

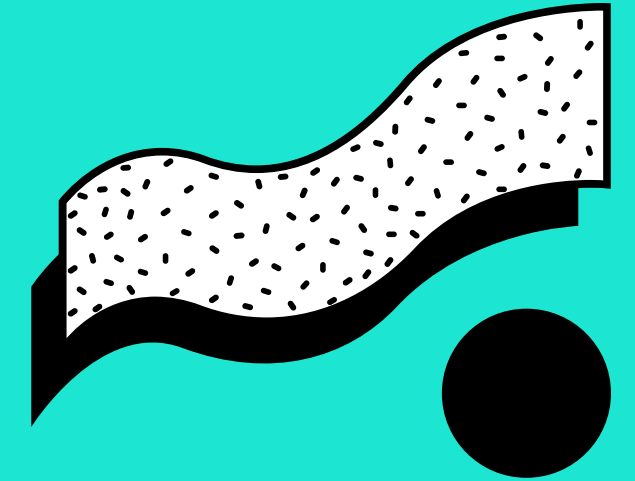


Problem Statement Title: Personalized Product Recommendations
Team Name: Neural Byte

Team members details

Team Name	Neural Byte		
Institute Name/Names	Chandigarh University		
Team Members >	1 (Leader)		
Name	Granth Gaurav		
Batch	2025		

USE-CASES



ENHANCED USER EXPERIENCE

P0

Tailored product recommendations to each user's interests, preferences, and historical interactions, leading to a more engaging and relevant shopping experience.

INCREASED CUSTOMER ENGAGEMENT

P1

By suggesting products that users are more likely to be interested in, the platform can encourage users to explore additional products, increasing their time spent on the platform.



CUSTOMER RETENTION

P2

Continuous personalized recommendations can create a sense of loyalty by making users feel understood and valued, leading to repeat visits and purchases.

SOLUTION STATEMENT

Developing an intelligent product ranking system that employs advanced algorithms combined to prioritize and recommend products based on user preferences and past behavior, enhancing user satisfaction and engagement.



**FROM ONLINE SHOPPING TO
VIDEO APPS, RECOMMENDERS
ACCOUNT FOR:**

40% of app installs on Google Play

60% of watch time on YouTube

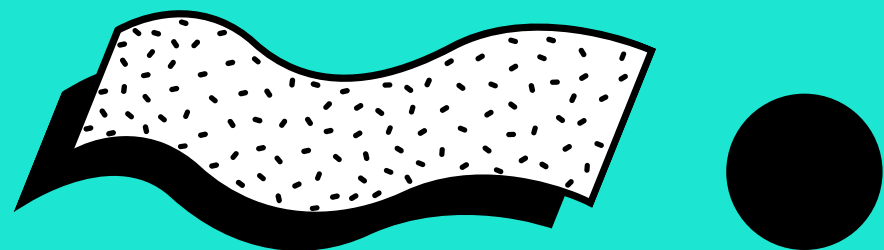
35% of purchase on Amazon

75% of movie watches on Netflix



PROPOSED APPROACH

Our approach calculates a user's interest in each product category based on their past interactions with products. We then apply both Collaborative and Content-based Filtering techniques to the data, also using the Louvain Clustering algorithm to detect user communities. The results from these methods are combined to generate a diverse and personalized set of recommendations for each user.



