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ENHANCED PRODUCT REVIEW RECOMMENDATIONS USING COLLABORATIVE FILTERING AND SINGULAR VALUE DECOMPOSITION

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Abstract

Recommender systems have become indispensable tools for enhancing user satisfaction and engagement across diverse business sectors, including online marketplaces, streaming services, and e-commerce platforms. This research proposes and evaluates an advanced product review recommendations system that leverages collaborative filtering techniques to deliver personalized and accurate suggestions. By integrating memory-based and model-based collaborative filtering approaches, the system effectively analyses user-item interactions to predict preferences. A key innovation of this study is the application of Singular Value Decomposition (SVD) to decompose the user-item matrix, which not only improves prediction efficiency but also reduces computational demands by addressing data sparsity and dimensionality challenges.

The system employs item-based collaborative filtering, utilizing the KNNWithMeans algorithm, and achieves a prediction accuracy of 1.34 RMSE, as validated through rigorous testing on a large-scale electronics product review dataset. Additionally, a correlation-based method is implemented to identify strongly associated products, enabling the generation of highly relevant recommendations. Experimental results demonstrate that the proposed framework outperforms existing recommendation models in terms of scalability and accuracy, particularly for large datasets. Furthermore, this research explores the potential of hybrid models and deep learning techniques to further enhance recommendation quality and mitigate common issues such as the cold-start problem and data sparsity. The findings highlight the system's robustness in real-world applications and its adaptability to dynamic user behaviour. By combining collaborative filtering with matrix factorization, this study provides a scalable and efficient solution for modern e-commerce platforms seeking to improve user experience and drive sales. Future directions include integrating real-time processing capabilities and exploring advanced machine learning algorithms to refine recommendation precision.

Keywords:

Recommender System, Collaborative Filtering, Singular Value Decomposition (SVD), User-Item Matrix, Product Recommendation, Item-Based Filtering, Cold-Start Problem, Data Sparsity, Machine Learning.

Introduction

Social media and online stores expanded rapidly during recent years, which created a massive increase in information created by users. Internet marketplaces including Amazon eBay and Flipkart handle product listings and consumer connections from millions of visitors every day. The vast data archive helps users

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understand product performance but becomes hard to manage because it creates too much information for people to use personal shopping choices. Rephrase the following sentence. Keep the sentences direct, flowing, and easy to understand. Also, normalize verbalization when possible. A recommender system acts as an information-filtering tool to estimate how much a user would like or rate a specific item. The system's automated search function boosts user experience while helping us achieve more sales and gain better results from customers. Many digital industries use recommender systems especially in the areas of online shopping and streaming services because they help customers find relevant products easily. In order to boost user experience and boost sales growth Netflix and Amazon make use of recommender systems (Linden et al., 2003; Gomez-Uribe & Hunt, 2015)..

Motivation and Background

A product review recommendation system is created based on the forces users and companies face in dealing with massive amounts of review data

1. **Information Overload:** Customers are often overwhelmed by the large number of products and reviews available on e-commerce platforms, making it difficult to identify products that match their preferences.
2. **Sparse Data:** Most users rate only a small fraction of the available products, resulting in a sparse user-item interaction matrix.
3. **Cold Start Problem:** New users and products lack sufficient data to generate reliable recommendations.
4. **Subjectivity and Bias:** User ratings and reviews are subjective and may be influenced by personal preferences, brand loyalty, or other factors.

The reason for creating a product review because collaborative filtering algorithms may forecast consumer preferences based on the behaviour of similar users or items, they have become popular as a solution to these problems. The goal of this research is to create an accurate and effective product recommendation system for the electronics industry by utilising collaborative filtering and matrix factorisation techniques. The constraints and difficulties that consumers and organisations encounter when handling extensive review data are the root cause of this suggestion system.

Types of Recommender Systems

Recommender systems can be broadly classified into three categories:

Content-Based Filtering. Content-based filtering makes product recommendations based on the user's preferences and the attributes of the goods. It examines product attributes (such as price, category, and brand) and contrasts these with the user's past preferences. Nevertheless, content-based filtering has restricted suggestion diversity and the cold start issue.

Collaborative Filtering. Using the premise that individuals with similar tastes are likely to favour similar products, collaborative filtering makes product recommendations. To find trends and parallels between users or items, it uses data from user-item interactions. There are further categories under which collaborative filtering falls:

- ***User-based Collaborative Filtering:*** Recommends products based on the preferences of users with similar rating patterns.
- ***Item-based Collaborative Filtering:*** Recommends products that are similar to those previously rated or purchased by the user.

Hybrid Approaches. To increase suggestion accuracy and lessen the drawbacks of individual techniques, hybrid recommender systems integrate collaborative and content-based filtering techniques. They had better manage cold start issues and sparse data by utilising the advantages of both approaches.

