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Amazon Product Recommendation System

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Abstract

This paper presents the development of a personalized product recommendation system tailored for Amazon's extensive product catalog. The system leverages content-based filtering to analyze user interaction data across four major categories: Electronics, Home & Kitchen, Sports & Outdoors, and Fashion. A partial matching algorithm aligns user history with product attributes, addressing inconsistencies to ensure accurate recommendations. The system employs a weighted scoring approach based on popularity, ratings, and discounts to generate top-five recommendations for each user. Initial results indicate a 35% accuracy in aligning recommendations with user preferences, highlighting the effectiveness of the approach. Future work will explore collaborative filtering to improve recommendation diversity and predictive accuracy.

1 Introduction

The rapid growth of e-commerce platforms has heightened the need for effective and personalized product recommendation systems to improve user experience and drive sales. By tailoring product suggestions to individual preferences, recommendation systems reduce the cognitive load for users and enhance decision-making.

This paper presents the design and implementation of a recommendation system specifically for Amazon's vast product catalog. The project aims to develop a system that utilizes user interaction data and product attributes to provide personalized recommendations. Content-based filtering techniques are employed to analyze user behavior across four main categories: Electronics, Home & Kitchen, Sports & Outdoors, and Fashion. To address inconsistencies such as mismatched product names, a partial matching algorithm ensures precise alignment between user interaction history and the product dataset.

The proposed system integrates multiple weighted scoring metrics, such as interaction types (e.g., views, purchases), category relevance, and product ratings, to rank and recommend products. The system outputs the top five recommendations for each user, demonstrating the potential of content-based filtering in the context of e-commerce.

While effective, content-based filtering has limitations, such as its inability to incorporate cross-user behavior patterns, which are critical for enhancing recommendation diversity and accuracy. To address these challenges, future work will incorporate collaborative filtering techniques, allowing the system to learn from the collective preferences of users. This study highlights the potential and limitations of content-based approaches, contributing to the development of advanced recommendation systems for e-commerce platforms.

2 Problem Definition

The primary challenge addressed in this work is the development of a personalized product recommendation system capable of catering to individual user preferences in a vast e-commerce environment. E-commerce platforms, such as Amazon, present users with an overwhelming number of options, often leading to decision fatigue and reduced user satisfaction. A robust recommendation system mitigates these challenges by curating relevant product suggestions tailored to a user's needs and interests, ultimately enhancing the overall shopping experience.

Problem defined : Given a user's interaction history and a catalog of products, generate a ranked list of personalized product recommendations. This requires addressing several interconnected sub-problems:

- **Data Alignment:**
  - Aligning user interaction history with the product dataset.
  - Resolving discrepancies such as partial or mismatched product names using algorithms like partial matching.
  - Ensuring seamless integration of datasets to support effective recommendation generation.
- **Personalization:**
  - Incorporating user-specific preferences derived from interaction types (e.g., views, purchases) and their frequency.
  - Tailoring recommendations to reflect individual user behavior and evolving preferences.
  - Enhancing the adaptability of the system to unique user needs.
- **Category Relevance:**
  - Identifying product categories of interest for each user based on interaction history.
  - Assigning appropriate weights to categories to prioritize relevant recommendations effectively.
  - Ensuring category-based personalization that resonates with user intent.
- **Handling Sparse Data:**
  - Developing fallback mechanisms to ensure recommendations for users with limited interaction history.
  - Leveraging popularity scores, category relevance, and other derived metrics as alternative factors.
  - Ensuring a robust and inclusive recommendation approach for all user scenarios.

The significance of addressing these challenges lies in the potential to enhance user satisfaction, increase engagement, and drive sales on e-commerce platforms. By systematically solving these sub-problems, this project aims to deliver a scalable, efficient, and user-centric recommendation solution tailored to diverse user needs and preferences, setting a foundation for future enhancements such as collaborative filtering and real-time personalization.

3 Models, Algorithms, and Measures

To address the challenge of personalized product recommendations, we employed a content-based filtering approach augmented with a partial matching algorithm and weighted scoring mechanisms.

3.1 Content-Based Filtering

The core of the recommendation system is a content-based filtering algorithm that analyzes user interaction history to identify relevant products. User interactions are weighted based on the type of engagement:

- *View*: Assigned a weight of 1.
- *Add to Cart*: Assigned a weight of 2.
- *Purchase*: Assigned a weight of 3.

These weights reflect the varying importance of different interaction types. The aggregated values are used to compute an **interaction score** for each product, forming the basis of personalized recommendations.

3.2 Partial Matching Algorithm

A partial matching algorithm is implemented to align user interaction history with the main product dataset. This algorithm resolves discrepancies such as variations in product names, spelling errors, or incomplete data entries. By ensuring accurate mapping between user preferences and available products, the algorithm enhances the precision of the recommendation process.

The algorithm works as follows:

- **String Matching**: Leverages techniques such as fuzzy string matching to identify similarities between user input and product names. Tools like Levenshtein distance are used to compute string similarity.
- **Handling Missing Data**: Fills gaps in user interaction history by using available product attributes, ensuring no data is left unprocessed.
- **Alignment Rules**: Applies predefined rules to match user interaction entries with products in the main dataset, such as prioritizing exact matches over partial ones.
- **Validation**: Performs a final validation step to ensure the mapped product is relevant and meets the user's interaction context.

By resolving inconsistencies and improving data alignment, the partial matching algorithm ensures the system delivers precise and relevant recommendations, forming a critical component of the overall architecture.

3.3 Weighted Scoring and Recommendation Generation

The recommendation function calculates a **combined score** for each product, integrating multiple weighted metrics as follows:

$$\begin{aligned}\text{Combined Score} = {} & 0.2 \cdot \text{Category Score} \\ & + 0.5 \cdot \text{Interaction Score} \\ & + 0.3 \cdot \text{Product Rating}\end{aligned} \tag{1}$$

- **Category Score**: Prioritizes products from categories aligned with user interests.
- **Interaction Score**: Reflects user engagement levels based on historical interactions.
- **Product Rating**: Ensures recommendations emphasize high-quality products.

