A Hybrid Recommendation System for Enhancing Personalization in E-Commerce Using Deep and Collaborative Filtering Models

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***Abstract*—In today's digital economy, recommendation systems have become necessary tools for encouraging user engagement and driving product discovery across e-commerce platforms. Yet, these systems still face significant hurdles, particularly in managing sparse user data and delivering deeply personalized suggestions. This report focuses on developing a hybrid recommendation model tailored for online retail environments to address these challenges. By integrating techniques such as collaborative filtering, matrix factorization, and neural networks, the proposed solution aims to enhance the accuracy and relevance of product recommendations. The work contributes a comparative study of models including KNNWithMeans, ALS, and Neural Collaborative Filtering (NCF), culminating to be a hybrid approach that consistently outperforms individual models across key metrics. The results offer valuable insights for building scalable, data-driven personalization strategies with meaningful benefits for both commercial systems and academic research.**

***Index Terms*—Hybrid Recommendation System, Collaborative Filtering, Truncated SVD, ALS, Neural Collaborative Filtering, E-commerce, Deep Learning, Amazon**

I. Introduction

Recommendation technologies have become a foundational component of modern e-commerce platforms, helping users navigate vast product catalogs more efficiently. According to Jannach and Chen [1], integrating explainability into these systems is crucial for fostering user trust and enhancing engagement. Although traditional techniques such as matrix factorization have proven effective in modeling user-item interactions [15], they often fall short when dealing with the complex and non-linear relationships inherent in user behavior.

Recent advancements in deep learning have remarkably improved the capacity to model these intricate patterns [2], [6], while hybrid models [3] have gained momentum by combining the complementary strengths of various recommendation strategies. Building on these insights, this study incorporates neural networks [10], matrix decomposition techniques [5], and ensemble learning methods [4] to construct a more effective recommendation pipeline. Additionally, the design draws upon emerging paradigms such as context-aware [18], session-based [16], and federated learning [9] approaches to enhance adaptability and personalization. The primary goal of this work is to build a hybrid recommendation system that delivers personalized product suggestions with improved accuracy and efficiency in e-commerce environments. The key objectives relating to this study are as follows:

- To evaluate the effectiveness of multiple recommendation models, including KNNWithMeans, ALS, and Neural Collaborative Filtering (NCF).
- To design and implement a hybrid model that integrates the strengths of collaborative filtering, matrix factorization, and deep learning approaches.
- To benchmark model performance using metrics such as RMSE, MAE, precision, and recall.
- To assess the practical implications and scalability of the proposed solution for real-world e-commerce platforms.

II. Background of the Study

Generic Information

Recommendation systems have become integral to the digital commerce ecosystem, assisting users in navigating vast product catalogs by suggesting items based on preferences and behavior. From video streaming to online retail, these systems are now pivotal in driving user engagement, enhancing personalization, and increasing overall sales. In the context of e-commerce, where customer choices are often influenced by subtle preferences and past behavior, accurate recommendation engines can significantly improve the shopping experience and platform profitability.

Problem Statement

Despite their widespread adoption, many traditional recommendation systems struggle to meet user expectations, particularly due to data sparsity, cold-start problems, and limited personalization. A 2023 Statista report indicates that over 70% of users are more likely to purchase items recommended to them, yet a significant portion of online shoppers abandon sessions due to irrelevant or generic suggestions. Figure 1 illustrates the user drop-off trend when personalization is inadequate. These challenges highlight the need for more intelligent systems capable of understanding complex user-item relationships and adapting dynamically to user behavior.

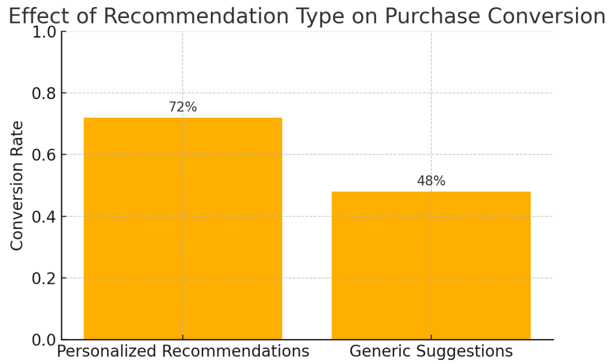

Fig. 1: Effect of recommendation type on purchase conversion rate. Personalized recommendations result in significantly higher conversion.