01

USER INTEREST CALCULATION

02

HYBRID-BASED FILTERING

03

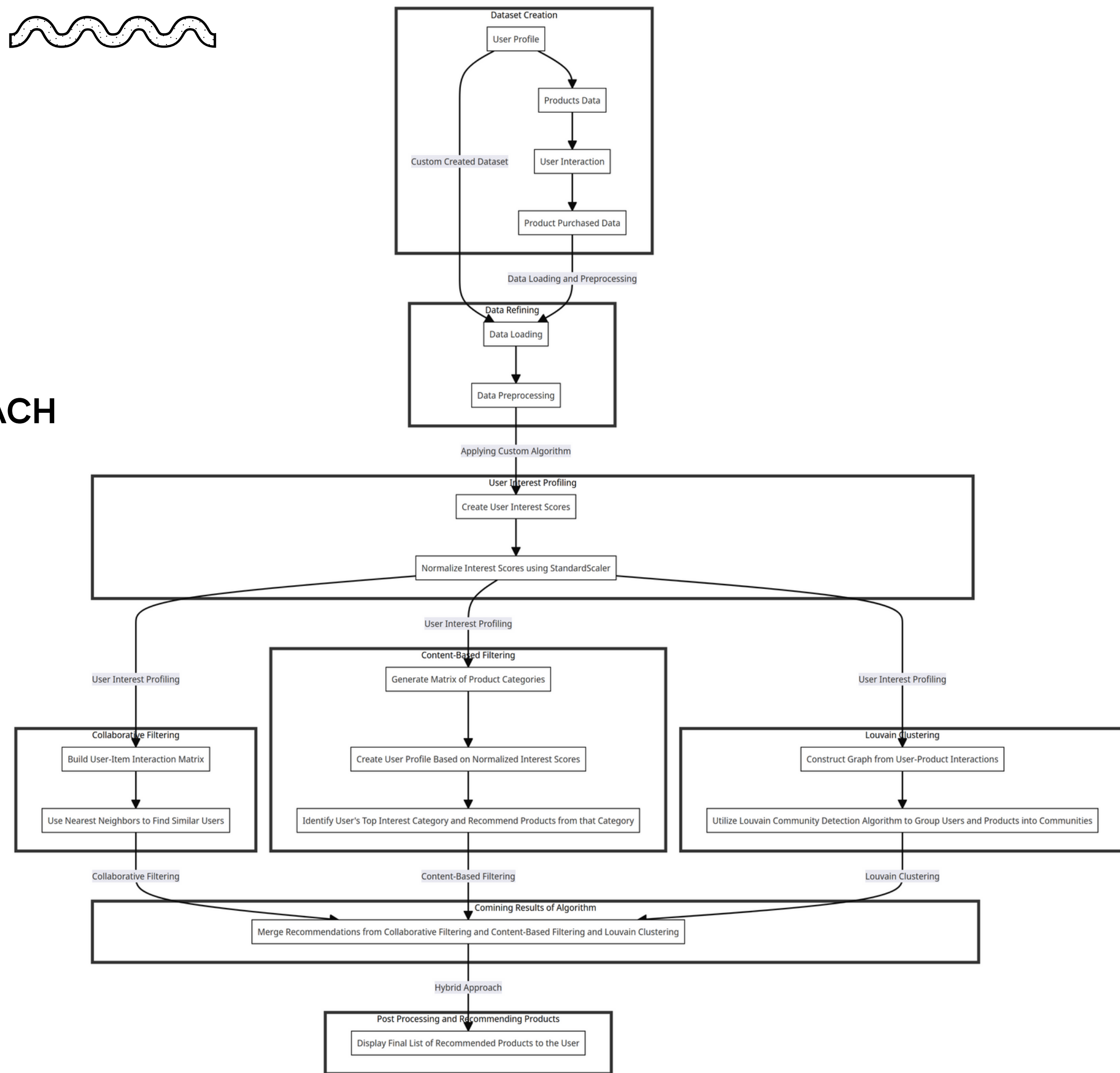
COMMUNITY DETECTION

03

COMBINNING RESULTS FROM
ABOVE AND
RECOMMENDATION

SOLUTION ARCHITECTURE

DETAILED FLOWCHART OF PROPOSED APPROACH



01 DATA COLLECTION & USER INTEREST PROFILING

	User ID	Age	Gender	Location	Subscription Status
0	1867	40	Other	Goa	Free
1	192196	26	Male	Goa	Free
2	2947027	41	Female	Odisha	Free
3	412464778	51	Male	Gujarat	Free
4	8926359	47	Male	Madhya Pradesh	Free

	Purchase ID	User ID	Product ID	Purchase Timestamp	Rating
0	8638	1867	7109	2023-02-25 21:20:16	3.30
1	306	1867	41731074	2023-03-09 17:02:42	1.86
2	7354314	1867	307	2023-07-08 19:14:25	3.27
3	832167	1867	18581990	2023-01-30 08:20:29	1.67
4	17465902	1867	6659212	2023-03-04 14:04:08	3.81

	Interaction ID	User ID	Product ID	Interaction Type	Interaction Timestamp
0	0	1867	65663	Added to Cart	2023-03-03 10:06:24
1	1	1867	29042	Viewed	2023-04-24 08:31:32
2	2	1867	991294	Added to Cart	2023-06-30 10:23:55
3	3	1867	7109	Purchased	2023-02-22 23:38:06
4	4	1867	342	Added to Cart	2023-03-09 10:03:20

	User ID	Category	Interest Score	Avg Purchase Rating	Final Interest Score
0	0	Beauty	11.685000	3.895	7.790000
1	0	Books	NaN	0.000	NaN
2	0	Electronics	4.150000	2.075	3.112500
3	0	Home	7.200000	2.400	4.800000
4	1	Beauty	3.583333	2.150	2.866667

