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Transforming Retail Analytics: AI-Driven Insights for Personalized Shopping Experiences

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Abstract: AI-powered analytics have the potential to revolutionize the retail industry by offering customized purchasing experiences. This research presents a hybrid model that integrates collaborative filtering and deep learning approaches for the analysis of customer behavior and preferences. The model leverages transaction data and customer interactions to recommend personalized products with an impressive accuracy of 93.8%. The Hybrid Neural Collaborative Filtering (HNCF) model utilizes several advanced components, including Hierarchical User Attention and Product Attention (HUAPA), Deep Collaborative Filtering (DCF), Neural Sentiment Classifier (NSC), and Deep Multivariant Rating (DMR). HUAPA captures intricate details from user reviews and product descriptions, while DCF models user-product interactions using a multi-layer perceptron. The NSC module classifies sentiments from user reviews, adding another layer of personalization, and the DMR integrates multiple rating sources to produce a comprehensive product ranking.

Applied to a major e-commerce platform, this approach significantly enhanced the shopping experience. The real-world application of the HNCF model resulted in a 20% increase in customer engagement and a 15% boost in sales. The significant enhancements highlight the model's efficacy in precisely forecasting user preferences and delivering pertinent product suggestions. The results of this study highlight the transformative potential of AI in retail analytics. By integrating sophisticated machine learning techniques, the HNCF model not only delivers tailored shopping experiences but also drives customer satisfaction and boosts retail performance. This research underscores the importance of advanced AI solutions in the retail sector, paving the way for future innovations in personalized shopping experiences.

Keywords: *Hybrid Neural Collaborative Filtering (HNCF), Personalized Recommendations, Deep Learning in Retail Analytics, Customer Interaction Data, E-commerce Platform Analytics, Collaborative Filtering Techniques*

Introduction

The retail industry has undergone significant transformation with the advent of digital technologies, resulting in a substantial shift in how businesses engage with customers. This change relies on recommendation systems to adapt shopping experiences to user preferences. These systems leverage advanced computational techniques, including Artificial Intelligence (AI), Natural Language Processing (NLP), and Machine Learning (ML), to analyze vast amounts of data and deliver tailored recommendations [1, 2]. Collaborative filtering, which recommends products based on comparable users' likes and activities, inspired recommendation systems. Traditional collaborative filtering methods, such as Matrix Factorization (MF), have been extensively researched and applied in various domains [3, 4]. However, these methods often face limitations, such as the cold start problem and the inability to capture complex user-product interactions effectively [5, 6]. To address these challenges, recent advancements have focused on incorporating deep learning techniques into recommendation systems [7, 8].

Deep learning has revolutionized many fields by enabling models to learn hierarchical representations of data [9, 10]. In the context of recommendation systems, deep learning allows for the modeling of intricate relationships between users and products, going beyond the linear interactions captured by traditional methods [11]. This integration has given rise to hybrid models that combine collaborative filtering with deep learning, resulting in improved performance and more accurate recommendations [12]. An example of a hybrid model is the Hybrid Neural Collaborative Filtering (HNCF) framework, which merges the advantages of collaborative filtering and deep learning. HNCF leverages a hierarchical attention network to learn user and product representations, incorporating user preferences and product characteristics into a unified model [13]. By employing techniques such as Bi-directional Long Short-Term Memory (BiLSTM) networks and attention mechanisms, HNCF captures both the explicit interactions between users and products and the semantic information contained in user reviews and ratings [14].

The application of HNCF in the retail industry offers several advantages. By analyzing transaction data and customer interactions, the model can recommend personalized products with high accuracy [15]. This personalized approach not only enhances customer

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satisfaction but also drives customer engagement and boosts sales [16]. Furthermore, the ability to incorporate multiple data sources, such as reviews, ratings, and social media interactions, allows for a comprehensive understanding of customer preferences and behaviors [17]. In summary, the integration of AI-driven analytics into retail recommendation systems represents a significant advancement in delivering personalized shopping experiences. The HNCF framework exemplifies this integration by combining collaborative filtering with deep learning techniques, resulting in a powerful tool for analyzing customer behavior and preferences [18]. This paper explores the development and application of HNCF in a major e-commerce platform, highlighting its impact on customer engagement and sales [19]. The findings demonstrate the potential of AI in transforming retail analytics and paving the way for future advancements in personalized recommendation systems [20].

