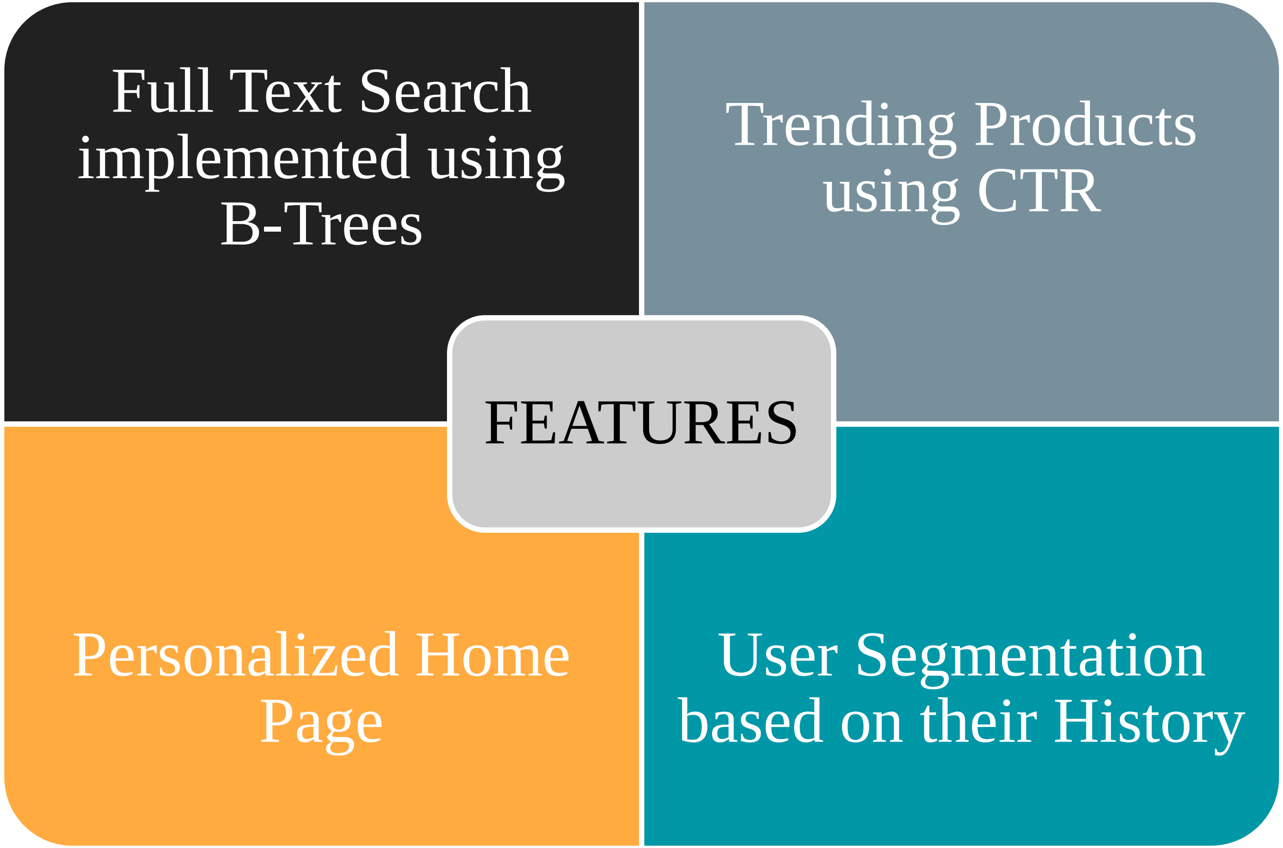


Image dataset
Data Preprocessing
Extract Feature (Resnet 50)
User Input
Data Preprocess
Similarity Function
Top N Recommendations


Full Text Search implemented using B-Trees
Trending Products using CTR
FEATURES
Personalized Home Page
User Segmentation based on their History

Use-Cases

P0. User Engagement:

- Recently Viewed Items: Displaying items a user has recently viewed, making it easier for them to revisit products of interest.