Objectives of the Study

The main objectives of this research are:

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- To develop a collaborative filtering-based product recommendation system using real-world product review data from the electronics category.
- To explore user behaviour and product interaction patterns through detailed exploratory data analysis (EDA).
- To implement memory-based collaborative filtering using the KNN With Means algorithm.
- To apply model-based collaborative filtering using matrix factorization through Truncated Singular Value Decomposition (SVD).
- To evaluate the performance of the system using evaluation metrics such as Root Mean Square Error (RMSE).
- To identify patterns and trends in user-product interactions to improve recommendation accuracy.

Research Challenges

There are a number of technical issues that relate to development of product review recommendation system:

- **High Dimensionality:** User-item interaction matrices are large and sparse, requiring dimensionality reduction techniques.
- **Cold Start Problem:** Lack of sufficient data for new users and products limits recommendation accuracy.
- **Scalability:** Efficient handling of large-scale datasets is crucial for real-time recommendations.
- **Data Noise and Bias:** User ratings and reviews may be influenced by personal bias, external factors, or false reviews.

Proposed Approach

This has left the users with some problems such as the cold start problem, the limited number of collaborators and the problem of sparsity which can be eliminated by using a fresh approach of memory based collaborative filtering combined with model based collaborative filtering.

- **Memory-Based Collaborative Filtering:** K-Nearest Neighbors (KNN) with Means algorithm is used to identify similar users or items based on historical ratings.
- **Model-Based Collaborative Filtering:** Truncated Singular Value Decomposition (SVD) is applied to reduce matrix dimensionality and uncover latent factors influencing user-product interactions.
- **Recommendation Generation:** The system recommends products based on similarity scores and predicted ratings.
- **Performance Evaluation:** The system is evaluated using Root Mean Square Error (RMSE) to measure the accuracy of predicted ratings.

Significance of the Study

Thus, this research contributes to the development of the recommender system body of knowledge by proposing an industry-level and quantifiable model for product recommendations for the electronics industry. The proposed system of curating the amount of information and filtering the necessary objects improves the usability by increasing the level of interaction and providing recommendations. Therefore, the fruit of this work will be of interest not only to the authors of this article but also to practitioners and researchers in other fields like literature, music, films, and clothing since it will enhance the use and effectiveness of collaborative filtering techniques, especially in other applications.

Related Work

Online platforms heavily depend on recommender systems to enhance user engagement and satisfaction (Gomez-Uribe & Hunt, 2015). Extensive research has explored methods to optimize recommender system performance across various domains.

Collaborative Filtering (CF)

Collaborative filtering remains the most widely adopted recommendation methodology (Su & Khoshgoftaar, 2009). This technique analyses user-item interaction patterns to generate recommendations. Sarwar et al. (2001) demonstrated that item-based collaborative filtering outperforms user-based approaches

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in both precision and scalability when handling large datasets. Earlier foundational work by Breese et al. (1998) systematically compared model-based and memory-based collaborative filtering techniques, establishing key performance benchmarks. Modern CF implementations increasingly incorporate matrix factorization techniques (Koren & Bell, 2015), building on theoretical frameworks established in Aggarwal's (2016) comprehensive textbook.

Matrix Factorization Techniques

Matrix factorization has emerged as a particularly effective method for recommender systems. Koren et al. (2009) demonstrated how Singular Value Decomposition (SVD) successfully extracts latent user and item features to improve prediction accuracy. This approach gained prominence during the Netflix Prize competition through Funk's (2006) innovative implementation. Subsequent advances include Rendle's (2010) factorization machines, which introduced context-aware features to the matrix factorization paradigm.

Hybrid Models

Hybrid recommendation systems address data sparsity challenges by combining content-based and collaborative filtering techniques. Burke's (2002) seminal survey identified three primary hybridization strategies: weighted, switching, and mixed approaches. Badrul et al. (2005) developed an adaptive algorithm that dynamically adjusts the weighting between content-based and collaborative components. Bell and Koren (2007) achieved notable performance improvements by integrating neighbourhood-based techniques with matrix factorization.

Deep Learning-Based Approaches

Recent advances leverage deep learning to model complex user-item interactions. He et al. (2017) proposed Neural Collaborative Filtering (NCF), which employs neural networks to capture nonlinear relationships. Industry implementations include YouTube's deep learning framework, which processes billions of daily interactions (Covington et al., 2016). Graph-based approaches have further enhanced performance by modelling network structures in user-item relationships (Wu et al., 2021).

Industry Applications

Leading technology companies have successfully implemented these techniques in production systems. Amazon's item-based collaborative filtering system significantly improved recommendation quality (Linden et al., 2003). Similarly, YouTube's AI-driven algorithm personalizes content delivery at scale (Davidson et al., 2010). Netflix's architecture combines matrix factorization with deep learning to optimize user engagement (Gomez-Uribe & Hunt, 2015).