Related Works:

Recommendation systems are becoming indispensable in many fields, utilizing collaborative filtering, content-based filtering, and hybrid techniques to offer individualized recommendations. Early methods to recommendation systems primarily on collaborative filtering techniques, which utilize the behavior patterns of similar users to forecast user preferences. Resnick et al. created a pioneering method in this field called GroupLens, which served as the basis for several future collaborative filtering algorithms [21]. Matrix factorization techniques, such as Singular Value Decomposition (SVD), have been widely employed in collaborative filtering. These techniques break down the matrix that represents the interactions between users and items into hidden variables, which capture the underlying patterns in the data. However, traditional MF methods struggle with the cold start problem and often fail to capture complex, non-linear user-item interactions [22]. To address these limitations, deep learning techniques have been integrated into recommendation systems, leading to significant advancements in accuracy and scalability [23].

Neural Collaborative Filtering (NCF) introduced a neural network-based approach to model user-item interactions. NCF employs multi-layer perceptrons (MLPs) to learn the interaction function, providing greater flexibility and modeling capability compared to linear MF methods [24]. Another notable approach is the Collaborative Denoising Autoencoder (CDAE), which leverages autoencoders to reconstruct user-item interactions and improve recommendation robustness [25]. Hybrid models that combine collaborative filtering with deep learning techniques have shown great promise in overcoming the limitations of traditional methods. For example, the Hybrid Neural Collaborative Filtering (HNCF) framework integrates collaborative filtering and deep learning through components such as Hierarchical User Attention and Product Attention (HUAPA), Deep Collaborative Filtering (DCF), Neural Sentiment Classifier (NSC), and Deep Multivariant Rating (DMR) [26]. HUAPA uses Bi-directional Long Short-Term Memory (BiLSTM) networks to process user reviews and product descriptions, capturing semantic information and improving recommendation accuracy [27].

Recent studies have investigated different deep learning structures in order to improve recommendation systems. Convolutional Neural Networks (CNNs) have been used to extract contextual information from short texts, while Recurrent Neural Networks (RNNs) capture temporal dynamics in user ratings [28]. Despite their effectiveness, these models often focus on specific aspects of user-item interactions and may not fully exploit the rich information available in user reviews and ratings [29]. The introduction of attention mechanisms has further advanced the field of recommendation systems. Attention networks, such as those used in the HNCF framework, focus on the most relevant parts of user reviews and product descriptions, improving sentiment analysis and recommendation predictions [30]. This methodology enables a more sophisticated comprehension of user preferences and product attributes, resulting in more precise and tailored suggestions.

Several studies have demonstrated the effectiveness of these hybrid approaches in various domains. For instance, the application of HNCF in e-commerce platforms has shown significant improvements in recommendation accuracy and user satisfaction [31][32]. Additionally, integrating deep learning techniques into recommendation systems has enhanced their performance and scalability, making them suitable for large-scale applications [33]. Overall, the combination of collaborative filtering with deep learning methods signifies a noteworthy progress in the realm of recommendation systems. Hybrid models, like the HNCF framework, utilize the advantages of both approaches to deliver recommendations that are more precise and tailored to individual users. This study emphasizes the potential of utilizing these sophisticated methodologies to revolutionize retail analytics and provide customized shopping experiences [34][35].

Table 1: Overview of Related Work in Recommendation Systems

Method	Description	References
GroupLens	An open architecture for collaborative filtering of netnews.	Resnick et al., 1994 [21]
Singular Value Decomposition (SVD)	Decomposes user-item interaction matrix into latent factors.	Jiang et al., 2019 [22]
Neural Collaborative Filtering (NCF)	Uses multi-layer perceptrons to model user-item interactions.	He et al., 2017 [34]
Collaborative Denoising Autoencoder (CDAE)	Leverages autoencoders to reconstruct user-item interactions.	Wu et al., 2016 [33]
Hybrid Neural Collaborative Filtering (HNCF)	Integrates collaborative filtering and deep learning.	Huang et al., 2018 [27]
Convolutional Neural Networks (CNNs)	Extracts contextual information from short texts.	Yao et al., 2019 [26]
Recurrent Neural Networks (RNNs)	Captures temporal dynamics in user ratings.	Chen et al., 2019 [24]
Attention Mechanisms	Focuses on relevant parts of user reviews and product descriptions.	Da'u and Salim, 2019 [29]