P1. Discovery and Exploration:

- Similar Products: Offering alternatives to a product a user is currently viewing, expanding their options.
- - Trending or Popular Items: Showcasing popular products to users, increasing their exposure to trending items.

P2. Personalized Deals and Offers:

- Personalized Product Suggestions: Recommending products to users based on their browsing history, purchase behavior, and preferences, increasing the chances of conversions.
- Similar Products Suggestions: Suggesting complementary products that are often purchased together, encouraging cross-selling.

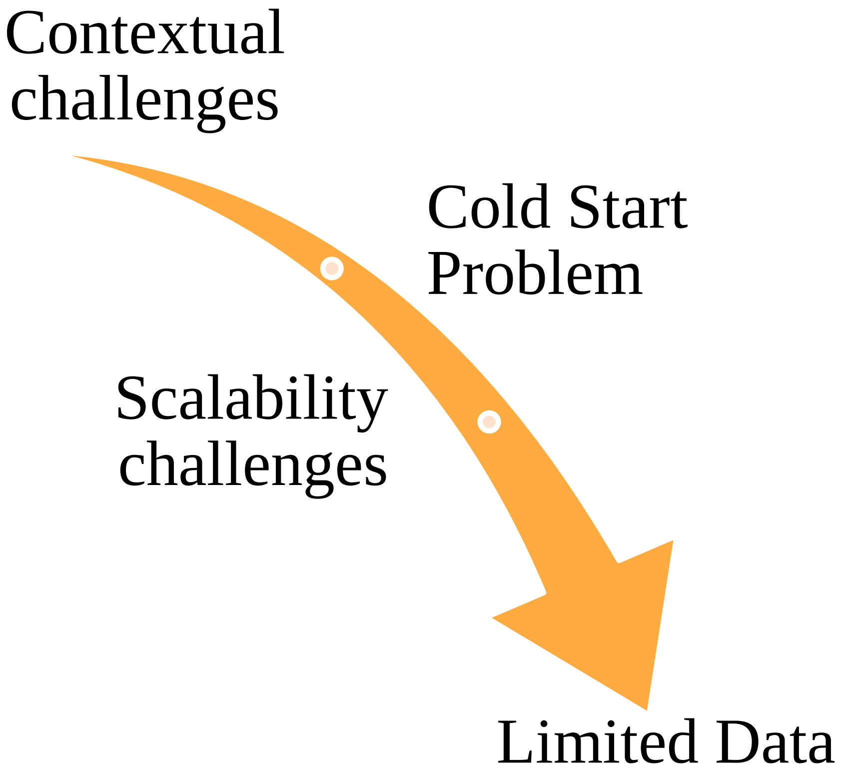
P3. Cross-Device and Multi-Platform Recommendations

- Consistent Experience: Ensuring that recommendations are consistent across different devices and platforms to provide a seamless user journey.

P4. User-Generated Content Recommendations:

- Product Reviews and Ratings: Displaying products with high user ratings or positive reviews to instill confidence in the purchase decision.

Limitations



Future Scope

We will also take into account demographic factors (such as location, weather, etc.) to provide a more precisely targeted response.

Using the item-item similarity and factorization machine method, we will offer a better product section in comparable values of item characteristics. For instance, if a user is seeking for a smart phone, the system will suggest a better selection based on its features.

Evaluation Metrics of our Recommender Model

```
Evaluating Collaborative Filtering (SVD Matrix Factorization) model...
448 users processed

Global metrics:
{'modelName': 'Collaborative Filtering', 'recall@5': 0.2357298474945534, 'recall@10': 0.3053982086661825
```

	hits@5_count	hits@10_count	interacted_count	recall@5	recall@10	User-ID
10	260	338	1389	0.187	0.243	11676
31	191	242	1138	0.168	0.213	98391
45	20	31	380	0.053	0.082	189835
30	85	102	369	0.230	0.276	153662
70	29	35	236	0.123	0.148	23902
7	30	49	204	0.147	0.240	235105
47	22	30	203	0.108	0.148	76499
50	26	36	193	0.135	0.187	171118
42	62	72	192	0.323	0.375	16795
43	20	30	188	0.106	0.160	248718

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Thank You