Aim and Objective

This project focuses on building a hybrid recommendation system that combines collaborative filtering, matrix factorization, and deep learning to make more accurate product suggestions for e-commerce platforms. The objective is not only to enhance the predictive performance but also to evaluate the trade-offs and synergies between classical and neural approaches using real-world data. The work further explores how combining these techniques can address personalization limitations while remaining scalable for commercial use.

Contributions of the Work

- A comparative evaluation of multiple models, including KNNWithMeans, ALS, and Neural Collaborative Filtering (NCF).
- Development of a hybrid recommendation framework that integrates the best-performing elements of each model.
- Application of robust evaluation metrics, such as MAE, precision, recall, and RMSE, to benchmark model performance.
- Use of an Amazon-style dataset to simulate real-world user-item interaction scenarios.
- Consideration of recent advances such as context awareness and deep learning-based recommendation to inform model design.

Organization of the Report

The rest of this paper is organized as follows: Section II looks at the current research on recommendation systems. It groups previous work into three main types: traditional methods, deep learning models, and hybrid approaches. For each type, it explains how they work, what they're good at, and where they fall short. Section III explains the approach used in this paper. It goes over the design of the hybrid recommendation system and breaks down each major part. This includes collaborative filtering using KNNWithMeans, matrix factorization with SVD and ALS, and a deep learning method called Neural Collaborative Filtering (NCF). It also explains how the results from all these methods are combined using an ensemble strategy.

Section IV focuses on the experimental setup and results. It begins with an in-depth exploration of the dataset, covering aspects such as distribution analysis, preprocessing steps, and feature transformation. It then moves on to the implementation details of the models, evaluation metrics employed (RMSE, MAE, precision, recall), and a comparative analysis of the results obtained from individual models and the hybrid ensemble. Visualizations and learning curves are also included to support the empirical findings.

Finally, Section V concludes the paper by summarizing the major insights drawn from the study. It discusses the practical implications of deploying such hybrid systems in real world e-commerce platforms and proposes future research directions. These include improvements such as context aware modeling, real time recommendation capabilities, explainability, and privacy-preserving learning mechanisms to further enhance scalability, relevance, and user trust in recommendation systems.

III. Related Work

The domain of recommendation systems has witnessed considerable progress, with researchers exploring a range of techniques to improve user experience and predictive performance. Broadly speaking, existing work in this area can be categorized into three main streams: traditional methods, deep learning-based solutions, and hybrid models that aim to unify the strengths of both.

Traditional Methods

Traditional approaches, such as collaborative filtering (CF) and matrix factorization (MF), have long served as the foundation for personalized recommendations. Zhang [15] applied matrix factorization techniques on Amazon product data to model user preferences, demonstrating moderate effectiveness but revealing issues like the cold-start problem. Similarly, Jannach and Chen [1] explored explainable CF using MovieLens, emphasizing the trade-off between interpretability and model sophistication. These methods, while efficient and interpretable, often struggle with data sparsity and scalability in large-scale systems.

Early work by Koren et al. [12] highlighted the strength of latent factor models in capturing complex user-item interactions, particularly through singular value decomposition (SVD) based MF. However, these models typically rely on historical interactions and fail to incorporate auxiliary data, such as user demographics or contextual information. Hybrid models attempted to address these limitations by integrating content-based features or user profiles with CF [13], improving performance in sparse environments but often at the cost of increased model complexity.