	Product ID	Product Name	Category	Price	Brand	Features	Average Rating	Number of Ratings	Availability
0	19611	gun Electronics	Electronics	332.201943	Gonzalez, Rivera and Green	4K resolution, Bluetooth connectivity, Wireles...	4.39	295	Out of Stock
1	94589	authority Electronics	Electronics	336.608005	Ball Ltd	Wireless charging, 4K resolution, Touchscreen ...	2.38	305	In Stock
2	669771	type Electronics	Electronics	426.109655	Wells-Webster	Bluetooth connectivity	3.43	441	In Stock
3	763094	ok Electronics	Electronics	56.389406	Finley, Hill and Hansen	4K resolution	2.44	455	In Stock
4	23288	help Electronics	Electronics	30.224928	Ball Ltd	Bluetooth connectivity, 4K resolution	2.24	230	In Stock

SAMPLE OF CUSTOM CREATED DATA

Initial step was gathering data for this I built a Python Script which created necessary real-world like data, the datasets includes data of **User Profile, User Interaction, Product Details, Purchased Details.**



The "**Interest Score**" is a calculated metric that represents a user's level of interest in a specific product category.

It is computed by **combining weighted interaction type** (based on interaction type) and **average purchase ratings to a product.**

COLLABORATIVE FILTERING

- Built a **User-Item** interaction matrix from purchase history.
- Used **Nearest Neighbors** to find similar users for collaborative filtering.
- Significance: Collaborative filtering leverages user behavior for personalized suggestions.

CONTENT-BASED FILTERING

- Generated a **Matrix of product categories**.
- Created a user profile based on normalized interest scores.
- Significance: Content-based filtering matches user preferences with product attributes.

02 HYBRID FILTERING & LOUVAIN CLUSTERING

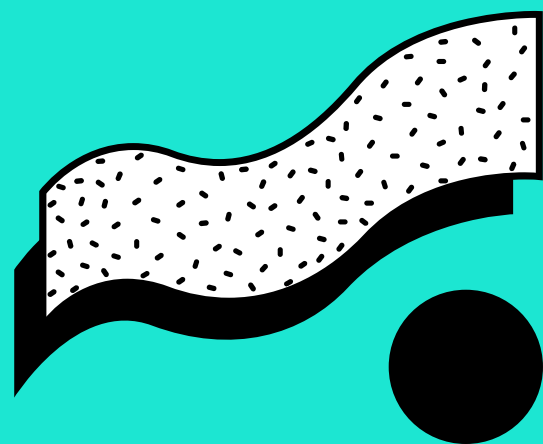
LOUVAIN CLUSTERING

- Constructed a **Graph** from **User-Item** interactions.
- Utilized Louvain **Community Detection** algorithm to group users and products into communities.
- Identified the user's community and products in the same community.
- Significance: Community detection enhances personalization by considering user groups with shared preferences.

03 COMBINING ALGORITHM RESULTS & POST PROCESSING

Collaborative and content-based filtering, and community detection techniques used to recommend products by creating a unified set of recommendations.

These techniques results are **Combined as Set Union based on different weights calculated through Linear Regression**, ensuring a holistic and personalized recommendation.



The Recommendation of product were further processed on the basis whether the **User have already purchased or the items are already added to cart or the product is out of stock**, then those products are removed from final recommendation to user.

For New User's a curated list of top rated and purchased products are recommended.