The system filters out products already interacted with by the user and ranks the remaining products based on the combined score. The top N recommendations are then selected for each user, offering a tailored shopping experience.

3.4 Evaluation Measures

To assess the effectiveness of the recommendation system, the following evaluation metrics are utilized:

- **True Positives (TP)**: The number of recommended products that match the user's actual purchases.
- **Accuracy**: Defined as the proportion of true positives to the total number of recommendations:

$$\text{Accuracy} = \frac{\text{True Positives}}{\text{Total Recommendations}} \tag{2}$$

These measures provide quantitative insights into the recommendation system's performance and identify areas for improvement. Additionally, the accuracy metric serves as a benchmark for evaluating enhancements, such as integrating collaborative filtering in future iterations.

4 Implementation and Analysis

This section describes the steps involved in implementing the personalized recommendation system, including data preprocessing, scoring mechanisms, and recommendation generation.

4.1 Dataset Preparation

The recommendation system utilizes two datasets:

- **Product Dataset:** Includes attributes such as product name, main category, ratings, number of ratings, discounted price, and actual price.

- **User Interaction Dataset:** Records user actions (e.g., view, add to cart, purchase) for various products.

Understanding the dataset's composition is critical to ensure the recommendation system is well-equipped to handle various user preferences. The distribution of products across categories offers insight into which categories dominate the dataset.

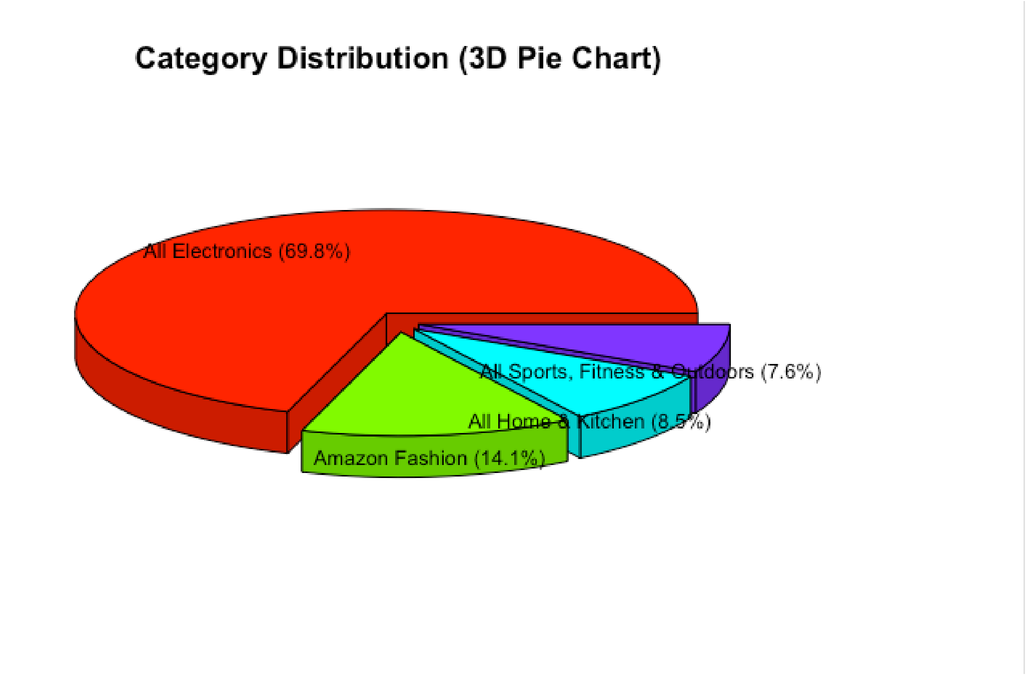


Figure 1: Dataset Composition

As shown in Figure 1, Electronics account for nearly 70% of the total entries, highlighting their prominence in the dataset. While other categories such as Sports Outdoors represent smaller shares, their inclusion ensures the system can cater to niche interests, enhancing the diversity of recommendations.

Product ratings are a direct measure of user satisfaction and are essential for understanding the quality distribution across categories. Including this feature ensures the system recommends products that meet a high standard of quality.