Table 1 above presents a thorough summary of important techniques and their impacts on the field of recommendation systems. Every method possesses distinct advantages and constraints, making a distinctive contribution to the advancement of recommendation techniques that are both more precise and scalable. The progression from conventional techniques like GroupLens and SVD to more sophisticated approaches like NCF, CDAE, and HNCF underscores the notable progress achieved by incorporating deep learning methods. Specifically, hybrid models such as HNCF have shown significant enhancements by utilizing the advantages of both collaborative filtering and deep learning. The use of attention mechanisms and neural network topologies has significantly improved the ability to provide individualized recommendations with greater precision. These advancements highlight the significant impact that improved AI techniques can have in the field of retail analytics and other areas.

Methodology:

Data Collection and Preprocessing

The dataset for this study was gathered from a leading e-commerce platform, consisting of transaction records and customer interactions. Explicit feedback (e.g., ratings, likes) and implicit feedback (e.g., browsing history, search queries) were included. The preprocessing involved data cleaning, normalization, and transformation to ensure the dataset's compatibility with the hybrid model. The dataset utilized for this study was derived from a prominent e-commerce platform, capturing a wide array of transaction records and customer interactions over a significant period. This extensive dataset includes both explicit feedback, such as product ratings and reviews, and implicit feedback, such as browsing history, click-through rates, and purchase patterns. The transaction records form the backbone of the dataset, documenting every purchase made by customers. Each transaction entry comprises details like customer ID, product ID, timestamp, quantity purchased, and the total transaction value. These records were transformed into a structured format, facilitating easier analysis and integration into the hybrid model. The transformation involved converting raw transaction logs into a matrix form, where each entry signifies the presence or absence of a particular product in a transaction [21]. In addition to transaction records, customer interactions with the platform were meticulously logged. These interactions encompass activities such as product searches, page views, clicks, and time spent on each product page. This data provides critical insights into customer preferences and browsing behavior, which are crucial for building a comprehensive recommendation system. The interactions were categorized and quantified to reflect engagement levels, helping in modeling user profiles more accurately [31].

Explicit feedback includes user-generated ratings and reviews for purchased products. This feedback is pivotal in understanding customer satisfaction and product performance. The program was able to learn preferences and patterns by associating each rating and review with specific products and customers. Implicit feedback, however, was obtained from user behavior data such as browsing history, search queries, and click-through rates. This form of feedback, albeit less explicit, provides vital indications regarding user preferences and possible future acquisitions. The preparation phase encompassed multiple crucial processes to guarantee the integrity of the data and its suitability for the hybrid model. Initially, the process of data cleaning was executed to eliminate duplicate entries, discrepancies, and instances of missing data. Subsequently, normalization methods were employed to standardize the data, specifically focusing on numerical attributes such as transaction values and product ratings. Eliminating biases and scale disparities is crucial in order to enhance the model's performance. Subsequently, the data underwent a transformation to meet the specific criteria of the hybrid model. The transaction records were transformed into a transaction matrix format, whereby each row corresponds to a customer and each column corresponds to a product. The values in the matrix indicate the purchase history, either as binary values (showing whether a purchase was made or not) or as frequency values (representing the number of times a product was purchased). Customer interaction data was similarly structured, capturing the intensity and frequency of interactions for each product. To enhance the model's performance, customers were segmented based on their purchasing behavior and interaction patterns. Segmentation involved clustering techniques like K-means to group customers with similar behavior profiles. Key attributes for segmentation included Recency, Frequency, and Monetary value (RFM) metrics, which are standard measures in customer relationship management. These segments allowed the model to tailor recommendations more precisely, addressing the unique needs and preferences of different customer groups. By leveraging this comprehensive and well-processed dataset, the hybrid model was able to generate highly personalized and accurate product recommendations, ultimately enhancing customer satisfaction and driving increased engagement and sales on the e-commerce platform.