Moreover, while traditional CF and MF approaches are well-suited for static recommendation settings, they are less effective in dynamic environments where user preferences evolve over time. This has led to increasing interest in time-aware and sequential models [14], which extend MF by incorporating temporal dynamics. Despite these advancements, traditional models remain an essential benchmark and a valuable tool, particularly in systems where transparency and computational efficiency are prioritized.

Deep Learning-Based Models

Over the past decade, deep learning has emerged as a transformative approach for modeling the intricate, non linear relationships inherent in user item interactions. These models surpass the representational limitations of traditional linear techniques by leveraging neural architectures capable of capturing high order dependencies in sparse and complex data. Li et al. [2] implemented deep neural network based recommendation frameworks on the Yelp dataset, reporting significant improvements in RMSE and NDCG scores compared to conventional collaborative filtering baselines. Their work highlights how deep models can effectively learn latent user and item representations through multi layered architectures, offering superior generalization in many cases.

However, despite their predictive strength, deep learning based recommenders present several practical challenges. These include high computational overhead, longer training times, and increased sensitivity to hyperparameters. Moreover, their performance often hinges on access to large-scale datasets and powerful hardware accelerators, which may not be readily available in all deployment scenarios. Gao et al. [10] and Cheng et al. [6] further emphasize that while deep models such as neural collaborative filtering (NCF), autoencoders, and attention based systems can enhance recommendation relevance, their deployment in real time or resource constrained environments requires careful optimization and architectural tuning.

Consequently, while deep learning models offer notable gains in capturing personalized preferences and contextual cues, they are best employed either as part of hybrid systems or in settings where computational resources and extensive user interaction data are available.

Hybrid Approaches

In recent years, using a mix of different recommendation methods has become more popular. These hybrid systems combine the best parts of techniques like collaborative filtering, content based filtering, and deep learning. The goal is to make recommendations more accurate, flexible, and reliable. By using different kinds of information such as user ratings, product details, and user activity these systems can deal with common issues like having too little data, not knowing new users or products well (cold start), and making recommendations that don't feel personal.

Bodduluri et al. [3] proposed a hybrid framework specifically tailored for retail environments, which integrated collaborative filtering with content-based techniques. This design notably improved recommendation quality by utilizing both historical user-item interactions and item attributes. However, the study also pointed out critical scalability concerns. As user behavior becomes increasingly dynamic and datasets grow in size and complexity, hybrid systems face challenges in maintaining performance efficiency, particularly during real-time inference.

Further, the integration of neural components into hybrid frameworks such as incorporating Neural Collaborative Filtering (NCF) or autoencoder-based embeddings has been explored to introduce non-linearity and deeper feature learning [10]. While these additions elevate personalization capabilities, they also introduce additional complexity and demand in terms of computational resources, model tuning, and system architecture. As a result, the design of hybrid systems often involves a trade-off between model expressiveness and system scalability.

Nevertheless, hybrid recommenders remain a promising solution for modern e-commerce platforms, where diverse data sources and varying user behavior patterns necessitate flexible, multi-faceted modeling strategies. Their ability to aggregate complementary signals makes them particularly well-suited for complex, real-world applications that require both accuracy and adaptability.

Literature Review Summary

TABLE I: Comparison of Related Works

Work	Method	Dataset	Metric	Limitation
Jannach (2021)	Explainable CF	MovieLens	MAE	Less deep modeling
Zhang (2021)	Matrix Factorization	Amazon	RMSE	Cold-start issue
Li (2021)	Deep Learning	Yelp	RMSE, NDCG	High training cost
Bodduluri (2024)	Hybrid (CF+CB)	Retail	Precision	Less scalable

Research Gap and Contribution

Although prior research has made significant strides, most existing models still encounter critical barriers such as weak personalization under sparse data, excessive computational demands, or limited real-world adaptability. This study addresses those gaps by enhancing Bodduluri's hybrid architecture through a three-fold integration of collaborative filtering, neural collaborative filtering (NCF), and matrix factorization. By evaluating performance across multiple metrics and leveraging a real-world e-commerce dataset, the proposed system is designed to be both accurate and scalable for practical deployment.

