Flipkart GRiD 5.0

Personalized Product Recommendations

Team Name: Code Crusaders

Team members details

Team Name	Code Crusaders		
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Batch	2024	2024	2024

EXPECTATION AND DELIVERABLES

Our project focuses on delivering the mentioned items and concepts

Trained VGG16 model checkpoints.	LightGBM-based ranking algorithm and associated code.
Implementation of RMSE evaluation and other relevant evaluation metrics.	Documentation explaining the analysis, approach, code
Code for image feature extraction using VGG16.	Implementation of SVD for feedback analysis.
Collaborative filtering code using KNN for personalized recommendations.	Detailed analysis of the system's performance using various datasets and scenarios.
Algorithm and code for content-based filtering.	A final report summarizing the findings, challenges faced, and suggestions for future improvements.
PCA implementation for data dimensionality reduction.	

Glossary

VGG16

A deep convolutional neural network architecture designed for image classification and feature extraction tasks. Used in the project to extract image features

RMSE - Root Mean Square Error

A metric used to measure the accuracy of predictions by calculating the square root of the average squared differences between predicted and actual values

Collaborative Filtering

A recommendation technique that predicts user preferences by identifying patterns and similarities between users' preferences and behaviors

KNN - K-Nearest Neighbors Filtering

A method within collaborative filtering that identifies the K most similar users/items to a given user/item for making predictions

Content-Based Filtering

A recommendation approach that leverages user participation in fashion contests or challenges to generate personalized recommendations

PCA - Principal Component Analysis

A dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional representation while retaining the most important information

Glossary

LightGBM

A gradient boosting framework optimized for speed and efficiency in handling large datasets, commonly used for ranking and classification tasks

SVD - Singular Value Decomposition

A matrix factorization technique used to analyze and decompose a matrix into its constituent parts, which can reveal latent factors and patterns

Embedding Layer

A neural network layer that learns and represents categorical variables, such as user and item IDs, in a continuous, lower-dimensional space

Latent Factors

Hidden variables or features that contribute to user preferences and item characteristics, often extracted using matrix factorization techniques

Dimensionality Reduction

The process of reducing the number of features in a dataset while preserving as much information as possible, aiming to improve computational efficiency and reduce noise

TFRS - Tensorflow Recommenders

TFRS is a library for building recommender system models

Use-cases

Personalized Recommendation System find usefulness in many spheres. Starting from E-Commerce to fitness, everything uses Personalized Recommendation to increase engagement. Some of many use cases are listed in this table.

#	Use cases of Personalized Recommendation System
P0	Personalized recommendations for E-commerce platforms
P1	Helps users achieve fitness goals by suggesting tailored workout routines
P2	Boosts ads engagement and conversion rates
P3	Enhances learning by suggesting courses aligned with a learner's goals
P4	Increased retention and engagement for streaming platforms
P5	Boosts travel bookings by suggesting appealing destinations
P6	Increases average order values by suggesting complementary dishes
P7	Encourages users to support causes aligned with their values and interests
P8	Helps users make informed investment decisions leading to higher returns