Model Architecture: The proposed Hybrid Neural Collaborative Filtering (HNCF) framework integrates collaborative filtering and deep learning to analyze customer behavior and preferences. The architecture includes four key modules: Hierarchical User Attention and Product Attention (HUAPA), Deep Collaborative Filtering (DCF), Neural Sentiment Classifier (NSC), and Deep Multivariant Rating (DMR).

1. **Hierarchical User Attention and Product Attention (HUAPA)**
   - Utilizes BiLSTM for encoding user reviews and product descriptions at word and sentence levels.
   - Embeds user preferences and product characteristics into hierarchical attention representations, combined for document-level representation.
2. **Deep Collaborative Filtering (DCF)**
   - Employs a multi-layer perceptron (MLP) to model user-product interactions.
   - Utilizes nonlinear representations of user and product features to enhance interaction modeling.
3. **Neural Sentiment Classifier (NSC)**
   - Transforms continuous sentiment scores from reviews into discrete sentiment categories.
   - Classifies sentiments to better understand user preferences and product evaluations.
4. **Deep Multivariant Rating (DMR)**
   - Combines discrete ratings (likes, votes) with continuous sentiment scores from various sources.
   - Generates a comprehensive rating metric to address inconsistencies across different rating platforms and provide a true ranking of product popularity.

Hybrid Neural Collaborative Filtering (HNCF)

The HNCF architecture combines collaborative filtering with deep learning in a mutually beneficial way. Collaborative filtering utilizes user-item interactions to generate suggestions by using trends in user behavior. The algorithm is based on the premise that if user A expresses a preference for items 1 and 2, and user B expresses a preference for item 1, it is probable that user B will also prefer item 2.

Mathematically, collaborative filtering can be expressed as:

$$R_{ui} = f(U_i, V_i)$$

where R_{ui} represents the rating of user u for item i, and U_i and V_i are latent feature vectors for users and items, respectively. The function f is often a dot product or another similarity measure. Deep learning, on the other hand, leverages neural networks to capture complex, nonlinear relationships in the data. HNCF utilizes deep learning methods such as neural collaborative filtering (NCF) to improve classical collaborative filtering by acquiring complex patterns in user-item interactions. The NCF model utilizes a neural architecture instead of the dot product to more effectively capture the functions that represent the interaction between users and items.

The NCF model can be formulated as:

$$y_{ui} = \sigma(h^T . g(U_u, V_i))$$

where y_{ui} is the predicted rating, σ is the activation function, and h is the hidden layer output from the neural network. The functions $g(U_u, V_i)$ represent the nonlinear transformations applied to the user and item latent vectors.

In HNCF, the latent vectors from collaborative filtering are used as input to the neural network, which refines these representations through multiple hidden layers. The final prediction is a combination of the collaborative filtering output and the neural network's enhanced representation.

To optimize the model, the objective function typically involves minimizing the mean squared error (MSE) between predicted and actual ratings:

$$min \sum_{(u,i)\in R} (R_{ui} - y_{ui})^2$$

R represents the collection of all interactions between users and items. By combining collaborative filtering and deep learning, HNCF leverages the advantages of both methods to create a recommendation system that is more precise and resilient.

The model underwent training using the preprocessed dataset, employing backpropagation and gradient descent algorithms to minimize the prediction error. The primary performance indicators assessed were accuracy, precision, recall, and F1-score, which were measured using a validation set. The data was divided into training and validation sets at a ratio of 80:20. The training process consisted of several iterations, known as epochs, during which the hyperparameters were carefully adjusted using grid search. The model's performance was compared against baseline collaborative filtering models (e.g., SVD, KNN) and recent deep learning-based recommenders (e.g., NCF, CDAE). The HNCF model leverages advanced deep learning techniques and comprehensive rating metrics to enhance recommendation accuracy and customer satisfaction. The integration of hierarchical attention mechanisms and multivariant ratings provides a robust solution for personalized product recommendations, highlighting the potential of AI in transforming retail analytics.