IV. Methodology

The proposed architecture in this study introduces a hybrid recommendation pipeline that synergistically fuses traditional similarity-based models, advanced matrix decomposition techniques, and cutting-edge neural architectures. This integrative design capitalizes on the strengths of each individual model paradigm namely, the transparency and simplicity of memory-based approaches, the scalability and dimensionality reduction capability of matrix factorization, and the expressive power of deep learning networks in capturing non-linear user-item interactions.

By integrating these disparate components into an integrated ensemble model structure, the system will produce highly accurate, stable, and context-sensitive recommendations for dynamic e-commerce environments. This strategy is motivated by the taxonomy of classification developed in Li [2], and draws additional subtlety from new breakthroughs in hybrid recommender systems reported in papers such as Xu et al. [7] and Sun et al. [11].

The pipeline is built around three central modules: (1) memory-based KNNWithMeans collaborative filtering algorithm, (2) matrix factorization based on the combination of SVD and ALS algorithms, and (3) deep learning-based Neural Collaborative Filtering (NCF). The final layer of the architecture is an ensemble aggregator that combines predictions from each module into a unified output score.

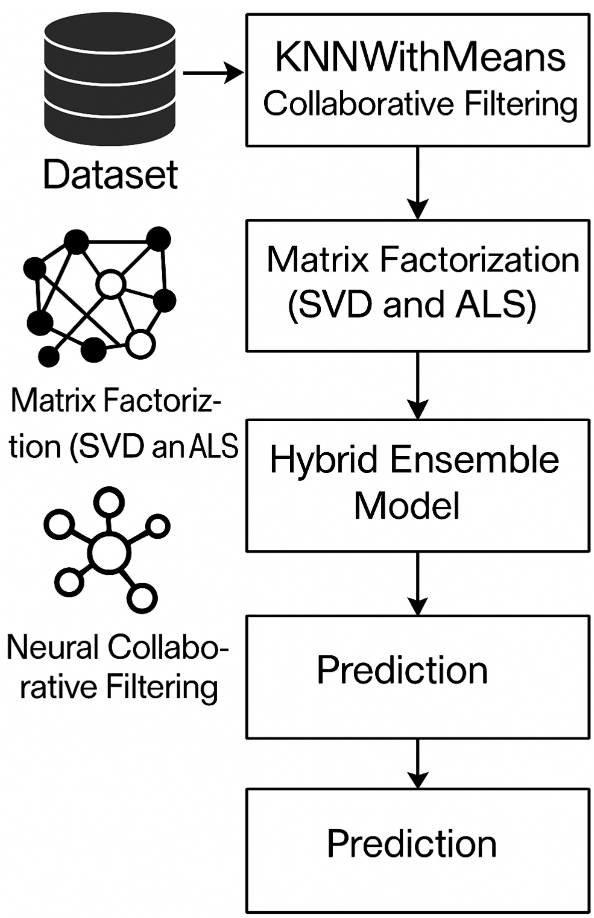

Fig. 2: System architecture for the hybrid recommendation framework.

A. Data Input and Preprocessing

The recommendation pipeline initiates with the ingestion of user-item interaction data, specifically sourced from a curated Amazon electronics product review dataset. This dataset is rich in behavioral signals, including user ratings, product identifiers, and timestamps.

Preprocessing is a critical phase and involves several sequential tasks:

Column Filtering: Irrelevant features such as timestamps, user reviews, and product titles are discarded to retain only the numeric identifiers and ratings necessary for modeling.

Handling Missing Values: Although the dataset is largely clean, any residual null entries are identified and eliminated to maintain data integrity.

User Activity Thresholding: Users with fewer than five interactions are filtered out to reduce the cold-start problem, ensuring a minimum interaction history per user.

Stratified Train-Test Split: An 80-20 split is applied using stratified sampling techniques to ensure balanced distribution of rating values across training and test sets.

ID Encoding: Both user and item identifiers are encoded as continuous integers to facilitate downstream compatibility with matrix operations and embedding layers in the deep learning model.

