



Problem Statement Title: *Personalised product recommendation*

Team Name: Team MahaDevs

TEAM

MEMBERS DETAILS

TEAM NAME	Team MahaDevs		
INSTITUTE NAME	University School of Automation & Robotics (USAR), GGSIPU		
TEAM MEMBERS	Leader (1)	Team Member(2)	Team Member(3)
NAME	Shubh Sardana	Aditya Singh	Ayush Gupta
BATCH	2025		



RECOMMENDING PRODUCTS BASED ON USER'S PAST PURCHASE HISTORY



1. Addressing Repetitive Purchases

- Why This Use Case?
 - Users often exhibit consistent fashion preferences, leading to repetitive purchases.
 - By leveraging past purchase history, we can cater to users' known preferences.

2. Transaction Handling Assumptions

Assumptions Made:

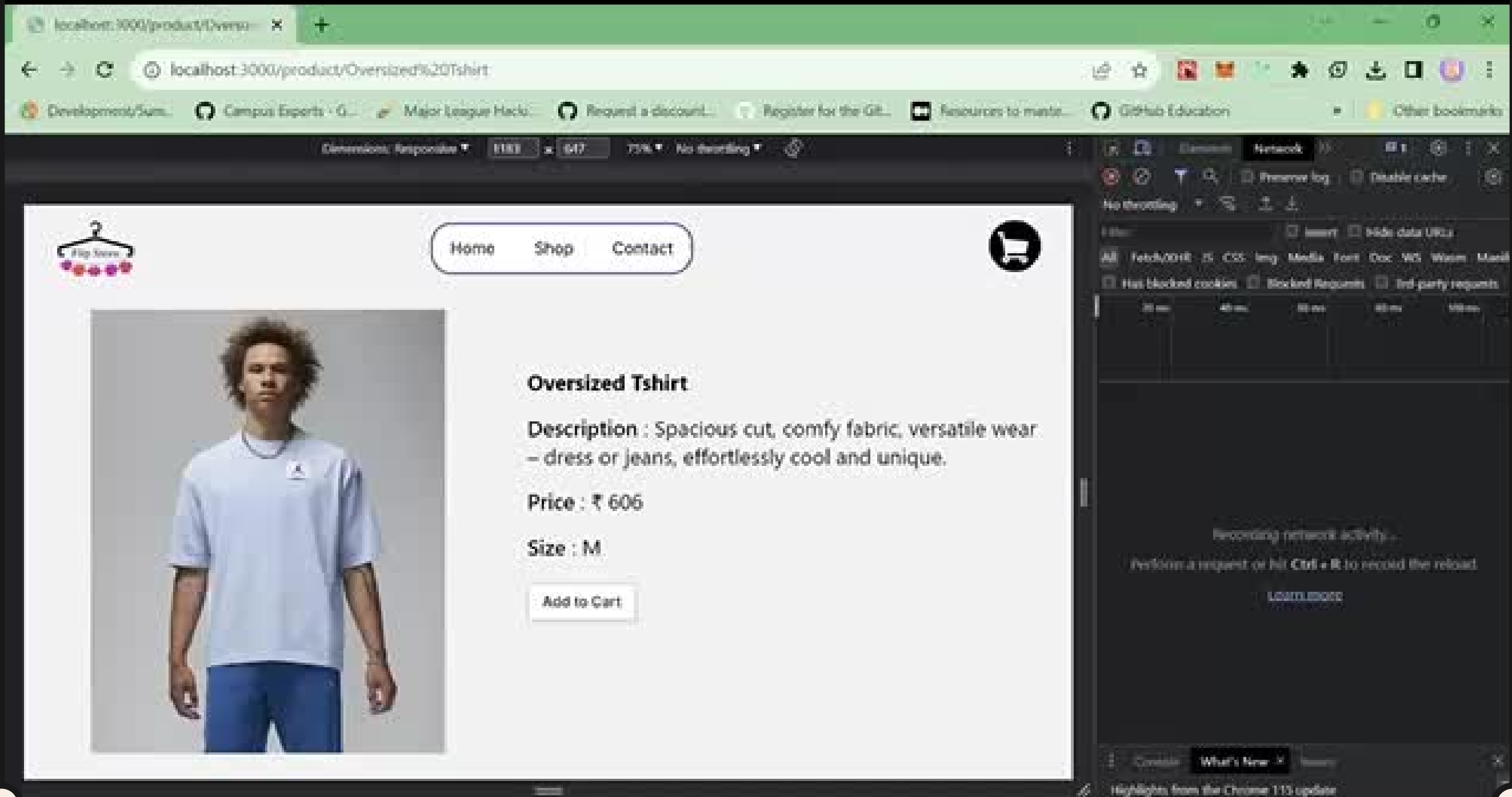
- Assumed that users may repeat transactions for the same items.
- Considered that previous identical transactions might be removed from the dataset.