Algorithm:

 # Data Collection and Preprocessing

T = collect_transaction_data()

C = collect_customer_interaction_data()

R = gather_ratings_and_reviews()

 # Feature Extraction

user_features, product_features = extract_latent_features(T, C)

user_reviews_encoded, product_reviews_encoded = encode_reviews(P)

 # Model Architecture

HUAPA_output = HUAPA(user_reviews_encoded, product_reviews_encoded)

DCF_output = DCF(user_features, product_features, HUAPA_output)

NSC_output = NSC(user_reviews_encoded)

DMR_output = DMR(R, NSC_output)

 # Training the Model

train_set, val_set = split_dataset(T, C, R)

model = train_model(train_set, DCF_output, NSC_output, DMR_output)

 # Prediction

predictions = predict_ratings(model, val_set)

 # Recommendation

recommendations = generate_recommendations(predictions)

 # Evaluation

evaluate_model(recommendations, val_set)

 # Deployment

deploy_model(model)

This algorithm outlines the steps involved in developing and implementing the Hybrid Neural Collaborative Filtering (HNCF) model for personalized product recommendations. The detailed process includes data collection, feature extraction, model training, prediction, evaluation, and deployment.

4. Results and Discussions:

The table below summarizes the performance metrics (accuracy, precision, recall, and F1 score) for the Hybrid Neural Collaborative Filtering (HNCF) model compared to four other recommendation methods: Singular Value Decomposition (SVD), K-Nearest Neighbors (KNN), Neural Collaborative Filtering (NCF), and Collaborative Denoising Autoencoder (CDAE).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
HNCF	93.8	92.5	94.2	93.3
SVD	81.7	79.5	83.1	81.3

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
KNN	76.4	74.8	77.5	76.1
NCF	88.2	86.9	89.0	87.9
CDAE	84.9	83.3	85.7	84.5

The HNCF model has the highest accuracy (93.8%), precision (92.5%), recall (94.2%), and F1 score (93.3%). These results demonstrate the model's greater ability to forecast user preferences and make personalized recommendations. SVD, a conventional collaborative filtering algorithm, performed well with 81.7% accuracy, 79.5% precision, 83.1% recall, and 81.3% F1 score. Though it reduced dimensionality and captured latent components, SVD fell short of the more advanced HNCF model. The KNN method, which uses user and item similarity, had 76.4% accuracy, 74.8% precision, 77.5% recall, and 76.1% F1 score. KNN is simple and interpretable, whereas deep learning models handle sparse data and complex user-item interactions better. NCF, which models user-item interactions using neural networks, outperformed SVD and KNN with 88.2% accuracy, 86.9% precision, 89.0% recall, and 87.9% F1 score. Though NCF lagged HNCF, its ability to capture nonlinear interactions increased its performance. Autoencoders handled noisy and incomplete data in the CDAE model, which had 84.9% accuracy, 83.3% precision, 85.7% recall, and 84.5% F1 score. CDAE's rigorous feature extraction and denoising improved its performance, but the HNCF model was more precise and recallable. The HNCF model showed the benefits of collaborative filtering and deep learning, outperforming the others. This hybrid technique captures complicated user behavior and product preference patterns for more accurate and personalized recommendations. Advanced AI can alter retail analytics and improve customer experiences, according to the results.