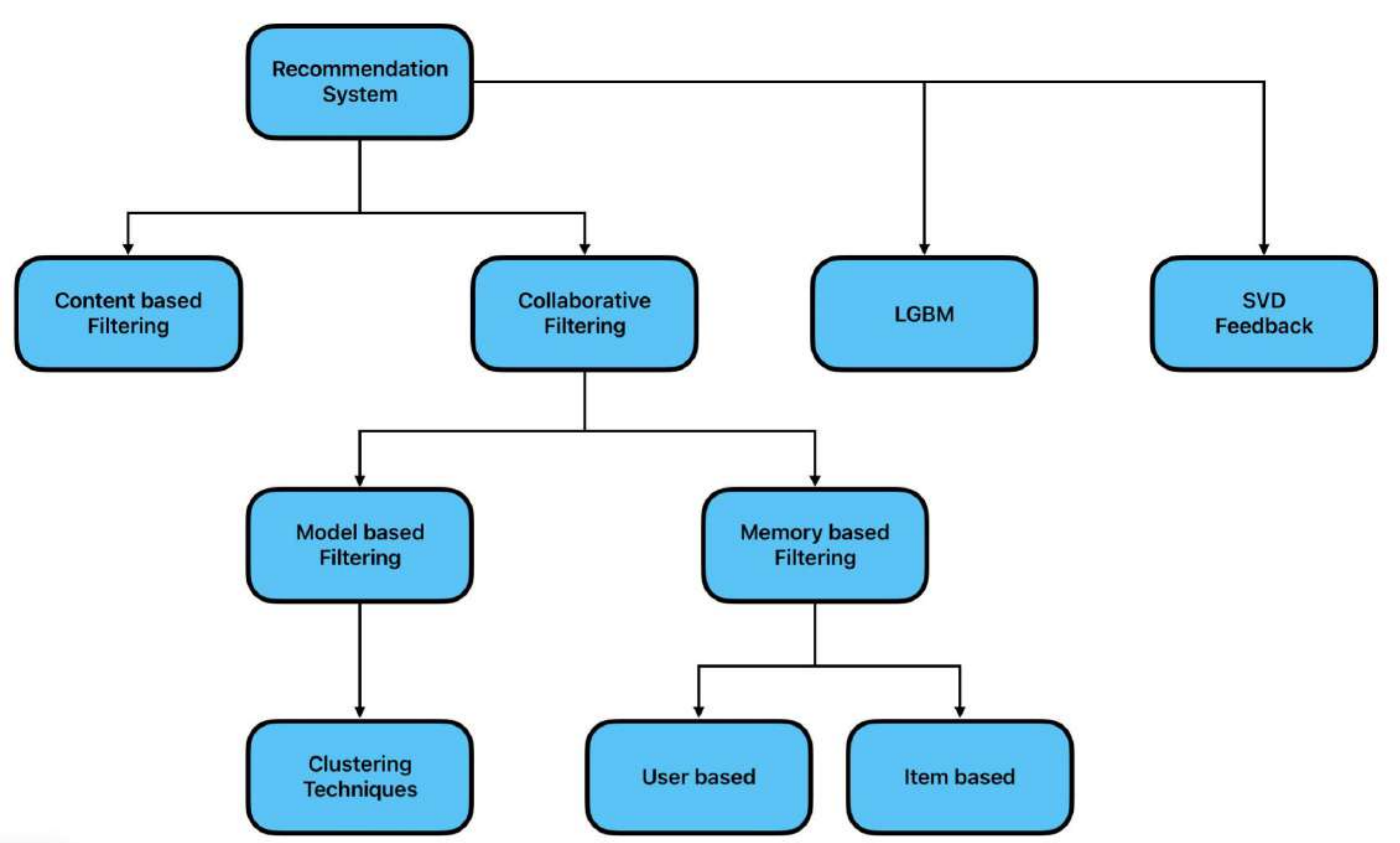
Sub-Problem & Solution Table

	Sub-problem	Solution
Image Feature Extraction	Extract meaningful features from fashion images to understand their visual characteristics	Utilize the VGG16 deep learning model to extract high-level image features, capturing patterns and visual elements
User Preference Prediction	Predict user preferences based on their interactions and behaviors	Implement collaborative filtering using K-Nearest Neighbors (KNN) to identify similar users and make item recommendations based on their preferences
Contest-Driven Recommendations:	Provide recommendations based on user participation in fashion contests	Develop an algorithm that considers user contest activity and generates fashion item suggestions aligned with contest themes a