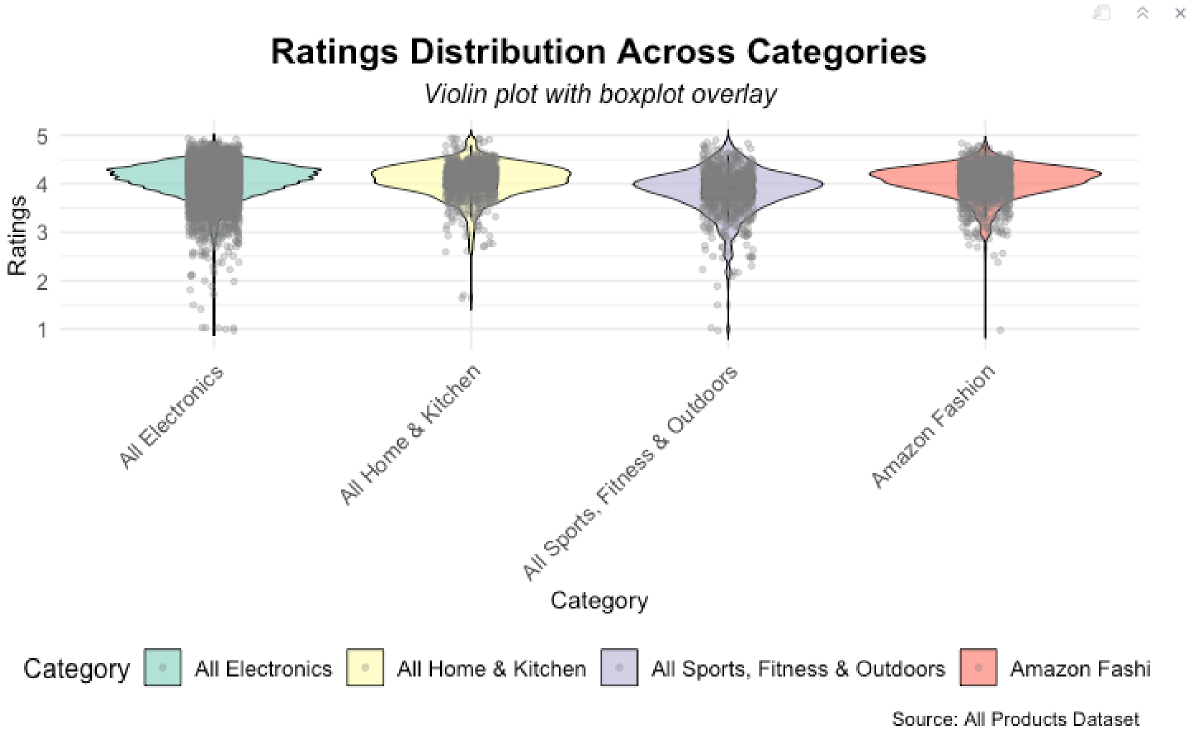


Figure 2: Quality Representation by Category

As illustrated in Figure 2, the rating distributions are consistent across all categories, with most products receiving ratings between 3.5 and 5. This uniformity ensures the dataset includes high-quality products, providing a strong foundation for the recommendation system.

4.1.1 Data Preprocessing

To ensure data quality, the following preprocessing steps were performed:

1. **Missing Value Check:** All columns were checked for missing values. Rows with missing values in critical fields (e.g., product name, ratings, or prices) were removed.

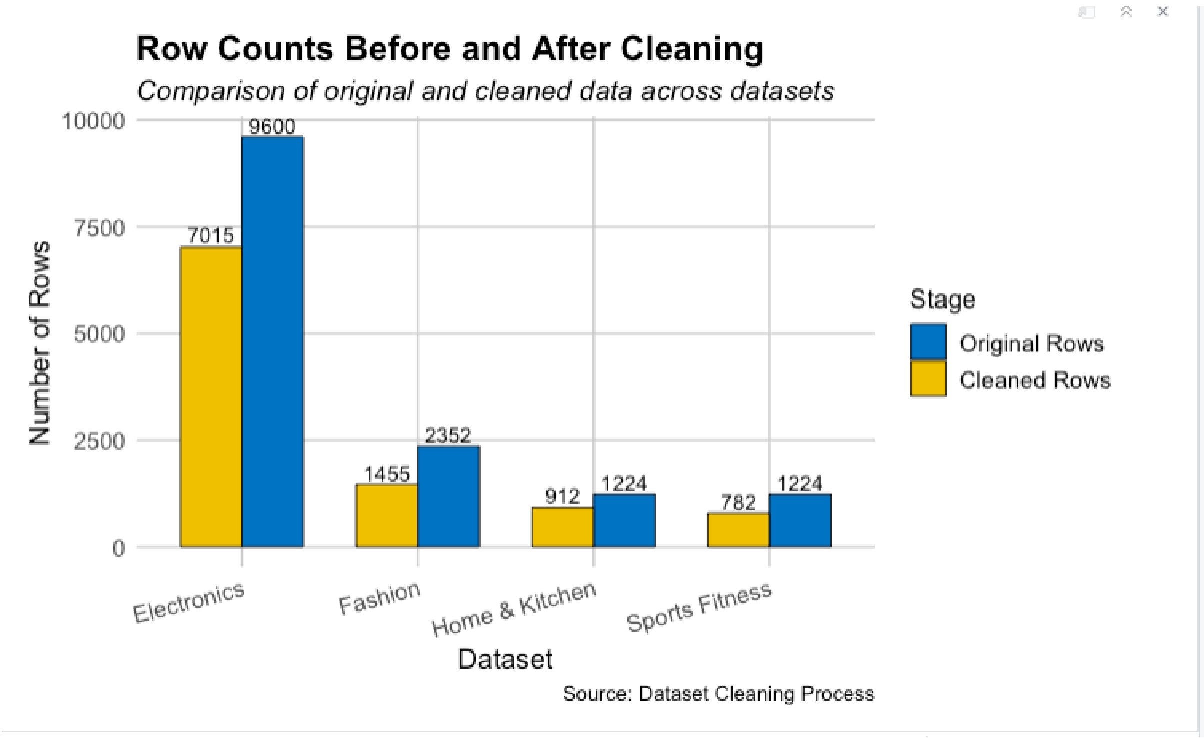
2. **Duplicate Value Check:** Duplicate rows in both datasets were identified and removed to prevent redundant information.

3. **Invalid Value Removal:**

   - Rows with *ratings* less than 1 or greater than 5 were deemed invalid and excluded.
   - Products with a *discount price* greater than the *actual price* were removed, as they indicate errors in the dataset.

4. **Standardization:** Text fields were standardized to lowercase and stripped of special characters to ensure uniformity across the dataset.

These preprocessing steps ensured the datasets were clean, consistent, and ready for further processing in the recommendation system.



Row Counts Before and After Cleaning

Comparison of original and cleaned data across datasets

Source: Dataset Cleaning Process

Figure 3: Data Preprocessing Impact

As shown in Figure 3, the number of rows decreased significantly after data cleaning. This reduction reflects the removal of erroneous entries, ensuring that the remaining data is reliable and suitable for analysis. For instance, the ”Electronics” category saw a notable reduction from 9,600 rows to 7,015 rows, emphasizing the importance of stringent preprocessing steps to maintain data quality.