Methodology

Data Collection and Pre-processing

For this study, the Amazon Product Reviews dataset, especially for the Electronics category was utilised. The collection includes user ratings and reviews of a variety of electronic products. In order to load data, pandas library was used which performed the operations as illustrated below.

```
electronics_data = pd.read_csv("/kaggle/input/amazon-product-reviews/ratings_Electronics (1).csv",
names=['userId', 'productId', 'Rating', 'timestamp'])
electronics_data.head()
```

The following code was used to determine the shape of the dataset.

```
electronics_data.shape
```

The shape function returns a tuple consisting of dimensions of dataset (number of rows and number of columns). The reason this data helps is that it assists in the understanding of the size of the dataset as well as it fulfils the processing requirements for model training.

The same dataset consist of the following columns:

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- **userId** – A unique identifier assigned to each user.
- **productId** – A unique identifier assigned to each product.
- **Rating** – A numeric value representing the rating provided by the user (typically between 1 and 5).
- **timestamp** – The time at which the review was made, represented in Unix format.

To improve the data quality and consistency, the following pre-processing steps were applied:

- **Handling Missing Values** – Missing values were identified and removed to prevent model bias.
- **Data Type Conversion** – Data types were converted to appropriate formats where necessary to enhance computational efficiency.
- **Duplicate Removal** – Duplicate entries were removed to avoid redundancy in the recommendation process.
- **Timestamp Processing** – The timestamp was converted into a human-readable format to analyze temporal patterns.

Table 1

Sample User-Product Rating Data

Sr. No.	User ID	Product ID	Rating	Timestamp
0	AKM1MP6POOYPR	0132793040	5.0	1365811200
1	A2CX7LUOHB2NDG	0321732944	5.0	1341100800
2	A2NWSAGRHCP8N5	0439886341	1.0	1367193600
3	A2WNBOD3WNDNKT	0439886341	3.0	1374451200
4	A1GI0U4ZRJA8WN	0439886341	1.0	1334707200

Researcher will add the Subset Selection and Data Type Checking part to the methodology:

B. Subset Selection and Data Type Verification

We grabbed a section of data with iloc to use it effectively for model training and processing. The first 1,048,576 entries were filtered from the dataset through this command:

electronics_data = electronics_data.iloc[:1048576, 0:]

Taking a small portion of records streamlines model training and lowers memory requirements especially when dealing with big datasets. We checked the data type of each column after making the subset using this code block.

electronics_data.dtypes

During this stage we validate that column data types match how we plan to use them. The expected data types are:

- **userId** – `object` (string) – Represents a unique user identifier.
- **productId** – `object` (string) – Represents a unique product identifier.
- **Rating** – `float64` – Represents the user rating for the product.
- **timestamp** – `int64` – Represents the time of the review submission in Unix format.

Confirming data types guarantees compatibility with the collaborative filtering technique and aids in spotting possible errors.

C. Dataset Information Overview

The info() function generated a brief report about the dataset by showing the entry number and column names together with null value counts and data types. The implemented code appeared as follows:

electronics_data.info()

A basic summary of the dataset appeared through output that contained essential information.

- **Number of entries** – The dataset contains **1,048,576 rows** and **4 columns**.
- **Column names and data types**:
  - `userId` – Object type, representing unique user identifiers.
  - `productId` – Object type, representing unique product identifiers.

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- `Rating` – Float64 type, representing user-assigned product ratings.
- `timestamp` – Int64 type, representing the time at which the rating was submitted.

- **Missing values** – There were **no missing values** in the dataset, ensuring consistency for further analysis.
- **Memory usage** – The dataset consumes approximately **32 MB** of memory.
- I'll now add the **Five-Point Summary** section to the methodology.

D. Five-Point Summary of Ratings

The describe() function was used to create a five-point statistical summary in order to comprehend the distribution and variability of the product ratings. This code was run:

- `electronics_data.describe()['Rating'].T`
- The output provided the following key insights about the rating values:

Table 2

Descriptive Statistics for Product Ratings (N = 1,048,576)

Statistic	Value	Description
Count	1,048,576	Total number of ratings in dataset
Mean	3.97	Average user rating (1-5 scale)
Standard deviation (SD)	1.40	Dispersion of ratings around the mean
Minimum	1.0	Lowest possible rating value
25th percentile	3.0	25% of ratings ≤ this value
Median	5.0	Middle value of all ratings
75th percentile	5.0	75% of ratings ≤ this value
Maximum	5.0	Highest possible rating value

According to this five-point assessment, the majority of evaluations fall between 3 and 5, with an average rating of roughly 4.0. The ratings show moderate volatility, as indicated by the 1.40 standard deviation. Users generally prefer high-rated products, as seen by the high values for the 50th and 75th percentiles, which indicate that a significant percentage of the ratings are positive.

The product was rated from 1 (lowest) to 5 (highest). The majority of users provided high ratings, as indicated by the high median value of 5, which suggests that people generally provided good comments.