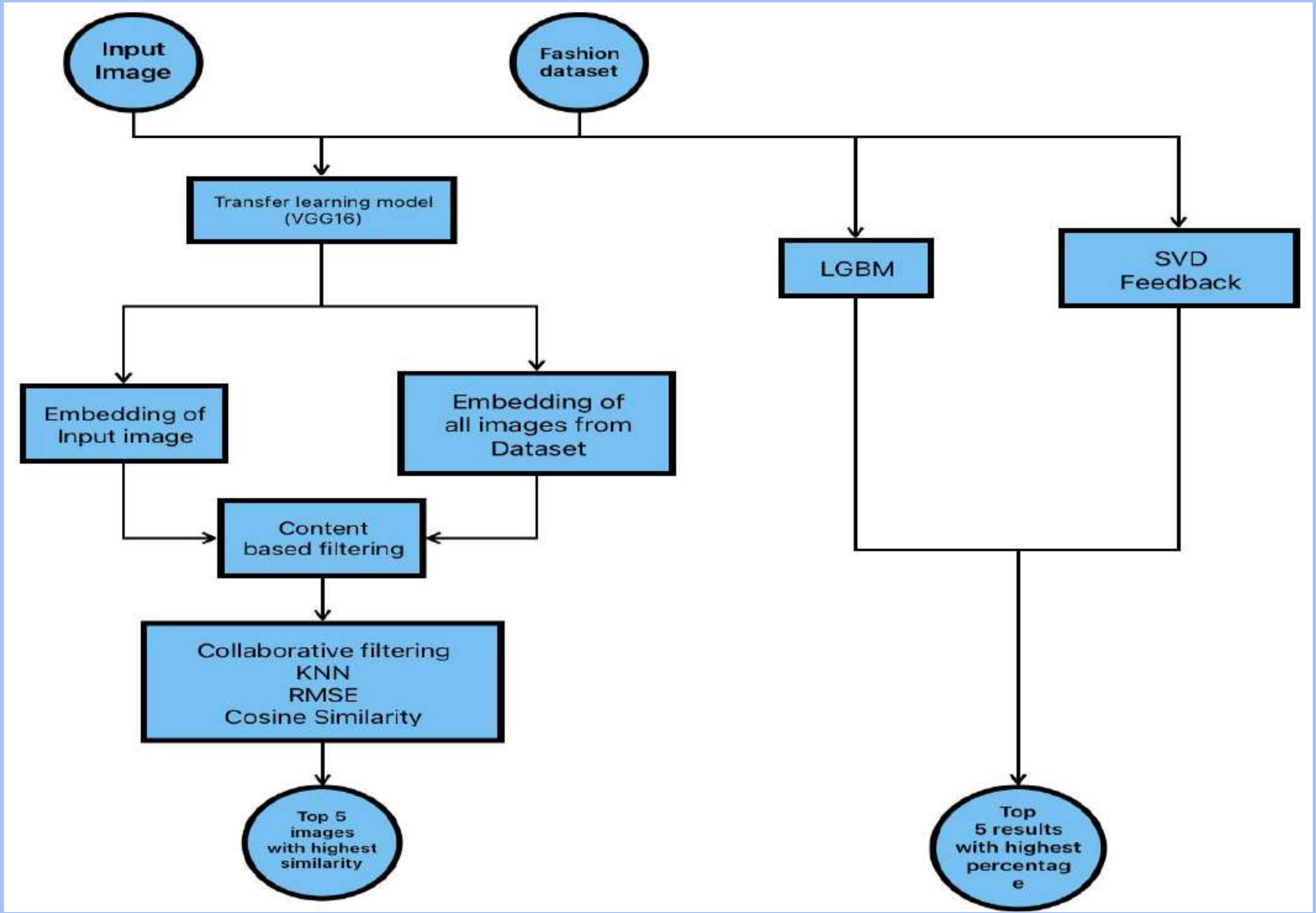
Sub-Problem & Solution Table

	Sub-problem	Solution
Data Dimensionality Reduction	Reduce the dimensionality of user-item interaction data for improved efficiency and noise reduction	Apply Principal Component Analysis (PCA) to transform the data into a lower-dimensional representation while preserving essential information
Ranking and Fine-Tuning	Rank recommended items to enhance the relevance of suggestions	Utilize LightGBM, a gradient boosting framework, to fine-tune the ranking of fashion items based on user preferences and other relevant factors
Feedback Analysis	Extract insights from user feedback to refine recommendations	Employ Singular Value Decomposition (SVD) to uncover latent factors that contribute to user preferences and item characteristics
Embedding for Representation	Transform categorical variables like user and item IDs into continuous representations	Integrate embedding layers into the model architecture to learn dense embeddings for users and items, enhancing recommendation accuracy