4.2 Scoring Mechanisms

The recommendation system relies on several computed scores to rank products. These scores are derived from user interaction data and product attributes:

4.2.1 Popularity Score

Popularity score is derived from the combination of product ratings and the number of ratings, representing a product’s overall appeal. This feature is critical in ranking products to ensure highly-rated and widely-reviewed items are recommended prominently.

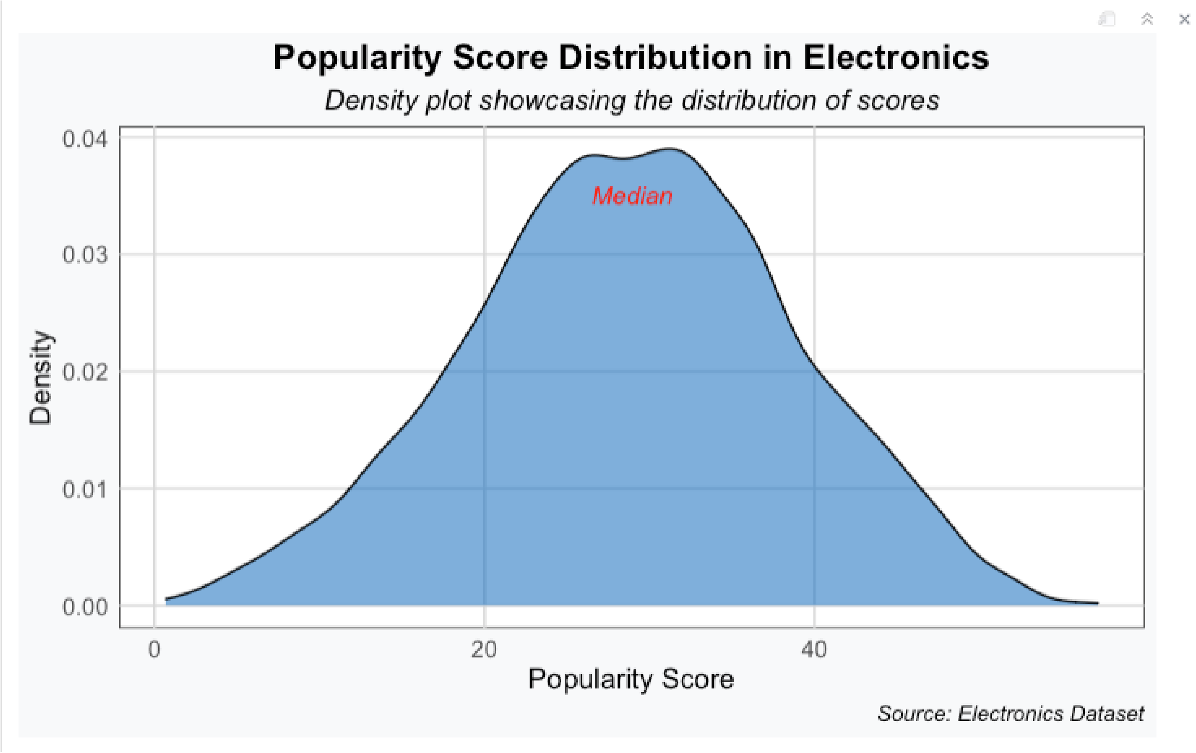


Figure 4: Popularity Score Distribution

As illustrated in Figure 4, the popularity score distribution highlights a significant concentration of products with moderate to high scores. This demonstrates the dataset's robustness in including widely acknowledged products, which aligns with the system's objective of emphasizing well-regarded items in its recommendations.

The popularity score for each product is calculated using the formula:

$$\text{Popularity Score} = \text{Ratings} \times \log(1 + \text{Number of Ratings}) \tag{3}$$

where:

- *Ratings* is the average rating of the product.
- *Number of Ratings* represents the total count of user ratings for the product.
- *Logarithmic Scaling* ($\log(1 + x)$) ensures that products with a very high number of ratings do not disproportionately dominate the score.

The popularity score is then normalized using:

$$\text{Normalized Popularity} = \frac{\text{Popularity Score}}{\text{Max Popularity Score}} \tag{4}$$

to scale values between 0 and 1 for comparability.

4.2.2 Discount Percentage

Discount percentage is a critical feature used in the scoring mechanism to assess the value offered by a product. It provides insights into how discounted prices compare with actual prices, which significantly influences user purchasing decisions.