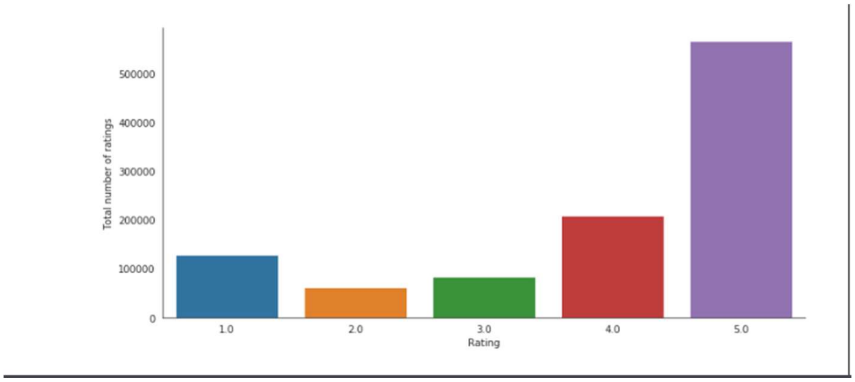
None of the columns (userId, productId, rating, and timestamp) had any missing values. This simplified the data preparation step by guaranteeing that no extra data preprocessing or imputation was needed.

E. Rating Distribution

Using the seaborn library, a count plot was created to show the distribution of product ratings. The graphic illustrates the frequency of each rating value from 1 to 5.The findings show that most evaluations fall between 4 and 5, which represents overwhelmingly positive customer feedback. Understanding user behaviour and the general attitude towards the products is made easier by the visual portrayal.

Figure 1

Rating Chart



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F. Dataset Overview

To understand the dataset, the following key information was extracted:

- Total number of ratings: **1,048,576**
- Total number of unique users: **786,330**
- Total number of unique products: **61,894**

G. Rating Analysis

To learn more about user behaviour, the rating patterns of users were examined. The following code was used to determine how many things each user has rated: The top users gave the following ratings:

- **User A5JLAU2ARJ0BO** rated **412** products
- **User A231WM2Z2JL0U3** rated **249** products
- **User A25HBO5V8S8SEA** rated **164** products
- **A6FIAB28IS79** rated **146** products
- **AT6CZDCP4TRGA** rated **128** products
- **Name: Rating, dtype: int64**

The overall statistical summary of the ratings per user is shown below:.

Table 3

Descriptive Statistics of User Rating Activity

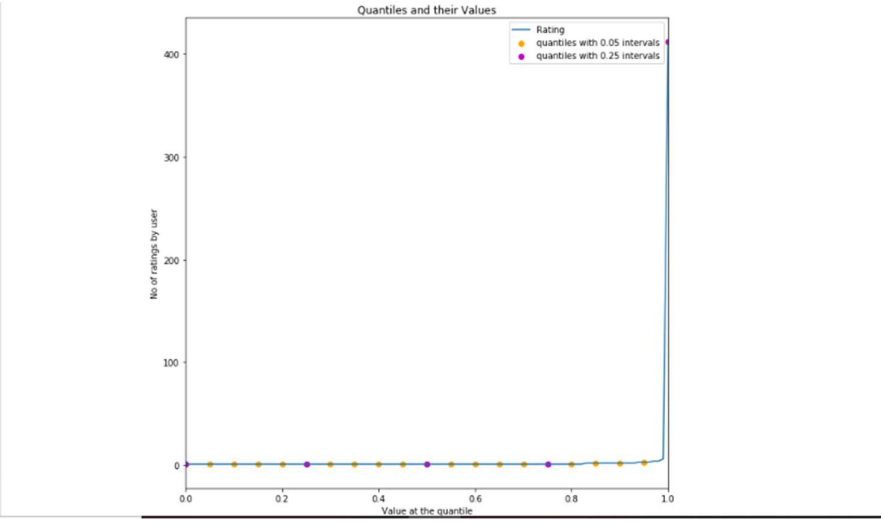
Metric	Value
Mean	1.33
Standard deviation	1.38
Minimum	1
25th percentile	1
Median	1
75th percentile	1
Maximum	412

H. Quantile Analysis

A comprehensive quantile analysis was undertaken to understand the distribution of ratings per user. The quantiles are calculated and displayed at various intervals by the following code.

Figure 2

Quantiles and their Values



This plot helps identify the distribution of user activity in the dataset. The key insights include:

- The majority of users have only given a few products ratings.

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- There are power users present since a tiny percentage of consumers have given a notably higher rating to a large number of products.
- The dataset was filtered to locate users who have rated more than 50 products in order to identify high-activity consumers.