Overall Approach



Model building and recommendation



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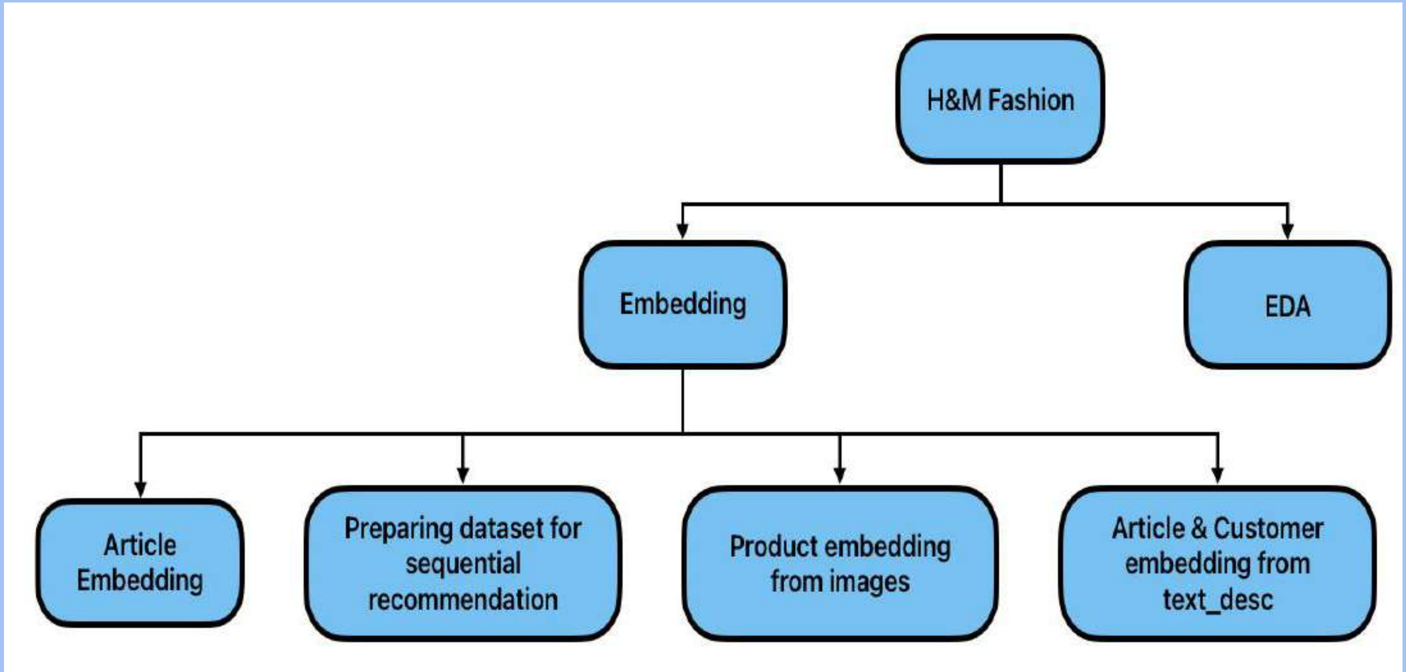
Analysis of data and image sampling for recommendation