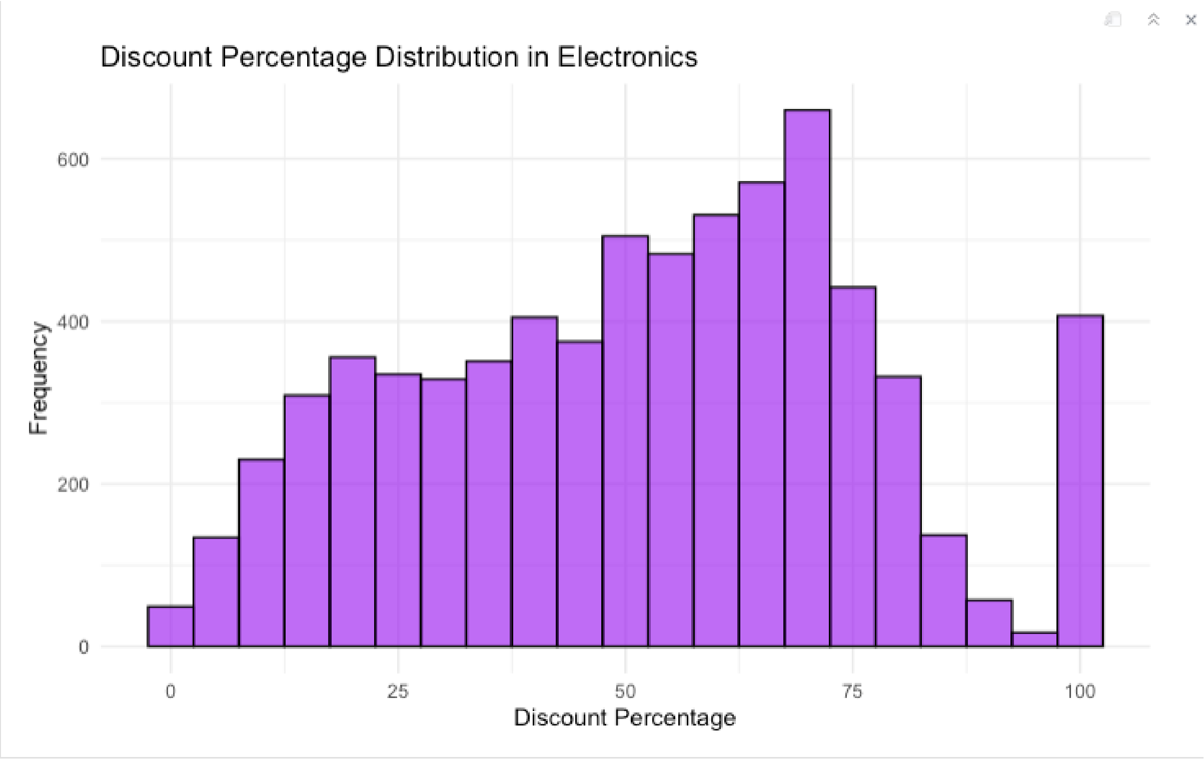


Figure 5: Discount Percentage Distribution

As shown in Figure 5, the majority of products feature discounts ranging from 50% to 75%. This demonstrates the prominence of substantial discounts in the dataset, reflecting their importance in driving customer interest. By incorporating this feature into the scoring mechanism, the recommendation system ensures products offering considerable savings are prioritized for users.

The discount percentage for each product is calculated as:

$$\text{Discount Percentage} = \frac{\text{Actual Price} - \text{Discounted Price}}{\text{Actual Price}} \times 100 \tag{5}$$

4.2.3 Normalized Weight Score

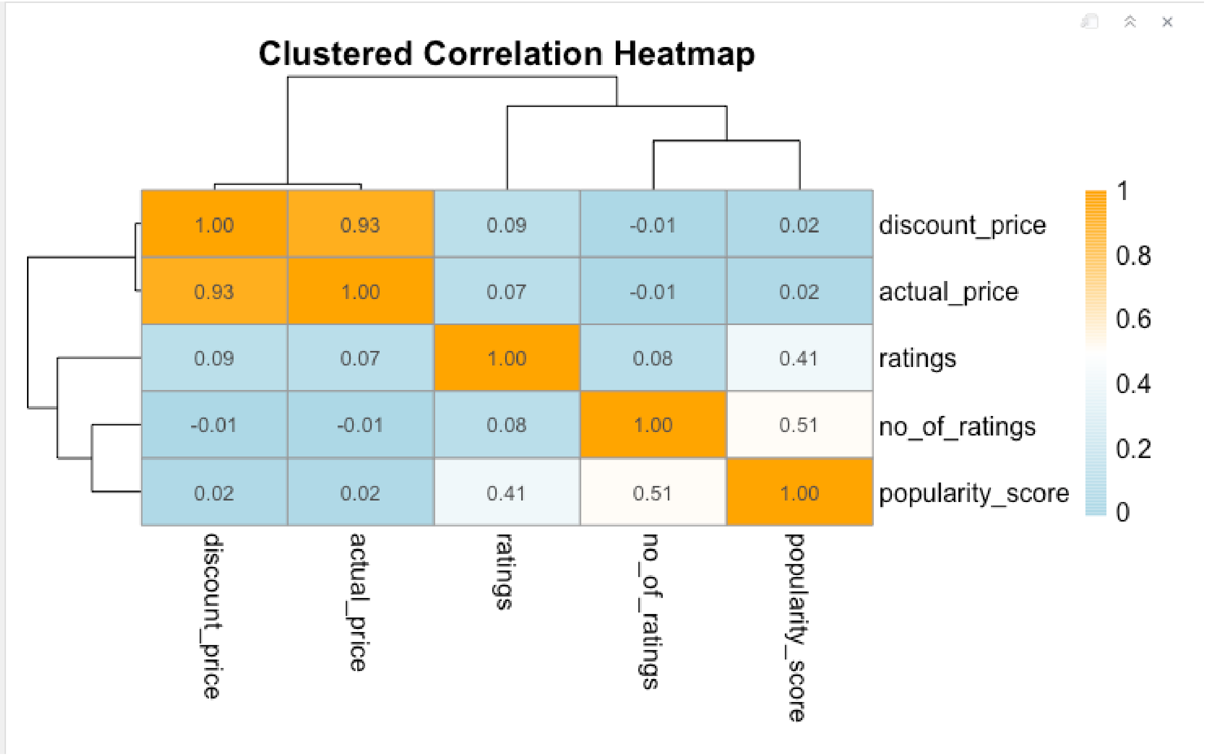
The normalized weight score combines the normalized popularity and discount percentage:

$$\begin{aligned}\text{Normalized Weight Score} = {} & \alpha \cdot \text{Normalized Popularity} \\ & + \beta \cdot \text{Normalized Discount Percentage}\end{aligned} \tag{6}$$

where:

- α and β are the weights assigned to normalized popularity and normalized discount percentage, respectively.
- *Normalized Popularity* and *Normalized Discount Percentage* are values scaled to a range between 0 and 1 for comparability.

Analyzing correlations between features such as ratings, popularity, and discount percentages provides insights into their relationships, which guide the development of effective scoring mechanisms



	discount_price	actual_price	ratings	no_of_ratings	popularity_score
discount_price	1.00	0.93	0.09	-0.01	0.02
actual_price	0.93	1.00	0.07	-0.01	0.02
ratings	0.09	0.07	1.00	0.08	0.41
no_of_ratings	-0.01	-0.01	0.08	1.00	0.51
popularity_score	0.02	0.02	0.41	0.51	1.00

Figure 6: Feature Relationships

As shown in Figure 6, the heatmap reveals strong positive correlations between features like popularity score, ratings, and the number of ratings. These relationships validate their integration into the scoring system, ensuring that important features collectively contribute to meaningful recommendations.