3. Solution Approach and Algorithm Choice

- Concluded that forming associations between products was crucial for capturing user preferences.
- Chose Apriori due to its simplicity and effectiveness in capturing frequent itemsets.

4. Validating Algorithm Performance

- Conducted experiments to compare Apriori with other algorithms.
- Evaluated performance metrics such as execution time and association accuracy.
- Apriori demonstrated satisfactory results for our small-moderate-sized dataset.





RECOMMENDING PRODUCTS BASED ON RATINGS FROM OTHER SIMILAR USERS



1. Leveraging User Similarity:

- Why This Use Case?
 - Users from the same region often share similar clothing and fashion patterns.
 - Recommending items based on similar users' preferences can lead to relevant suggestions.

2. Similarity Identification Assumptions

- Assumed that users with similar purchasing behaviors share common preferences.
- Considered that users' ratings reflect their satisfaction with items.

3. Validation through Experimentation:

- Conducted experiments to compare different collaborative filtering methods.
- Evaluated accuracy and performance of recommendation predictions.
- Memory-based Collaborative Filtering demonstrated superior results for our use case.

4. Solution Approach and Algorithm Choice

Utilizing Memory-based Collaborative Filtering:

- Chose Memory-based Collaborative Filtering with nearest neighbors algorithm.
- Nearest neighbors algorithm identifies users with similar trends using user rating data.

localhost:3000/home

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Curious to See What Matches Your Taste? Us Too. Let's Explore!

Unlock Your Unique Style: Ready to Find Your Ideal Products?

Curious to See What Fits Your Taste? Let's Drive Together!

Let's Dive Together!

Anarkali kurti

Synthetic Sandals

Oversized Tshirt

Suggested for you

Oversized Tshirt

₹ 600

Party wear boots

₹ 700

Running Shoes

₹ 1200

Network

28

Pause log Double click

No throttling

Filter

Insert Hide data URIs

Fetch/XHR JS/CSS Img Media Font Doc WS Wasm Manifest

Has blocked cookies Blocked Requests 3rd-party requests

20 ms 40 ms 60 ms 80 ms 100 ms

Recording network activity...

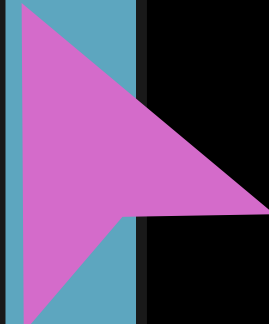
Perform a request or hit Ctrl + R to record the reload.

Learn more

What's New

Network conditions

Highlights from the Chrome 113 update





RECOMMENDING PRODUCTS TO NEW USERS BASED ON PRODUCT RATINGS



1. Engaging New Users with Ratings:

Why This Use Case?

- New users lack purchase history, requiring a different approach to engage them.
- Recommending highly-rated products can capture their interest and trust.