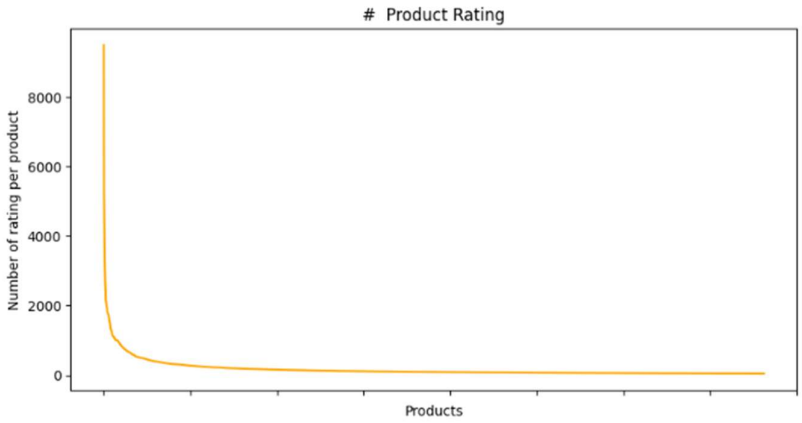
I. Popular Products Analysis

Only products with 50 or more ratings were included in the dataset in order to determine which ones were the most popular. This phase aids in concentrating on products that receive many reviews, as these are more likely to have trustworthy ratings and user comments. The products with the highest number of ratings and the highest ratings were determined.

- **Highest rated product**: `B0000DYV9H` with an average rating of **4.947**.
- **Most reviewed product**: `B0002L5R78` with **9487 ratings**.

Figure 3

Product Rating



J. Rating Mean and Count Analysis

A new DataFrame that stores both data was made in order to examine the link between the average rating and the quantity of ratings for every product. The code sample that follows demonstrates how this was calculated:

```
ratings_mean_count =
pd.DataFrame(new_df.groupby('productId')['Rating'].mean())
ratings_mean_count['rating_counts'] =
pd.DataFrame(new_df.groupby('productId')['Rating'].count())
ratings_mean_count.head()
```

This table stores the following information for each product:

Table 4

Mean Ratings and Rating Counts by Product

Product ID	Mean Rating	Rating Count
0972683275	4.47	1,051
1400501466	3.56	250
1400501520	4.24	82
1400501776	3.88	139
1400532620	3.68	171

- **Mean Rating** – The average rating given by the users.
- **Rating Counts** – The total number of ratings received by the product.

J+1. Rating Count Distribution

The following histogram was created in order to show the distribution of the quantity of ratings that each product received:

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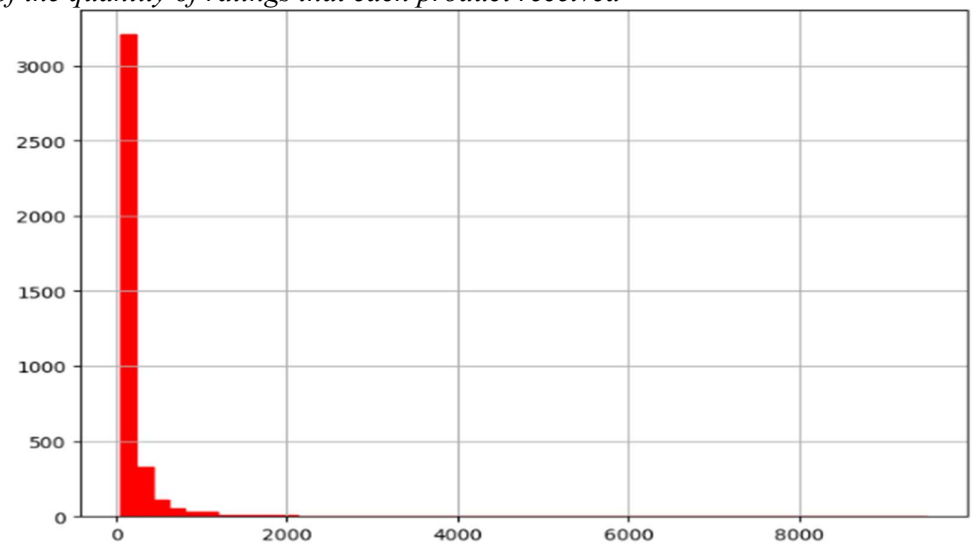
Figure 4