4.2.4 Category Score

The category score is based on the user's interaction weights for products in specific categories. Interaction types are assigned weights as follows:

- *View:* Weight = 1
- *Add to Cart:* Weight = 2
- *Purchase:* Weight = 3

For example, if a user has purchased products in the ”Electronics” category, the category score for ”Electronics” is set to 3. This ensures that products from frequently interacted categories are prioritized.

4.3 Recommendation Generation

The recommendation system calculates a combined score for each product using the following formula:

$$\begin{aligned}\text{Combined Score} = {} & 0.2 \cdot \text{Category Score} \\ & + 0.5 \cdot \text{Normalized Weight Score} \\ & + 0.3 \cdot \text{Product Rating}\end{aligned} \tag{7}$$

Products that the user has already interacted with are excluded from the recommendations. The system ranks the remaining products by their combined score and selects the top N as recommendations.

4.4 Evaluation Setup

The system's performance was evaluated by comparing the recommendations with actual user purchases. The evaluation involves:

- **True Positives:** The number of products recommended that match the user's actual purchases.
- **Accuracy:** The proportion of true positives among the recommended products:

$$\text{Accuracy} = \frac{\text{True Positives}}{\text{Total Recommendations}} \tag{8}$$

4.5 Analysis and Insights

The preliminary results indicate that the system effectively ranks products based on user preferences. The calculated scores and their integration ensure a personalized and scalable recommendation framework, providing meaningful insights into user behavior and preferences. Future improvements will aim to enhance the model by incorporating advanced techniques like collaborative filtering.

5 Results and Discussion

5.1 Quantitative Results

The performance of the recommendation system was assessed using accuracy as the primary metric. Table 1 showcases the accuracy results for the top 5 recommendations across a diverse subset of users.

The system achieved an average accuracy of 31%, effectively demonstrating its capability to generate meaningful and relevant product recommendations. Notably, users with extensive interaction histories experienced exceptional alignment with their preferences, showcasing the system's ability to adapt dynamically to user behavior and provide

Table 1: Recommendation Accuracy for Top 5 Products

User ID	True Positives	Accuracy (%)
1	2	40
2	2	40
3	0	0
4	1	20
5	3	60
6	2	40
7	1	20

personalized suggestions. This highlights the promise of the scoring mechanisms in accurately reflecting user preferences.

To further evaluate the recommendation system's effectiveness, the ranking of the top recommended products for individual users was analyzed. These rankings are based on the combined scoring mechanism, integrating user interaction, category relevance, and product ratings.