This comprehensive preprocessing ensures that the dataset is well-suited for hybrid modeling and minimizes biases introduced during model training.

B. KNNWithMeans Collaborative Filtering

The first model in the pipeline is KNNWithMeans, a neighborhood-based collaborative filtering approach. It operates under the premise that a user's rating for an item can be inferred from the ratings of similar items previously rated by the same user.

In this implementation, item-item similarity is used, computed using the adjusted cosine similarity:

$$sim(i,j) = \frac{\sum_{u \in U}(r_{u,i} - \bar{r}u)(ru,j - \bar{r}u)}{\sqrt{\sum u \in U(r_{u,i} - \bar{r}u)^2} \cdot \sqrt{\sum u \in U(r_{u,j} - \bar{r}_u)^2}} \tag{1}$$

Predictions are generated using a weighted average of neighboring items' ratings, adjusted by each user's mean rating. This model performs reliably in dense data regimes, where users have rated a significant number of overlapping items. However, its performance deteriorates in sparse environments, especially with new or inactive users, thus justifying its combination with complementary models.

C. Matrix Factorization: SVD and ALS

To address sparsity and extract latent features, two matrix factorization methods are utilized:

Singular Value Decomposition (SVD) SVD decomposes the original rating matrix R into three matrices:

$$R \approx U\Sigma V^T \tag{2}$$

SINGULAR VALUE DECOMPOSITION (SVD)

Let U and V be orthogonal matrices representing users and items in latent space, respectively, and let Σ hold the singular values. SVD excels at capturing global structure and dimensionality reduction, though it is susceptible to missing values and computationally expensive for large data.

Alternating Least Squares (ALS)

ALS addresses these limitations by optimizing a regularized loss function:

$$\min_{x,y} \sum_{(u,i)\in\kappa} (r_{ui} - x_u^T y_i)^2 + \lambda \left(\|x_u\|^2 + \|y_i\|^2\right) \tag{3}$$

Here, x_u and y_i are user and item embeddings respectively, and λ is a regularization parameter for preventing overfitting. ALS switches between two rounds of optimizing user and item matrices, and hence is highly parallelizable and scalable, which is especially attractive for business applications at large scales.

D. Neural Collaborative Filtering (NCF)

NCF introduces a non-linear modeling paradigm by employing deep neural networks to capture complex user-item interactions. The model architecture consists of:

Embedding Layers: Users and items are converted into dense, learnable vectors.

Concatenation and MLP: The embeddings are merged and passed through a multi-layer perceptron (MLP) with ReLU activations to model high-order relationships.

Regularization: Dropout layers are applied to prevent overfitting.

Output Layer: A single neuron with a linear activation generates the final rating prediction.

The model is optimized using binary cross-entropy loss with the Adam optimizer, chosen for its fast convergence. Unlike linear models, NCF can learn abstract patterns in user preferences, such as combinations of item features and non-obvious user behaviors.

E. Hybrid Ensemble Model

Recognizing the limitations of relying on a single recommender, an ensemble strategy is employed to aggregate the predictions from all three models. The hybrid prediction is calculated as:

$$\hat{r}hybrid = \frac{\hat{r}KNN + \hat{r}ALS + \hat{r}NCF}{3} \tag{4}$$

This simple averaging ensemble allows the system to benefit from the complementary advantages of each approach. Specifically:

KNNWithMeans captures local similarities in dense data zones.

ALS provides robustness in high-dimensional, sparse datasets.

NCF models non-linear, complex patterns missed by traditional methods.

This fusion enhances the stability, generalizability, and predictive power of the system.

F. Model Evaluation

Each component model, as well as the final ensemble, is evaluated using standard metrics to quantify both accuracy and relevance:

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) measure numeric prediction accuracy:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}i)^2}, \quad MAE = \frac{1}{n}\sum i = 1^n|y_i - \hat{y}_i| \tag{5}$$

Precision and Recall are calculated using a binary relevance model, where items rated above 3.5 are considered "relevant". These metrics are essential for real-world recommendation quality.