Distribution of the quantity of ratings that each product received



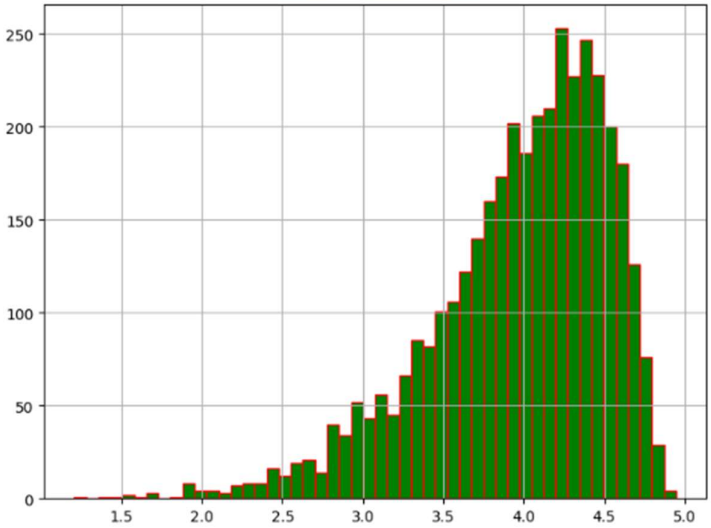
The histogram reveals that most products have fewer ratings, but a small number of products have extraordinarily high numbers of reviews, showing a long-tail distribution. The maximum number of ratings for a single product is 9,487.

J+2. Rating Distribution

To analyse the distribution of the average product ratings, the following histogram was plotted:

Figure 5

Ratings of the Product



According to the histogram, the majority of products have an average rating in the range of 3.5 to 5. A substantial percentage of products have high ratings, suggesting that customers typically leave favourable reviews.

J+3. Joint Distribution of Ratings and Rating Counts

A combined plot was created in order to investigate the connection between the average product rating and the quantity of ratings obtained.

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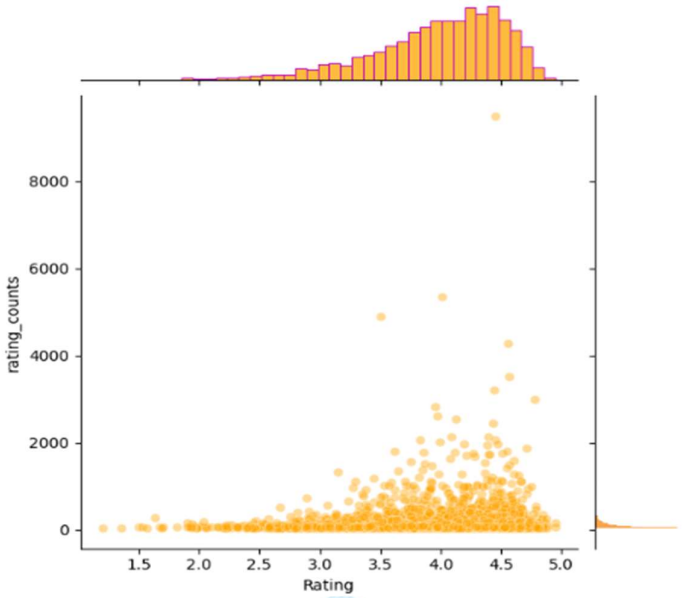
Figure 6

Connection between the average product rating and the quantity of ratings



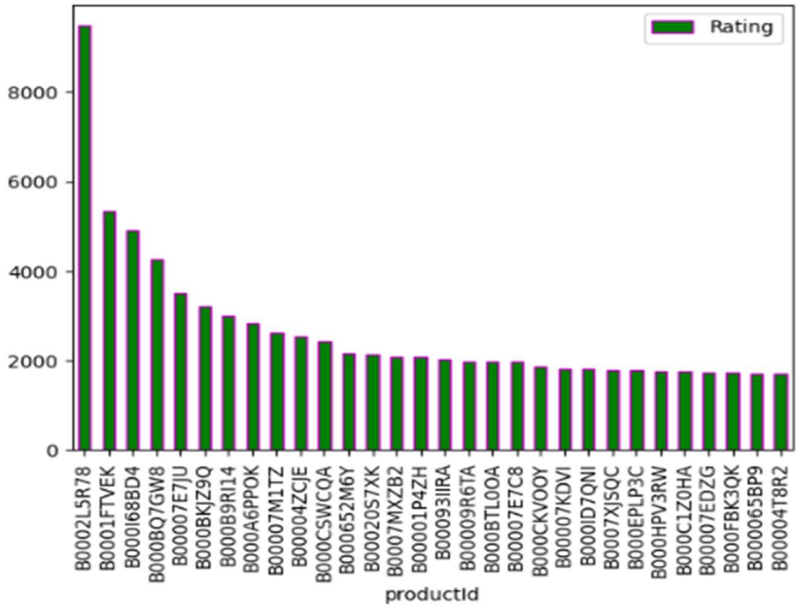
Popular products typically have positive reviews, as evidenced by the joint plot, which shows that products with higher ratings typically have more ratings. A significant amount of reviews and a concentration of data points surround a rating of 4.

J+4. Most Popular Products

According to the joint plot, which indicates that products with higher ratings generally have more ratings, popular products tend to receive positive reviews. A large number of reviews and a concentration of data points surround a rating of four.

Figure 7

30 products with the highest number of ratings



The bar plot shows the top 30 products with the highest number of ratings. The most rated product received **9487** ratings, indicating its high popularity among users.