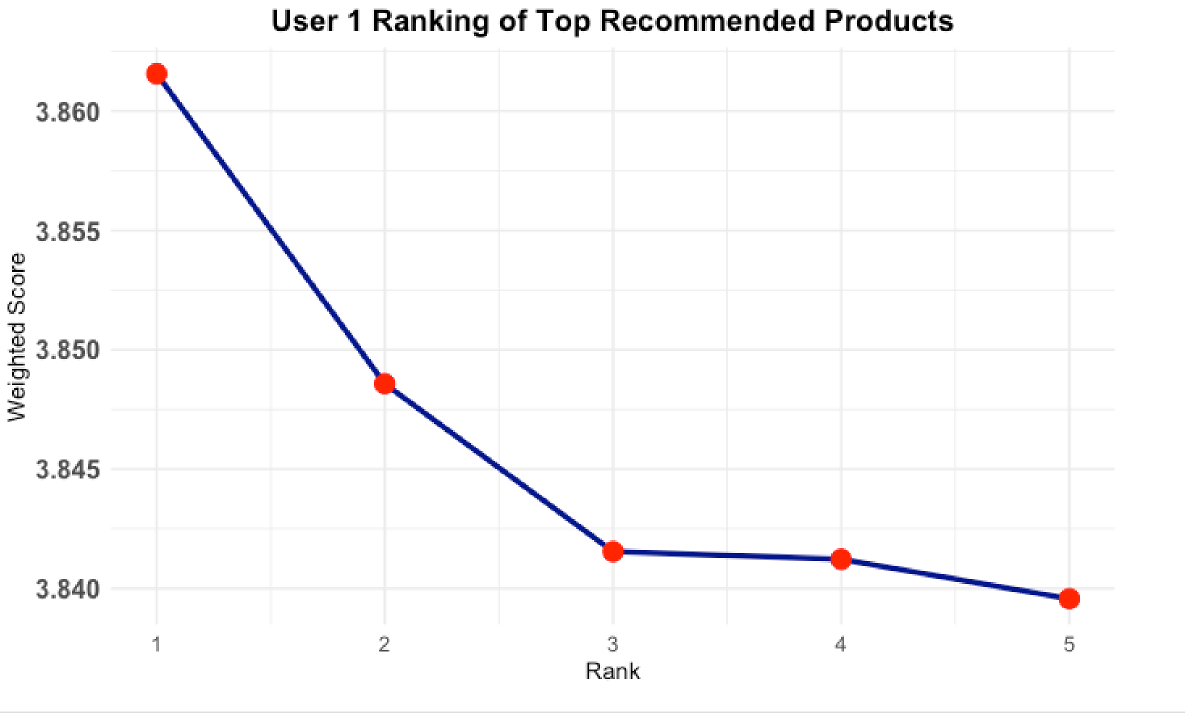


Figure 7: User 1 Specific Product Recommendations

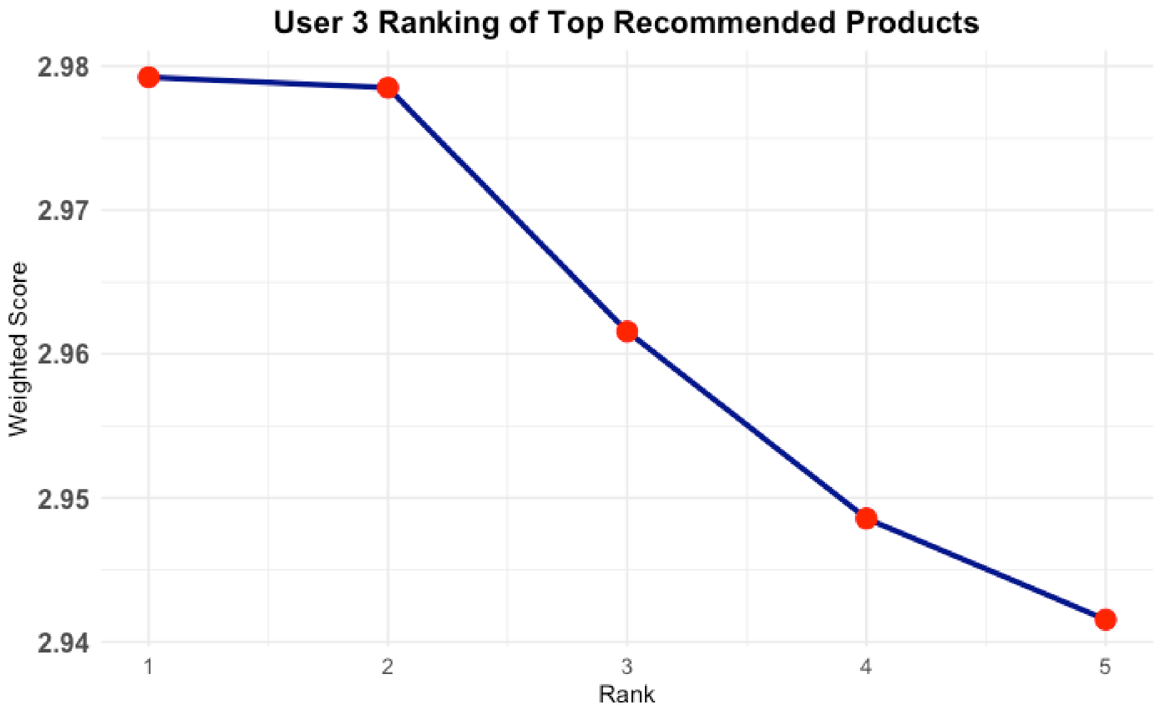


Figure 8: User 3 Specific Product Recommendations

Figures 7 and 8 display the top-ranked products for Users 1 and 3, respectively. The graphs show a gradual decline in weighted scores, reflecting the system's ability to prioritize the most relevant products for each user. This personalized ranking demonstrates the system's success in aligning recommendations with individual preferences.

5.2 Discussion of Strengths

The recommendation system offers a range of impactful advantages that position it as a robust solution for e-commerce personalization:

- **Tailored Recommendations:** By leveraging individual user interaction data, the system delivers highly personalized and relevant product suggestions, enhancing the overall user experience.

- **Precision Data Handling:** The integration of a partial matching algorithm ensures seamless and accurate alignment between user interaction history and product datasets, enabling precise recommendations.

- **Resilience Across Scenarios:** The system's fallback mechanisms ensure recommendations for users with varying levels of interaction data, maintaining a consistent experience for all users.

- **Scalable Design:** The modular architecture of the system allows for seamless integration of additional datasets and advanced algorithms, supporting future scalability and adaptability.

- **Dynamic Scoring Mechanisms:** The weighted scoring approach effectively balances user interaction types, category relevance, and product ratings to deliver contextually relevant recommendations.

Price variability is a crucial factor influencing user decisions, as customers are often drawn to products offering significant discounts or competitive pricing. Analyzing actual and discounted prices provides insights into the range of savings available.