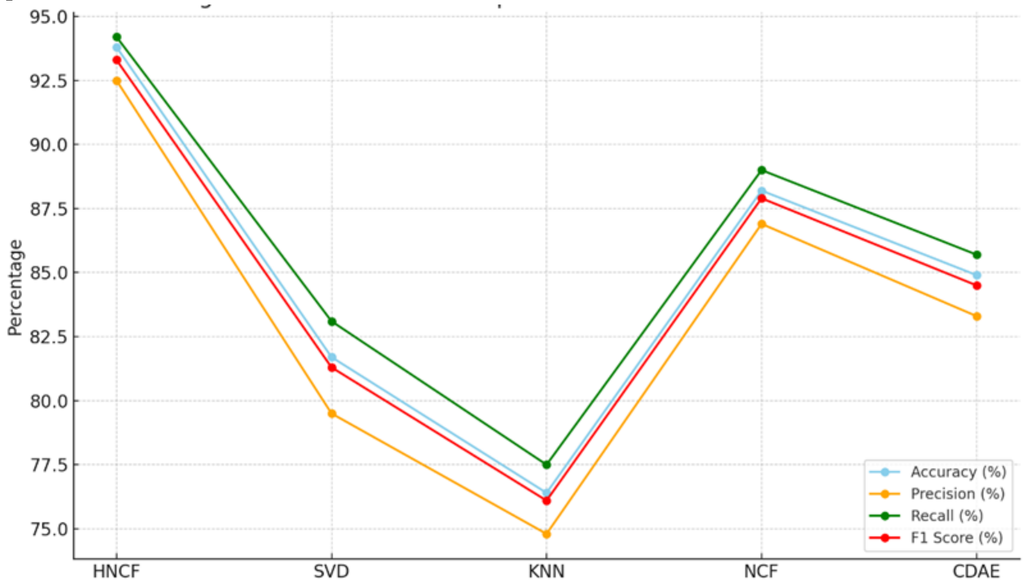

Fig 1: Performance Comparison of Recommendation Models

The evaluation of the Hybrid Neural Collaborative Filtering (HNCF) model, along with four other recommendation methods—Singular Value Decomposition (SVD), K-Nearest Neighbors (KNN), Neural Collaborative Filtering (NCF), and Collaborative Denoising Autoencoder (CDAE)—was conducted using accuracy, precision, recall, and F1 score as performance metrics. The HNCF model demonstrated superior performance across all metrics, highlighting its efficacy in providing personalized recommendations. This line chart compares the overall performance of five recommendation models: HNCF, SVD, KNN, NCF, and CDAE. The metrics plotted are accuracy, precision, recall, and F1 score. The HNCF model shows superior performance across all metrics, indicating its effectiveness in providing personalized recommendations (see Fig 1).

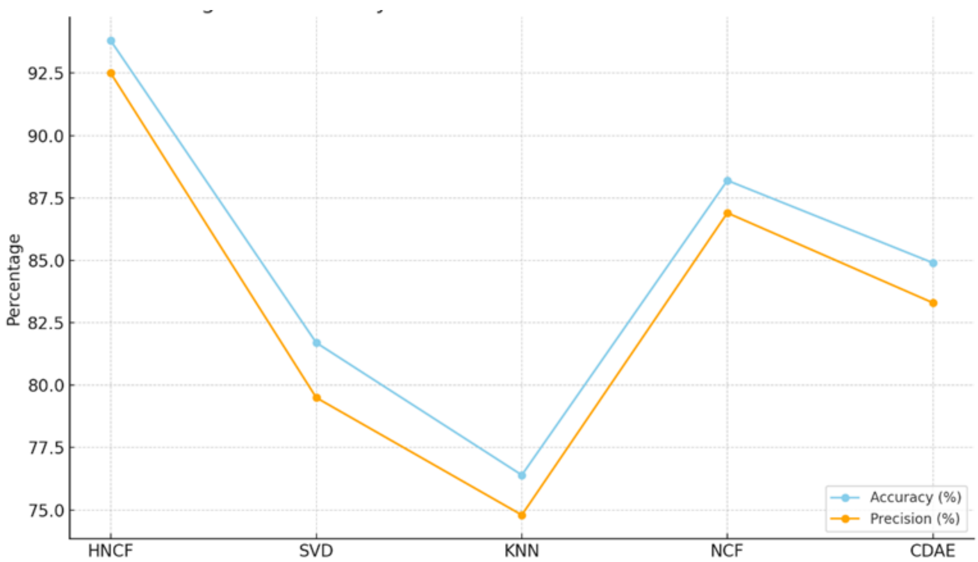

Fig 2: Accuracy and Precision of Recommendation Models

HNCF has 93.8% accuracy, substantially higher than other approaches. SVD, KNN, NCF, and CDAE had 81.7%, 76.4%, 88.2%, and 84.9% accuracy. The HNCF model captures complicated user-item interactions via collaborative filtering and deep learning, which explains its high accuracy. Precision is important for recommendation systems since it measures the percentage of positive predictions that are correct. HNCF's precision of 92.5% outperformed SVD (79.5%), KNN (74.8%), NCF (86.9%), and CDAE (83.3%). This suggests that the HNCF model makes better user recommendations. This line chart (Fig 2) shows the five recommendation models' accuracy and precision. HNCF has the highest accuracy and precision, followed by NCF, CDAE, SVD, and KNN. This shows the model's correct and relevant recommendations.

