Flipkart GRiD 5.0

Problem Statement Title: ***Personalized Product Recommendations***

Team Name: ***TRIUMPHING TRIO***

Team members details

Team Name	TRIUMPHING TRIO		
Institute Name/Names	Thapar Institute Of Engineering & Technology (TIET)		
Team Members >	**1 (Leader)**	**2**	**3**
Name	Manvendra Raj Singh	Vasu Agarwal	Manan Mehra
Batch	2025	2025	2025

Deliverables/Expectations for Level 2 (Idea + Code Submission)

- Please follow guidelines as mentioned in the problem statement Doc.

Glossary

- Describe/ Expand abbreviations if you have used any in the slides below

We have not used any abbrevaitions.

Use-cases

- List the use cases that are targeted/ identified.
- Prioritize the use cases in order of impact (P0, P1, P2 etc)

P0(very high impact)

- **Personalized Product Recommendations:** Provide personalized recommendations to users based on their browsing history, purchase behavior, and preferences. This enhances user experience, increases engagement, and drives sales.

- **P1(Significant impact)**
  Cross-Sell Recommendations: Recommend products that complement the items users have added to their cart or purchased. This can increase average order value and encourage users to discover related products.
- **Trending and Popular Products:** Showcase trending and popular products to help users discover what's currently in demand, thereby increasing the likelihood of purchases.

P2(Moderate Impact)

- **Recently Viewed Items:** Display recently viewed products to help users easily return to items they were interested in, reducing the friction of finding products again.
- **Similar Products:** Recommend items similar to the ones users have shown interest in, broadening their choices and increasing the chances of conversion.

P3(Some Impact)

- **User-Based Collaborative Filtering:** Leverage the preferences of similar users to make recommendations, even if the current user hasn't interacted with certain items.
- **Item-Based Collaborative Filtering:** Recommend items that are similar to those a user has interacted with, based on the behavior of other users who also engaged with those items.

Solution statement/ Proposed approach

Break the problem statement to smaller problems and describe briefly the solutions at an overall and sub-problem level.

Add a simple block diagram if ready.

Subproblems-:

-Recommendation system for users with a order history,reviews,etc.

In this subproblem we used a dataset with 4 fields(ProductId,UserId,Reviews,Timestamp) and applied the **Random Forest Algorithm** and then produced top 10 products based on the reviews and sales.

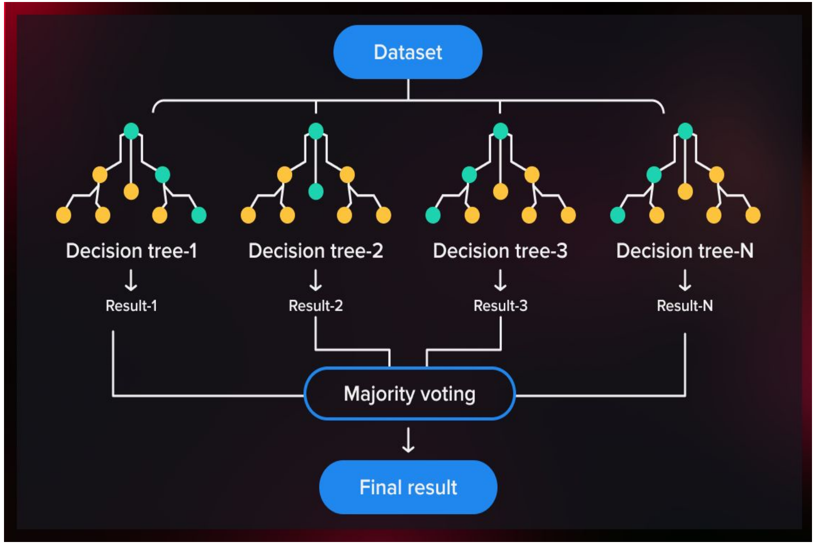
-Recommendation system for entirely new users with no history

In this subproblem we used a dataset with 2 fields(ProductId,Product Description) and applied the **K-Means Clustering alogrithm** and then predicted relevant products based on a keyword and the product descprition.

Overall we implemented both the algorithms parallely so as to target all kind of users and to increase the impact that we can have on a user by understanding the type of user that is outfront.

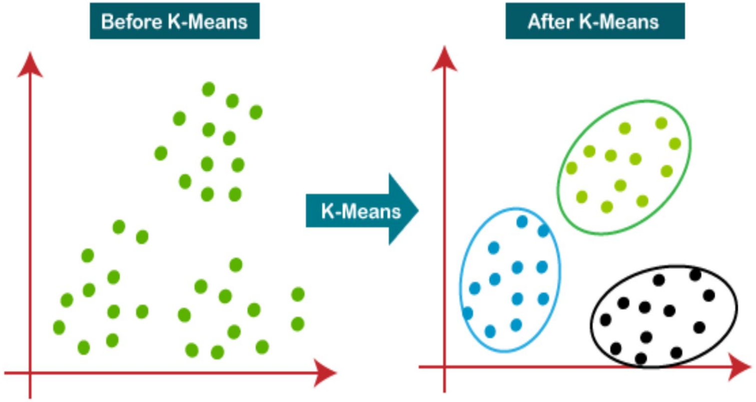
Algorithms Used:-

Random Forest- It is an ensemble learning algorithm used for classification and regression tasks. It creates a group of decision trees, each trained on a random subset of data and features. These trees then collaborate to make predictions. By combining their outputs, Random Forest boosts accuracy and minimizes overfitting. It employs a process called bagging, where multiple subsets of training data are used to build individual trees. During prediction, the algorithm employs majority voting (for classification) or averaging (for regression) across the trees to provide the final result. This approach enhances accuracy, handles noisy data, and identifies important features. However, it might not perform optimally in certain nonlinear scenarios. Overall, Random Forest is a powerful technique known for its robustness and predictive strength.