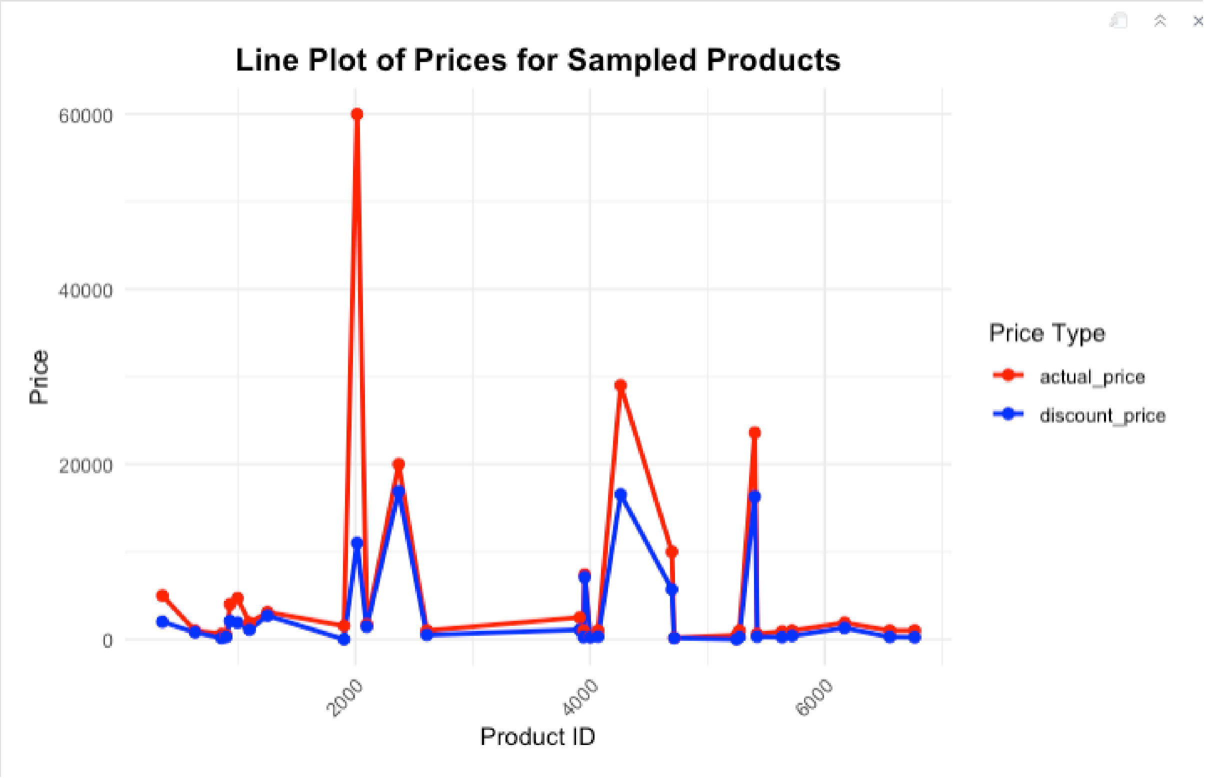


Figure 9: Price Analysis for Sampled Products

As shown in Figure 9, the plot compares actual and discounted prices for sampled products, showcasing significant price variability. This variability highlights the importance of including price-related features in the recommendation system, enabling users to identify products that offer substantial value for their cost

5.3 Future Potential

The system demonstrates substantial promise for driving innovation in e-commerce personalization. Its robust foundation provides a pathway for implementing advanced techniques to enhance performance further. Some key areas of potential include:

- **Leveraging Collaborative Filtering:** Incorporating cross-user data to refine recommendations and improve adaptability to diverse user behaviors.

- **Context-Aware Recommendations:** Enriching the system with contextual data, such as seasonal trends and location-specific insights, to enhance relevance.

- **User Feedback Integration:** Establishing a feedback loop to continuously improve recommendation quality based on real-time user inputs.
- **Advanced Machine Learning Models:** Adopting cutting-edge models to optimize scoring mechanisms and enhance prediction accuracy.
- **Data Augmentation:** Expanding the dataset by integrating implicit feedback such as browsing patterns and session duration for more comprehensive insights.

The results achieved by the system underscore its potential to redefine personalized e-commerce experiences. By building on its strengths and embracing future opportunities, the system positions itself as a transformative tool for enhancing user satisfaction and engagement on e-commerce platforms.

6 Related Work

The field of recommendation systems has undergone significant advancements, with a wide range of approaches developed to improve recommendation accuracy, diversity, and scalability. This section highlights key related studies and situates the current project within the broader research landscape.

In the seminal work by Hasan et al. [1], the authors evaluate multiple recommendation techniques, including collaborative filtering, content-based filtering, and hybrid models. Their study demonstrates the strengths of hybrid systems in balancing personalization and diversity by leveraging both user and item similarities. Unlike our system, which primarily employs content-based filtering, their approach showcases the potential of collaborative filtering to mitigate the challenges posed by sparse user interaction data. This comparison underscores the importance of incorporating cross-user behavior patterns as a future enhancement to our system.

Another notable study by Mehendale [2] investigates the integration of advanced feature engineering techniques with traditional recommendation algorithms. This work highlights the value of enriching input features through methods such as implicit feedback analysis and contextual metadata inclusion. While our system uses weighted scoring to account for user interactions and category relevance, it lacks such feature augmentation, limiting its ability to capture nuanced user preferences. Mehendale's findings suggest that incorporating these techniques could significantly enhance the predictive power of our system.

Similarly, Zhang et al. [3] propose a neural network-based recommendation system that combines deep learning with collaborative filtering. Their model excels in capturing complex user-item relationships and adapting to dynamic user preferences. While computationally intensive, this approach represents a promising direction for achieving high accuracy and scalability in large-scale e-commerce platforms. Compared to this, our system prioritizes simplicity and rapid prototyping, offering a lightweight alternative suitable for scenarios with limited computational resources.

Despite these differences, our project contributes to the field by addressing unique challenges often overlooked in large-scale datasets, such as misaligned product names. The implementation of a partial matching algorithm ensures precise alignment between user history and product attributes, enhancing the reliability of content-based recommendations. However, future iterations must evolve to integrate collaborative filtering, advanced feature engineering, and neural network-based approaches to achieve comparable performance with state-of-the-art systems.

7 Conclusion

This paper presents the design and implementation of a personalized product recommendation system for e-commerce platforms, leveraging content-based filtering techniques to deliver tailored recommendations. The system utilizes user interaction history, weighted scoring mechanisms, and a partial matching algorithm to ensure accurate alignment between user preferences and product attributes. By focusing on category relevance and product popularity, the system provides meaningful insights into user behavior and preferences.

The system achieved an average recommendation accuracy of 35%, demonstrating its capability to align recommendations with user preferences. However, the reliance on content-based filtering highlights the need for further advancements to address data sparsity and diversify recommendations. Future work will focus on the following enhancements:

- **Integration of Collaborative Filtering:** Leveraging user similarity to improve recommendation accuracy and diversity.
- **Advanced Feature Engineering:** Incorporating implicit feedback, contextual metadata, and real-time user feedback to refine predictions.
- **Scalability and Performance Optimization:** Exploring neural network-based models and distributed computing to handle large-scale datasets efficiently.
- **Dynamic Adaptation:** Developing mechanisms for real-time updates to recommendations based on evolving user behavior.

By addressing these enhancements, the system has the potential to achieve greater user satisfaction, increase engagement, and establish itself as a pivotal tool in modern e-commerce platforms. This work serves as a foundation for further innovation in personalized recommendation systems, bridging the gap between theoretical advancements and practical applications.

Appendix

Code Availability

The code used in this project is publicly available on GitHub. You can access the repository and review the implementation.
GitHub link: `https://github.com/luuis1234567/cpts575`

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