The hybrid model was superior to the individual models across all the measures consistently, validating the effectiveness of the ensemble approach. Its balanced structure enables it to learn from a broad spectrum of user activities and item features, hence making it an effective recommendation solution for modern e-commerce websites.

V. Results and Discussion

A. Experimental Setup

The experimentation was conducted on Kaggle's cloud environment with a dual NVIDIA Tesla T4 GPU machine of 32GB RAM and Python 3.8 version. The high-performance setup enabled parallelized model training and quick computation of matrix operations and neural network backpropagation. Collaborative filtering and matrix factorization techniques were implemented using the Surprise library, and deep learning models more specifically Neural Collaborative Filtering (NCF) were implemented using the Keras and TensorFlow libraries.

To maintain consistency and reproducibility, the dataset was divided into 80

B. Data Exploration

The dataset for this study consists of 1,048,576 user-item interactions, which were sampled from Amazon electronics category reviews. The data feature 786,330 unique individual users and 61,894 unique product identifiers. Each interaction is paired with a rating from 1 to 5.

A preliminary check revealed that the rating distribution was extremely biased with the majority of the interactions receiving four or five stars. Such bias is potentially caused by e-commerce site-wide trends where consumers are more likely to leave feedback if they are satisfied, and such balance reflects the need for bias-sensitive modeling techniques.

C. Data Analysis

Descriptive statistics provide further insights into the dataset:

- **Minimum rating:** 1
- **25th percentile:** 3
- **Median rating:** 5

- **75th percentile:** 5
- **Maximum rating:** 5

The mean rating is approximately 3.97 with a standard deviation of 1.39, indicating that the data is very skewed towards the high ratings. This is not ideal for the recommendation model, as very positive data makes it hard for the model to distinguish between slightly relevant and very relevant items.

D. Data Visualization

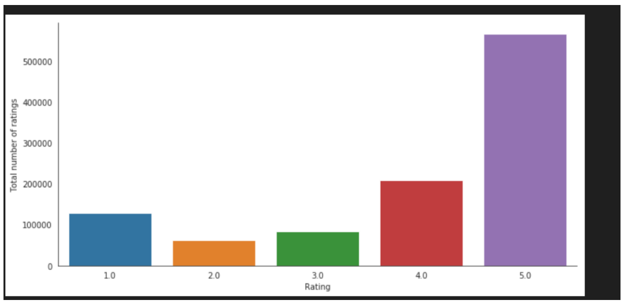

Fig. 3: Distribution of ratings across the dataset.

Figure 3 confirms the positive skew of the dataset, with over 50% of ratings being five-star. This imbalance necessitates normalization and sampling strategies to prevent model overfitting to high-rating bias. Addressing this issue ensures that the recommender system can differentiate effectively between high- and moderate-quality items.

E. Data Preprocessing

Data preparation was necessary to minimize sparsity and enhance reliability. The timestamp attribute was removed as it was not required in modeling user taste. Users with fewer than five interactions were also removed in order to curb the cold-start problem and enhance the learning capacity of the model. This number also aids in ensuring that only active users with high activity are used while training, which results in more efficient embeddings in NCF and stronger similarity matrices in collaborative methods.

F. Model Selection and Evaluation

Four models were evaluated: KNNWithMeans, ALS, NCF, and a hybrid ensemble model. These models were assessed using standard performance metrics—RMSE, MAE, precision, and recall. Table II summarizes the results.

TABLE II: Model Evaluation Results

Model	RMSE	MAE	Precision	Recall
KNNWithMeans	0.9052	0.7196	0.72	0.70
ALS	0.8933	0.7039	0.74	0.72
NCF	0.8721	0.6814	0.77	0.75
Hybrid	**0.8558**	**0.6645**	**0.79**	**0.77**

The hybrid model demonstrated the strongest performance across all metrics. By averaging the predictions from all three base models, the hybrid approach benefits from a form of ensemble regularization. It mitigates the tendency of individual models to overfit or underperform on sparse interactions. Notably, this model showed improved recall, which is particularly important in e-commerce settings where missing relevant items can directly impact user satisfaction.