2. Assumptions for New Users:

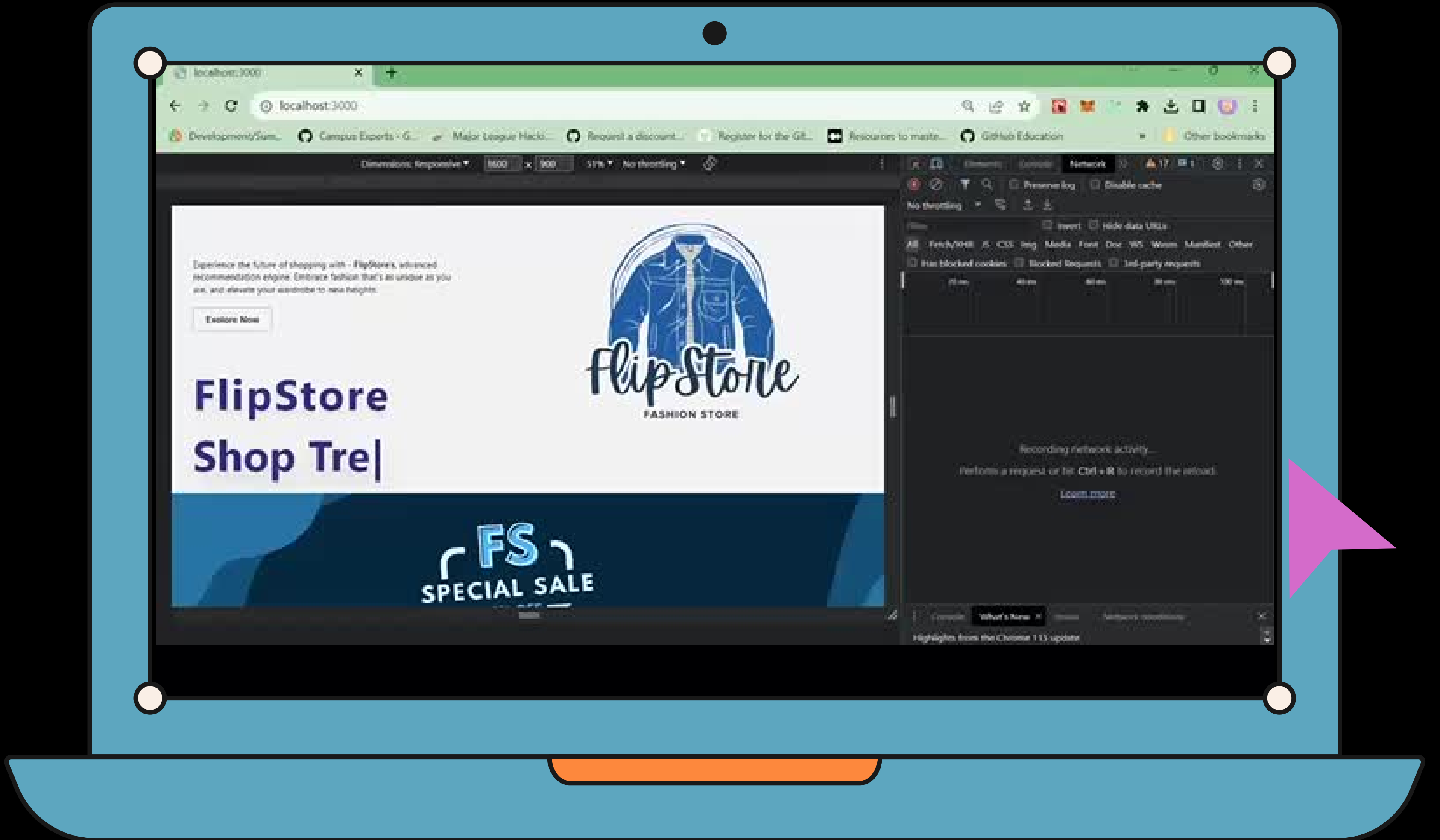
- Assumed that new users' preferences can be inferred from popular product ratings.
- Considered that top-rated items have a higher likelihood of appealing to new users.

3. Validation through Experimentation:

- Conducted experiments comparing different product recommendation methods for new users.
- Evaluated conversion rates and user engagement metrics.
- Ratings-based Filtering with the hybrid strategy demonstrated improved engagement.

4. Solution Approach and Algorithm Choice:

- Ratings-based Filtering with Hybrid Strategy:
- Adopted a hybrid strategy using both ratings count and average ratings.
- Filtered products based on a combination of ratings and average ratings.





RECOMMENDING SIMILAR PRODUCTS BASED ON PRODUCT ADDED IN THE CART



1. Enriching Cart Experience:

Why This Use Case?

- Providing alternate choices for items in the user's cart enhances their shopping experience.
- Diversifying options encourages users to explore more products.

2. Assumptions for Cart Recommendations

- Assumed that users seek variety and options while making a purchase.
- Considered that products similar to those in the cart would be appealing alternatives.

3. Validation through Experimentation:

Item-based Collaborative Filtering Considered:

- Initially explored Item-based Collaborative Filtering for finding item similarities.
- However, observed lower accuracy in recommendations, leading to its discarding.

4. Solution Approach:

Cart-based Recommendation with Grouping:

- Grouped similar items into categories for effective cart recommendations.
- Recommended a random item from the corresponding category when an item was added to the cart.