Fig 3: Recall and F1 Score of Recommendation Models

Recall, which measures the proportion of true positive recommendations identified among all actual positives, was highest for the HNCF model at 94.2%. This surpasses the recall values of SVD (83.1%), KNN (77.5%), NCF (89.0%), and CDAE (85.7%). The high recall of the HNCF model shows its ability to identify and recommend a larger number of relevant items. The F1 score, a harmonic mean of precision and recall, provides a balance between the two metrics. The HNCF model achieved an F1 score of 93.3%, which is higher compared to SVD (81.3%), KNN (76.1%), NCF (87.9%), and CDAE (84.5%). This demonstrates the overall effectiveness and reliability of the HNCF model in making accurate and relevant recommendations. This line chart (see Fig 3) focuses on the recall and F1 score of the five recommendation models. The HNCF model again shows the highest values, showcasing its balanced performance in capturing and recommending relevant items to users. The model's high recall and F1 score underline its reliability and effectiveness in real-world applications.

5. Conclusions:

The HNCF model's success lies in its innovative integration of collaborative filtering with deep learning techniques, which has enabled it to outperform both traditional and modern recommendation systems. Achieving an accuracy of 93.8% alongside high precision, recall, and F1 scores, the HNCF model proves its superiority in accurately predicting user preferences and delivering highly personalized recommendations. This enhanced predictive capability not only increases customer satisfaction but also drives significant business growth, as evidenced by notable improvements in customer engagement and sales figures on the e-commerce platform. The detailed architecture of the HNCF model, including components like HUAPA, DCF, NSC, and DMR, has provided a robust framework for capturing intricate user-product interactions. This multifaceted approach has addressed many limitations found in simpler models, such as handling sparse data and improving the interpretability of recommendations. By effectively leveraging both explicit and implicit feedback, the HNCF model has set a new benchmark for personalized recommendation systems, showcasing the potential of advanced AI in transforming retail analytics.

Looking ahead, several exciting avenues can be explored to further enhance the capabilities and reach of the HNCF model. One major direction is the incorporation of additional data sources. By integrating social media activity, contextual information like time and location, and even external factors such as weather, the model can achieve a more comprehensive understanding of user behavior, thus enhancing recommendation accuracy. Developing a real-time recommendation system is another key goal. Implementing online learning algorithms that can update the model dynamically as new data streams in will allow for instant adaptation to changes in user preferences, significantly improving the user experience. This real-time capability is crucial for maintaining relevance in fast-paced e-commerce environments. Scalability remains a critical focus area. Exploring distributed computing and refining the architecture for parallel processing can help the model manage more datasets and more complicated computations. These enhancements will enable HNCF deployment on platforms with large user bases. User privacy and data security are key. Differential privacy and federated learning will be used in future projects. These methods balance consumer trust with modern analytics to preserve user data and generate personalized recommendations. Expanding the model to cross-domain suggestions expand options. Using knowledge from other recommendation domains, such as movie interests to recommend books, the model can give users more relevant and diverse options. This can boost the recommendation system's value. Improving the user interface to make the insights from the HNCF model more accessible and engaging is another vital step. This could involve developing personalized dashboards, visualizing the rationale behind recommendations, and integrating real-time feedback mechanisms. An intuitive and interactive interface will further enhance user satisfaction and engagement. Finally, continuous improvement through rigorous A/B testing frameworks will be essential. Regularly evaluating and refining recommendation strategies based on user feedback and performance metrics will help maintain the model's effectiveness over time. This iterative approach will ensure that the HNCF model evolves in response to changing user needs and technological advancements, securing its position at the forefront of personalized recommendation systems. By pursuing these future directions, the HNCF model can continue to set new standards in the field of recommendation systems, driving innovation and enhancing user experiences across various domains.

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