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Result based on Input

Fig 1: Recommendations based on input

Result based on user history

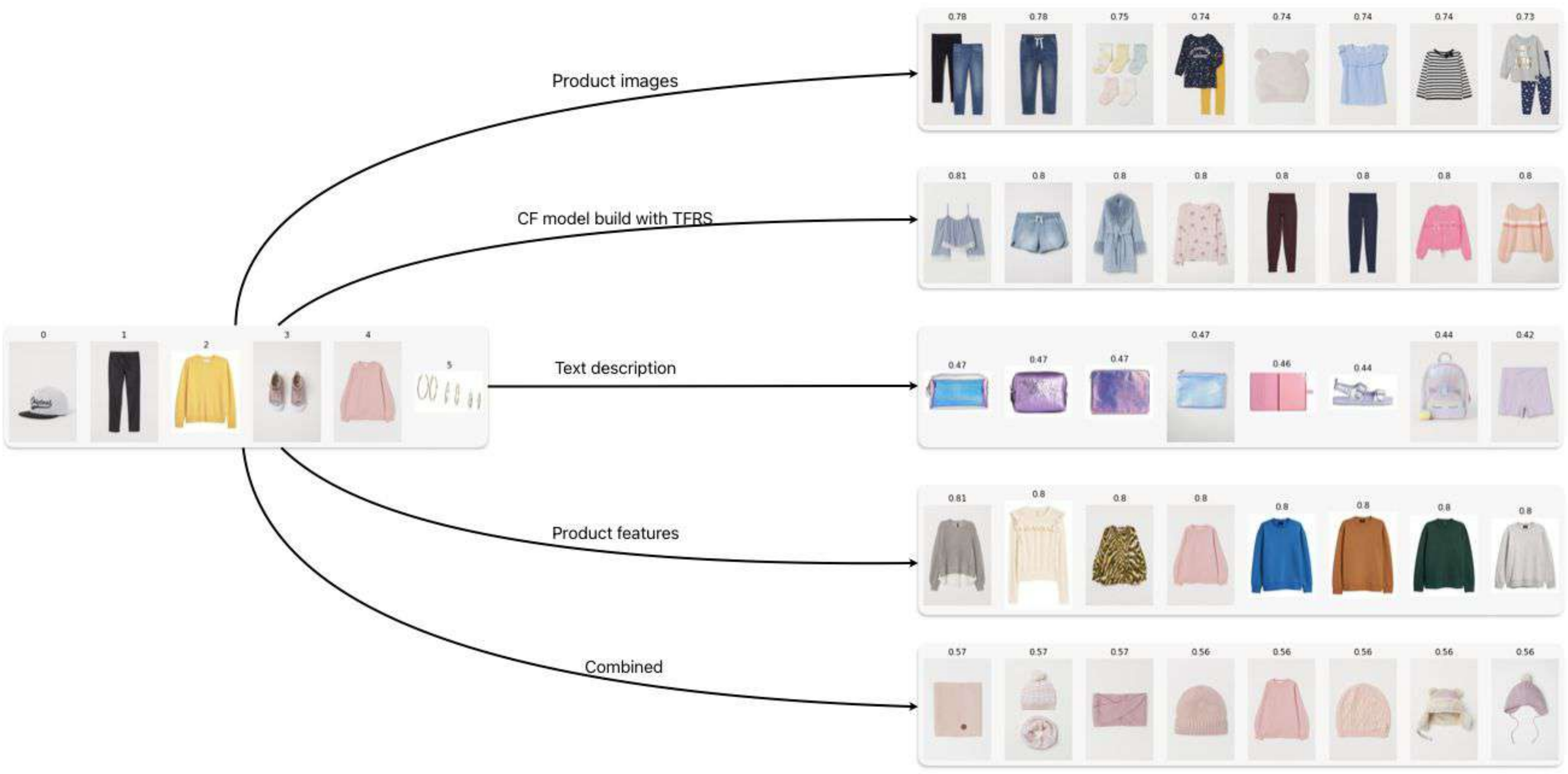

Fig 2: Recommendations based on user history

Limitations and Benefits

LIMITATIONS

- **Cold Start Challenge:** New users may get less accurate recommendations
- **Algorithmic Fairness:** Bias is introduced if the training data is skewed
- **User Feedback Incorporation:** SVD may not capture the full scope of user feedback sentiments
- **Learning Curve:** Integration of multiple algorithms makes the mantainance more complex.
- **Data Sparsity:** Sparse data can lead to inaccurate results, when there's a lack of interactions

BENEFITS

- **Personalized Recommendations:** Suggestions to users based on their past behavior and preferences.
- **No Explicit Feature Engineering:** Model learns directly from user-item interactions, making it adaptable to a wide range of domains.
- **Model Interpretability:** Matrix factorization(like ALS), offers insights into the underlying latent factors that contribute to user preferences
- **User Diversity:** Model accounts for user diversity by identifying niche preferences among user segments

FUTURE SCOPE

The future scope of the project aims to refine and expand the recommendation system to stay aligned with evolving user needs, technological advancements, and industry trends.

- **GenAI**: Once the recommendation system is up we can use a chat based filtering to suggest content to the user
- **Mobile Application Development**: Expand the system to a mobile app, enhancing convenience and user interaction
- **Interactions Beyond Purchases**: Include features to track user interactions like sharing, bookmarking, and following
- **Global Fashion Insights**: Incorporate regional and cultural fashion trends and suggest according to festivals
- **Algorithmic Fairness and Bias Mitigation**: Implement fairness-aware techniques to address potential biases and ensure recommendations are equitable for all users
- **Integration of Contextual Data**: Incorporate real-time fashion trends and user preferences based on current context to enhance recommendation accuracy

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Dataset Used - Dataset

Thank You