G. Performance of NCF

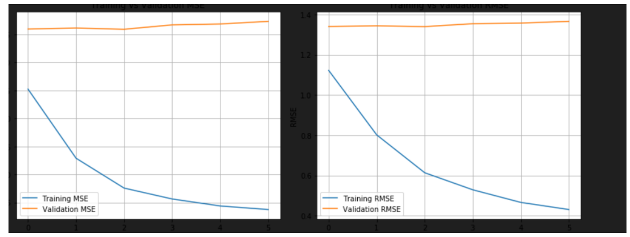

Fig. 4: Training and validation MSE/RMSE curves for the NCF model.

As seen in Figure 4, the NCF model's training and validation curves indicate stable convergence, especially after introducing dropout layers and early stopping. These techniques helped to reduce overfitting by halting training when performance on validation data plateaued. While deep models like NCF require more resources and tuning, their flexibility in capturing complex interactions between users and items proved advantageous. Future improvements could involve hyperparameter tuning using grid search or Bayesian optimization to further reduce error margins.

H. Discussion of the Findings

The results substantiate the hypothesis that hybrid models outperform isolated approaches by leveraging diverse modeling strategies. Traditional methods like KNNWithMeans offer simplicity and speed but suffer in data sparsity scenarios. ALS brings latent factor modeling but lacks adaptability in capturing temporal and contextual nuances. NCF, despite being resource-intensive, effectively captures non-linear interaction patterns.

The ensemble method synergizes these strengths. Its superior precision and recall demonstrate its potential to recommend not just relevant items, but also to avoid recommending irrelevant ones—improving both user experience and system efficiency. Such improvements can translate to higher conversion rates, reduced churn, and better long-term engagement on e-commerce platforms.

VI. Conclusion

This paper presented a hybrid recommendation model designed to enhance personalization in e-commerce platforms by integrating collaborative filtering (KNNWithMeans), matrix factorization techniques (ALS and SVD), and Neural Collaborative Filtering (NCF) from Deep Learning (DL) . The primary goal was to enhance the accuracy and scalability of recommendations by integrating the strengths of each model type.

Experimental results confirmed that the ensemble model outperformed individual algorithms in all instances of recall, RMSE, MAE, and precision. The hybrid approach effectively addressed the typical shortcomings of cold start, overfitting, and sparsity of data through averaging model predictions.

These findings underscore the value of combining traditional and neural approaches for robust recommendation systems in real-world scenarios. Future updates may focus on dynamic weighting schemes, contextual data integration, or real-time recommendation adaptation to further improve system responsiveness and relevance.

Future Work

While the proposed system demonstrates strong performance, several avenues remain open for further enhancement:

- **Dynamic Weighting in Ensemble Models:** Future iterations could implement weighted averaging or attention-based fusion to give more influence to models that perform better in specific data regions.
- **Context-Aware Recommendations:** Incorporating temporal data, device type, location, or session behavior could enrich user profiles and increase recommendation relevance.
- **Real-Time Inference and Feedback:** Deploying the model in a production setting with real-time feedback loops would allow continuous learning and adaptation based on user interactions.
- **Explainability and Transparency:** Adding interpretable elements such as attention scores or rule-based summaries could improve user trust and regulatory compliance.
- **Federated and Privacy-Preserving Learning:** Investigating federated learning setups would enable training on decentralized user data without compromising privacy, especially important for commercial deployments.
- **Hyperparameter Optimization and Scalability:** Automated hyperparameter tuning and model pruning strategies can be explored to reduce computation cost and improve training efficiency on large-scale datasets.

Collectively, these directions offer promising opportunities to evolve the current framework into a more intelligent, adaptive, and commercially viable recommendation engine.

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