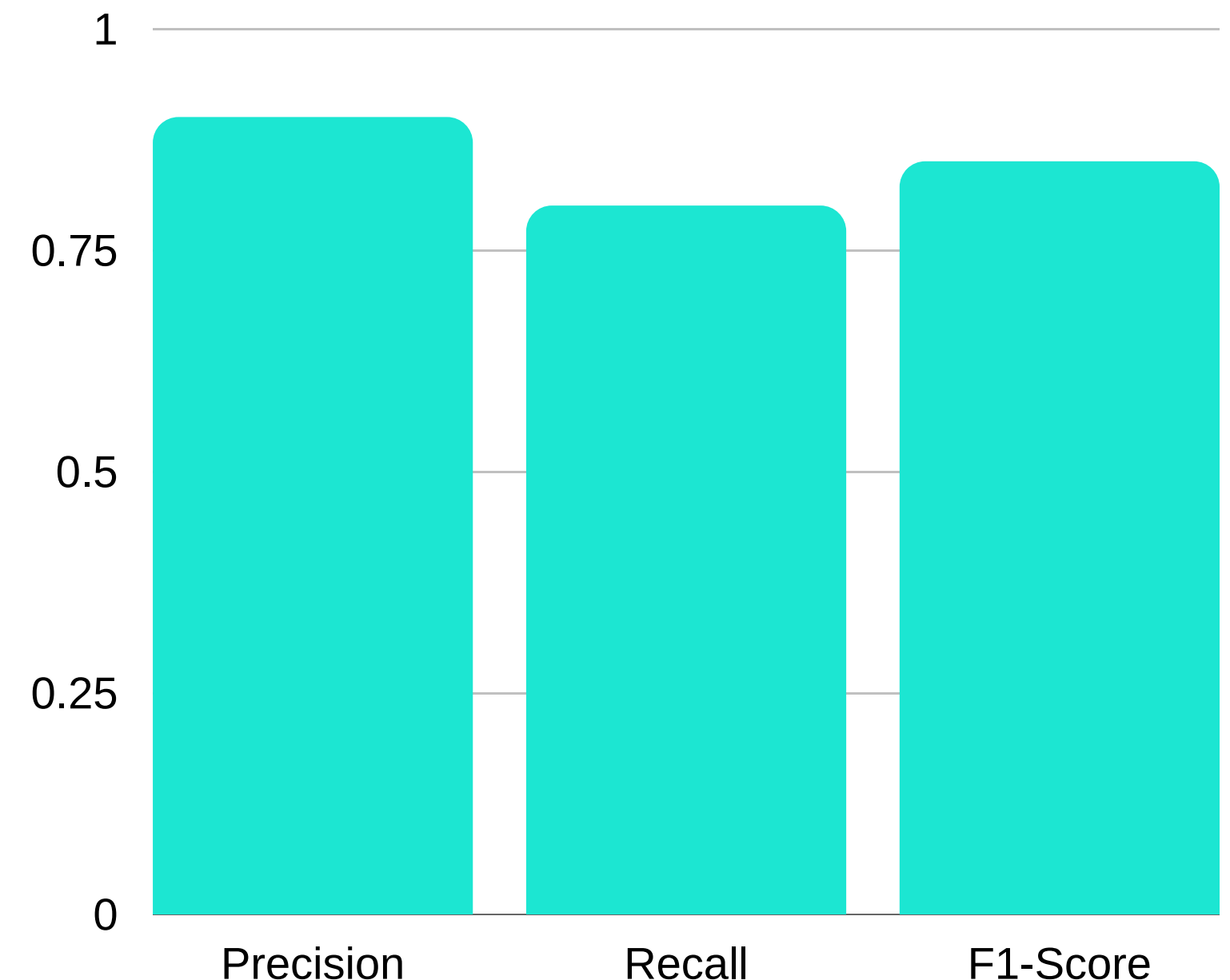
EVALUATION

The system's evaluation involved assessing **Precision, Recall, and F1-Score** metrics for recommending the top N products to users.

In the absence of actual ground results to evaluate the recommendation system, a **Simulation was conducted using relevant items based on the user's actual purchases and add-to-cart actions.**

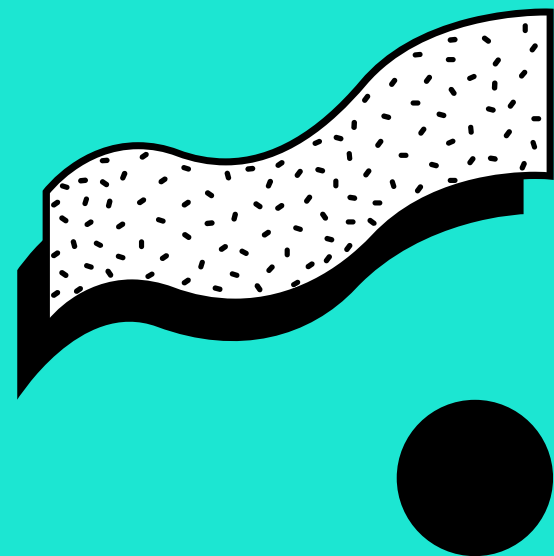


By comparing simulated recommendations with actual relevant products, we calculated average precision, recall, and F1-Score@N to gauge the system's accuracy, coverage, and overall performance.



ACTUAL RESULT GRAPH WITH SIMULATED DATA

LIMITATIONS



COLD START PROBLEM

The system may struggle to make accurate recommendations for new users who haven't yet provided sufficient interaction data, leading to less personalized suggestions.

DATA SPARSITY

If users have limited interactions or preferences, the system might not have enough data to generate accurate recommendations, reducing the quality of suggestions.

STATIC PREFERENCES

User preferences can change over time, but the system may not adapt quickly, leading to recommendations that are outdated or no longer relevant.

FUTURE SCOPE

By embracing these future scopes, we are confident in our ability to create a recommendation system that not only meets our current needs but also anticipates and adapts to the evolving preferences and expectations of the users.

EXTERNAL DATA SOURCES

Incorporating external data sources, such as social media activity or trending topics, can enrich the recommendation process and provide a broader understanding of user preferences.



CONTEXTUAL UNDERSTANDING

To incorporate contextual understanding, such as time of day, user location to fine-tune recommendations. The recommendations are not only with preferences but also relevant to the immediate context.

CUSTOMIZABLE RECOMMENDATIONS

Offering users the ability to customize their recommendation settings—such as adjusting the balance between novelty and familiarity—will empower them to curate their own experience.



Thank You