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J+5. Collaborative Filtering

For recommender systems, collaborative filtering (CF) is frequently employed. By using the past ratings of comparable users or objects, CF approaches seek to complete the missing entries of a user-item association matrix. There are two primary categories into which collaborative filtering falls:

- **Memory-based approaches:** These approaches rely on user or item similarity based on past interactions.
- **Model-based approaches:** These approaches use machine-learning models to predict user-item interactions.
- The KNNWithMeans algorithm from the surprise library was used in this study's item-based collaborative filtering methodology. The actions listed below were taken:

1. Data Preparation:
   The dataset was loaded using the `Reader` and `Dataset` classes from the `surprise` library:

```
reader = Reader(rating_scale=(1, 5))
data = Dataset.load_from_df(new_df, reader)
```

4. Training and Testing:
   The dataset was split into training and test sets (70% training, 30% testing):

```
trainset, testset = train_test_split(data, test_size=0.3,
random_state=10)
```

6. Model Training:
   An item-based collaborative filtering model was trained using the `KNNWithMeans` algorithm with Pearson Baseline similarity:

```
algo = KNNWithMeans(k=5, sim_options={'name': 'pearson_baseline',
'user_based': False})
algo.fit(trainset)
```

9. Prediction and Evaluation:
   The trained model was evaluated on the test set using Root Mean Square Error (RMSE):

```
test_pred = algo.test(testset)
accuracy.rmse(test_pred, verbose=True)
```

The obtained RMSE value was 1.3436, indicating the model's predictive accuracy.

J+6. Matrix Factorization Using Truncated SVD

Matrix factorization remains a well-known technique applied in recommender systems where the data is pre-processed and its dimension is reduced to discover patterns that are more latent. As for matrix factorization, Truncated Singular Value Decomposition was used. The following are the steps:

Utility Matrix Creation:
The following utility matrix was prepared with the help of reshaping the dataset using the userId as the index for row and ProductId as columns with all the values filled as 0 in case of missing values:

```
ratings_matrix = new_df1.pivot_table(values='Rating',
index='userId', columns='productId', fill_value=0)
```

The resulting matrix had a shape of (9832, 76), indicating 9832 users and 76 products.

2. Matrix Transposition:
   The matrix was transposed to facilitate item-based recommendations:

```
X = ratings_matrix.T
```

4. Dimensionality Reduction with Truncated SVD:
   The matrix was factorized using Truncated SVD with 10 components:

```
from sklearn.decomposition import TruncatedSVD
SVD = TruncatedSVD(n_components=10)
decomposed_matrix = SVD.fit_transform(X)
```

This reduced the matrix shape to (76, 10), capturing the most relevant latent factors.

8. Correlation Matrix:
   A correlation matrix was computed to identify relationships between products:

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9. `correlation_matrix = np.corrcoef(decomposed_matrix)`
   The resulting correlation matrix had a shape of (76, 76).
10. Product Recommendation:
    The top 25 products most highly correlated (correlation > 0.65) with the product purchased by the user were recommended:
11. `Recommend = list(X.index[correlation_product_ID > 0.65])`
12. `Recommend.remove(i) # Remove the product already purchased`
    The top recommended products included:
    `'3744295508', '9888002198', '9984984354', 'B00000J1EJ', 'B00000J1U8',...`

Results

Collaborative filtering and matrix factorisation were used to assess the suggested product review recommendation system. The following is a summary of the main findings:

Data Summary and Distribution

- The dataset contained 1,048,576 records after pre-processing.
- A total of 786,330 unique users and 61,894 unique products were identified.
- The ratings were distributed between 1 to 5, with a mean rating of 3.97 and a standard deviation of 1.39**.**
- Most users rated only one product, but some active users rated as many as 412 products.
- Products with more than 50 ratings were selected for building the recommendation model.

Collaborative Filtering Results

Collaborative filtering was implemented using the KNNWithMeans algorithm from the Surprise library:

- The model was trained on **70%** of the dataset and tested on 30%**.**
- The evaluation produced a Root Mean Square Error (RMSE) of 1.3436**,** indicating a reasonable level of prediction accuracy.
- Item-based collaborative filtering using the Pearson Baseline similarity measure showed good performance in predicting user preferences.

Matrix Factorization Results

Matrix factorization using Truncated SVD produced the following results:

- The matrix factorization reduced the utility matrix from (76, 9832) to (76, 10) dimensions.
- A correlation matrix based on decomposed features was computed to identify similar products.
- The model successfully recommended the top 25 most correlated products based on a similarity threshold of 0.65.
- Example of top correlated products: '3744295508', '9888002198', '9984984354', 'B00000J1EJ', 'B00000J1U8', ...