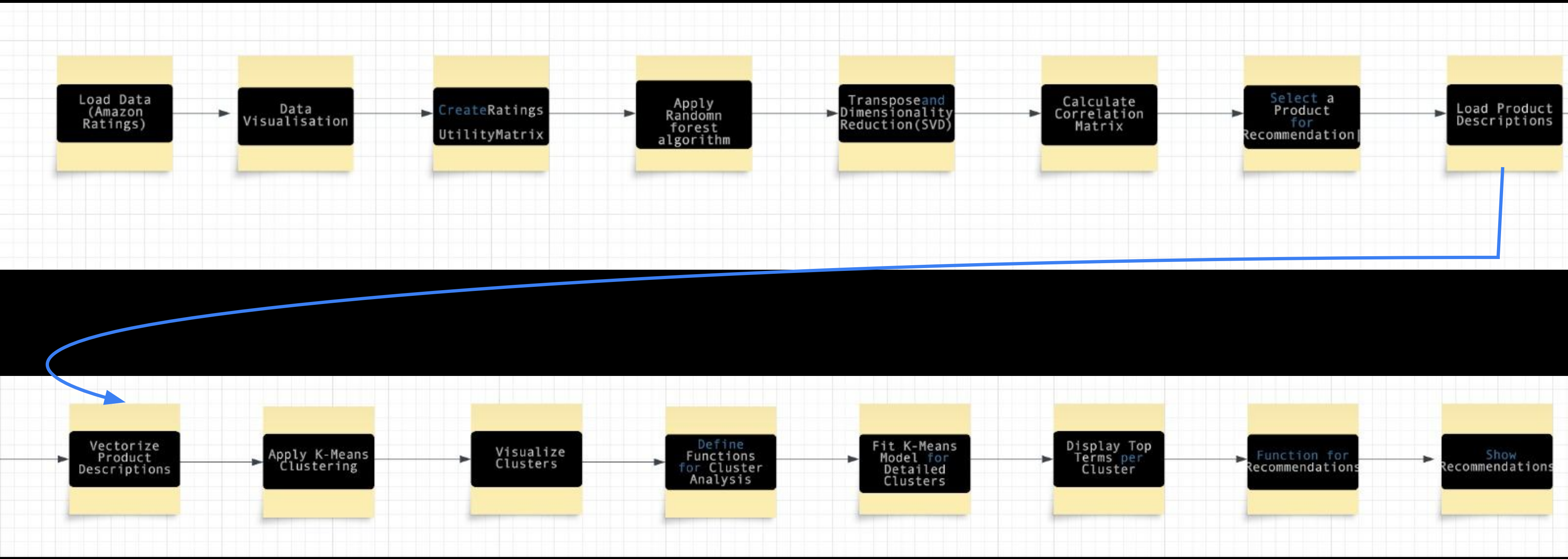


Algorithms Used:-

K-Means Clustering- K-means clustering is an unsupervis algorithm that groups similar data points into clusters It starts by randomly selecting cluster centers, then iteratively assigns data points to the nearest center a updates those centers based on the assigned points. The algorithm aims to minimize the distance between data points and their assigned cluster centers. K-means requires specifying the number of clusters (K) and runs until the centers stabilize. It's efficient for large datasets but can be sensitive to initial center choices and might not work well with complex cluster shapes. Th final outcome depends on K and the initial configuratio



Block Diagram-:



Limitations

List the limitations of this design/ solution that is being proposed here

Our Recommendation system has certain limitations like every other algorithm-:

- It fails to provide **Location-based recommendation.**
- It fails to provide **seasonal products's recommendation** and it does not take ito account the time and date.
- It fails to provide **Social Recommendations**, i.e. Incorporate social signals, such as items liked or shared by the user's friends, to provide relevant product suggestions.
- It fails to achieve **Up-Sell Recommendation**, i.e. Suggest higher-priced alternatives or upgraded versions of products users are interested in, leading to increased revenue per transaction.

Future Scope

Mention the future scope and upcoming details here

Real-time Personalization: Implement real-time personalization using dynamic user behavior data, allowing recommendations to adapt rapidly as users interact with the platform.

Contextual Recommendations: Integrate contextual information such as user location, weather, and time of day to offer even more relevant and timely product recommendations.

Multi-Modal Recommendations: Incorporate various data types like images, text, and user reviews to make recommendations more accurate and aligned with user preferences.

Deep Learning Techniques: Explore advanced deep learning techniques such as neural collaborative filtering, attention mechanisms, and sequence models to improve the accuracy of recommendations.

User Segmentation: Segment users into different groups based on preferences, demographics, and behavior to provide highly targeted recommendations for each segment.

A/B Testing and Experimentation: Continuously run A/B tests to evaluate the performance of different recommendation algorithms and fine-tune them based on real-time user feedback.

User Feedback Integration: Allow users to provide explicit feedback on recommendations, enabling the system to learn from direct input and improve the accuracy of future suggestions.

Multi-Language Recommendations: If your e-commerce platform caters to a diverse audience, consider expanding the recommendation system to support multiple languages.

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Thank You