localhost:3000/product/Oversized%20Tshirt

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Oversized Tshirt

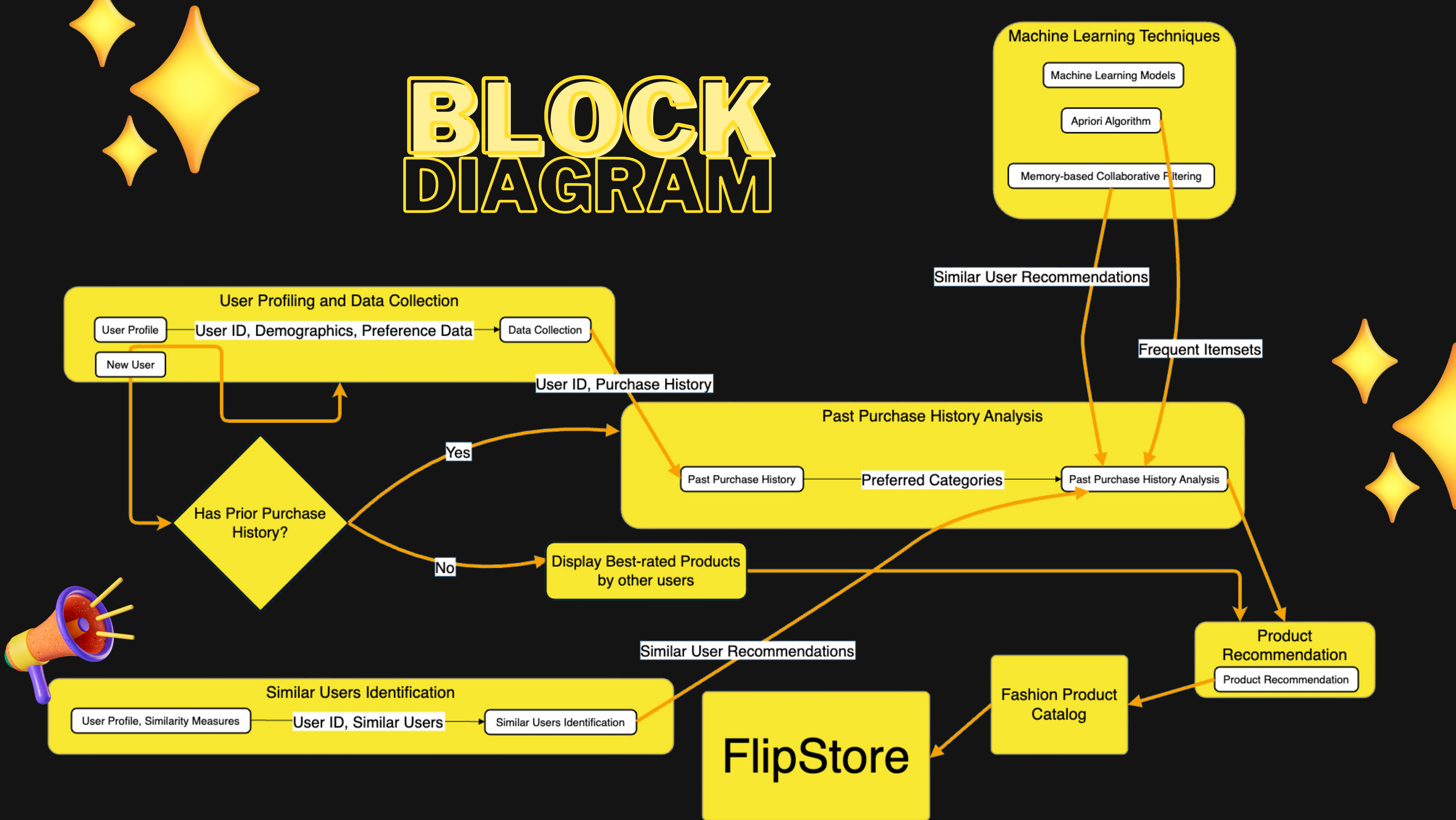
Description : Spacious cut, comfy fabric, versatile wear – dress or jeans, effortlessly cool and unique.

Price : ₹ 606

Size : M

Add to Cart

BLOCK DIAGRAM



LIMITATIONS



1. Dynamic Trend Evolution Challenges:

- Trend Identification Fluctuations: Recommendations might not fully align with users' preferences during transitional trend periods.

2. Limited Contextual Understanding:

Past Purchase History Limitation:

- The recommendations based on past purchase history might not fully grasp the nuanced context behind user preferences.
- Factors such as changing seasons, special occasions, or one-time purchases might not be effectively captured.

3. Homogeneity of Regional Trends:

Ratings from Similar Users Constraint:

- Relying solely on similar users from the same region might result in recommendations that lack diversity.
- Users within the same region can have unique style preferences that extend beyond regional norms.

What makes us unique?

What truly sets FlipStore apart is its fusion of cutting-edge AI, user-centric design, ethical AI practices, and commitment to sustainability. This combination creates a shopping platform that not only adapts to individual preferences but also empowers users to embark on a fashion journey that resonates with their style and values.

FUTURE SCOPE



Hyper- Personalized Recommendations:

- Granular Personalization:
 - Advancing recommendation systems to incorporate granular details like fabric preferences, color choices, and design elements.
 - Providing hyper-personalized product suggestions that resonate deeply with individual users.



Real-time Trend Analysis:

- Real-time Data Processing:
 - Processing data in real-time from social media, fashion blogs, celebrity endorsements, and fashion shows.
 - Analyzing user-generated content and influencer activity to detect rising trends.



FlipGPT

- Empowering Users with GenAI:
 - Introducing FlipGPT, a Conversational Fashion Outfit Generator powered by GenAI.
 - Users can interact with an AI-powered assistant to receive instant, personalized fashion outfit suggestions based on preferences and occasions.