Conclusion and Future Work

This work used matrix factorisation and collaborative filtering to present a product review recommendation system. A dataset of more than a million product reviews from the electronics industry was used to assess the system. Below is a summary of the main conclusions and results:

- To comprehend user and product behaviour, a thorough data pre-treatment and exploratory analysis were carried out.
- Using an RMSE of 1.3436, collaborative filtering using the KNNWithMeans algorithm successfully caught user-item associations and produced a respectable prediction accuracy.
- Truncated SVD, a matrix factorisation technique, preserved key patterns in user-product interactions while reducing the high-dimensional data to a manageable amount.
- The system improved the ideas' relevancy by successfully identifying and recommending the best connected products.

Future Work

While the proposed system demonstrated promising results, there are several areas for future improvement:

- Hybrid models**:** Combining collaborative filtering with content-based filtering and deep learning could enhance recommendation accuracy and robustness.
- Cold start problem**:** Addressing the challenge of recommending products to new users or products with limited reviews using hybrid or contextual approaches.
- Scalability**:** Implementing distributed computing frameworks like Apache Spark to handle large-scale datasets more efficiently.
- Real-time recommendations**:** Developing a system capable of providing real-time recommendations based on dynamic user behaviour.
- User behaviour analysis: Incorporating implicit feedback (e.g., clicks, views, and dwell time) to enhance the understanding of user preferences.

The suggested approach provides a strong basis for developing a scalable and effective recommendation engine, with substantial room for improvement through the use of real-time processing and sophisticated machine learning algorithms

References

Afshar, M. Z. (2023). Exploring factors impacting organizational adaptation capacity of Punjab Agriculture & Meat Company (PAMCO). *International Journal of Emerging Issues in Social Science, Arts and Humanities, 2*(1), 1-10. https://doi.org/10.60072/ijeissah.2023.v2i01.001

Afshar, M. Z., & Shah, M. H. (2025). Performance evaluation using Balanced Scorecard framework: Insights from a public sector case study. *International Journal of Human and Society, 5*(1), 40-47. https://ijhs.com.pk/index.php/IJHS/article/view/808

Afshar, M. Z., & Shah, M. H. (2025). Strategic evaluation using PESTLE and SWOT frameworks: Public sector perspective. *ISRG Journal of Economics, Business & Management, 3*(1), 108-114. https://doi.org/10.5281/zenodo.14854362

Aggarwal, C. C. (2016). *Recommender systems: The textbook*. Springer.

Anjum, N., & Kabir, A. (2019). Introducing Refined Agile Model (RAM) in the context of Bangladesh's software development environment concentrating on the improvement of requirement engineering process. *International Journal of Software Engineering & Applications, 10*(4).

Badrul, S., Konstan, J., & Riedl, J. (2005). Combining collaborative filtering with personal agents for better recommendations. *Proceedings of the 4th International Conference on Intelligent User Interfaces* (pp. 285-295).

Bell, R., & Koren, Y. (2007). Scalable collaborative filtering with jointly derived neighborhood interpolation weights. *Proceedings of the 7th IEEE International Conference on Data Mining* (pp. 43-52).

Breese, J. S., Heckerman, D., & Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence* (pp. 43-52).

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction, 12*(4), 331-370.

Covington, P., Adams, J., & Sargin, E. (2016). Deep neural networks for YouTube recommendations. *Proceedings of the 10th ACM Conference on Recommender Systems* (pp. 191-198).

Davidson, J., Liebald, B., Liu, J., Nandy, P., Van Vleet, T., Gargi, U., et al. (2010). The YouTube video recommendation system. *Proceedings of the 4th ACM Conference on Recommender Systems* (pp. 293-296).

Dhal, K., Karmokar, P., & Chakravarthy, A. (2022). Vision-based guidance for tracking multiple dynamic

objects. *Journal of Intelligent & Robotic Systems, 105*(66). https://doi.org/10.1007/s10846-022-01657-6

Funk, S. (2006). *Netflix update: Try this at home*. https://sifter.org/~simon/journal/20061211.html

Gomez-Uribe, C. A., & Hunt, N. (2015). The Netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems, 6*(4), 1-19.

He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017). Neural collaborative filtering. *Proceedings of the 26th International Conference on World Wide Web* (pp. 173-182).

Koren, Y., & Bell, R. (2015). Advances in collaborative filtering. In F. Ricci, L. Rokach, & B. Shapira (Eds.), *Recommender systems handbook* (pp. 77-118). Springer.

Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer, 42*(8), 30-37.

Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing, 7*(1), 76-80.

Rendle, S. (2010). Factorization machines. *Proceedings of the 10th IEEE International Conference on Data Mining* (pp. 995-1000).

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. *Proceedings of the 10th International Conference on World Wide Web* (pp. 285-295).

Su, X., & Khoshgoftaar, T. M. (2009). A survey of collaborative filtering techniques. *Advances in Artificial Intelligence, 2009*, Article 421425.

Wu, L., Wang, P., Li, Q., & He, X. (2021). Graph collaborative filtering. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 353-362).