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Improved recommender system using Neural Network Collaborative Filtering (NNCF) for E-commerce cosmetic product

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Abstract
This study presents an enhanced recommender system tailored for e-commerce platforms specializing in cosmetic products. Traditional recommender systems often need help providing accurate and personalized recommendations due to the complexity and subjectivity inherent in cosmetic preferences. In e-commerce, personalized product recommendations are crucial to improving user engagement and driving sales. This paper presents an innovative approach to enhance recommendation systems by leveraging neural network collaborative filtering techniques for the cosmetic product domain. The proposed method integrates neural networks into collaborative filtering, namely neural network collaborative filtering with improved preprocessing step. To validate the effectiveness of our proposed system, extensive experiments were conducted using real-world e-commerce cosmetic datasets "eCommerce Event History in Cosmetics Shop". Additionally, we evaluate the system's performance using historical e-commerce event data in cosmetics stores, demonstrating the system's effectiveness with mean reciprocal ratings (MRR) and normalized discount cumulative gain (NDCG). Evaluation Metrics of MRR and NDCG in this study got 0.56 and 0.60, respectively, with a split of the data: 70% train data, 15% validation data, and 15% test data. This study obtained better evaluation metrics than the previous study, which had an MRR of 0.31 and NDGC of 0.32. Furthermore, this model exhibits robustness against data sparsity and cold-start problems commonly encountered in e-commerce platforms. This research advances knowledge of recommendation systems and paves the way for more personalized and efficient online shopping experiences.

Keywords:
Collaborative Filtering;
Cosmetics;
E-commerce;
Neural Network;
Recommender System;

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INTRODUCTION

Recommender systems play a crucial role in eCommerce, especially in the cosmetics industry, by helping customers make purchase decisions. These systems analyzed user interactions, such as clicks, views, and purchases, to understand their preferences and predict the following item(s) for recommendation [1]. However, the ever-growing scale of products and users poses challenges in accurately and efficiently matching products to potential customers. Recommender systems are essential for providing personalized cosmetic product recommendations based on user attributes such as age, skin type, and preferences. These systems leverage ingredient analysis to recommend products that align with the user's desired cosmetic effects and skin type, addressing the challenge of interpreting complex ingredient lists [2, 3, 4].

Using machine learning and AI techniques, recommender systems enhance decision-making by providing accurate and reliable recommendations [5][6]. Recommender systems contribute to user satisfaction and confidence by enabling users to compare and visualize the differences between cosmetic items they own and those they are considering purchasing, thus facilitating informed decision-making [2, 7, 8]. These systems also aid in estimating the efficacy of cosmetics based on their ingredients, catering to the increasing demand for personalized and practical cosmetic recommendations [2].

Recommender systems utilize various techniques, including traditional approaches like sequence similarity and frequent pattern mining, factorization and latent representation methods like matrix factorization, and neural network-based strategies. Additionally, incorporating temporal information and domain knowledge specific to the fashion industry can significantly improve recommendation performance [9]. A recommendation system based on ingredient analysis and machine learning has been proposed in cosmetics to help users choose suitable products [10].

The changing times impact the use of technology in different areas of human life. These developments have a significant influence on trading activities. Activities that used to be done in person can now be done through the online store. Online stores influence consumers' habits when searching for or buying products. Indirectly, this habit affects how buyers make purchasing decisions [11]. This decision can be influenced by several factors, such as product price, product brand, product quality, product reviews from other users, and even the level of confidence in evaluating a product [12]. With these many factors, it is necessary to have a system that can always attract or increase the attractiveness of products in e-commerce to buyers.

One feature that can increase buyers' attractiveness is the recommendation system. The recommendation system displays products to buyers by collecting and analyzing compatibility between products and consumer characteristics. It is one of the features that has a vital role in determining consumer decisions in e-commerce. One business application has implemented a recommendation system, automated fashion, to suggest suitable items to consumers [13].

There are generally four types of recommendation systems, namely content-based, collaborative, context-aware, and hybrid filtering [14]. The technique often used is collaborative filtering (CF), which has two methods: memory-based and model-based. There are two memory-based techniques, namely user-based and item-based. However, these two techniques are classic recommendation algorithms that ignore the interaction between the user and the product. However, a new technique has emerged with deep learning that can be integrated with recommendation systems, namely the Neural Network Collaborative Filtering (NNCF). NNCF is a recommendation system technique that combines neural networks with collaborative filtering algorithms [15].

NNCF aims to improve the accuracy of recommendations by modelling the interactions between users and items using neural architecture. NNCF combines the strengths of collaborative filtering algorithms, such as user-based and item-based filtering, with the power of neural networks [15]. This integration allows for more accurate and personalized recommendations [16]. Unlike traditional collaborative filtering algorithms that use dot product operations, NNCF replaces this operation with a multi-layer perceptron, enabling the model to learn complex patterns and capture the collaborative filtering effect. NNCF addresses the cold start problem, where the system lacks sufficient data for new users or items, by integrating item features before the concatenation step in the model on memory-based depending on individual preferences that are available after being registered in the system and have used the system for some time. However, many users are not logged in or using the application for the first time. So, the recommendation system cannot work because there is no individual preference as a reference. This causes a cold-start problem [17].

NNCF has been explored and implemented to fine-tune product recommendations in e-commerce, showcasing its effectiveness with precision, recall score, and click-through rate [18]. One study adapted sentiment scores as ratings for skincare recommender systems, showing improved classifier performance [19]. Another study utilized user reviews from the Amazon dataset to examine the working of NNCF and highlighted the benefits of sentiment analysis in understanding user emotions and attitudes [20]. The research focused on fashion product recommendations through collaborative filtering, incorporating season and style features using convolutional neural networks [21].

Existing recommendation systems face scalability and efficiency problems due to the increasing numbers of users and products in the age of big data [22]. Preprocessing is crucial for recommender systems in big data. Data preprocessing is essential for creating input files with the appropriate format needed by a recommender system, and it helps achieve information-preserving data reduction [23]. Data quality is a prerequisite for successfully applying big data techniques, and data preprocessing is crucial for managing and using big data effectively. Preprocessing generates valuable data for decision-making and is not solely dependent on advanced algorithms [24]. Preprocessing big data involves dealing with challenges such as concept drift and data streams, considered significant challenges in the analysis process [25]. Preprocessing is essential for applying any analytics algorithm to obtain valuable patterns, and it is a key factor in the success of the analysis process in terms of efficiency and output information [26]. This study will use preprocessing on e-commerce data, especially E-commerce Events History in Cosmetics Shop. E-commerce Events History in Cosmetics Shop is also used by Szabo and Genge [27]. The accuracy result shows a recall of 0.31. NNCF and the combination of preprocessing are expected to improve this accurate metric.

METHOD

This section describes research methods related to neural network collaborative filtering. The research began with preparing datasets, preprocessing, splitting data, preparing models with NNCF, and conducting evaluations. The initial stage in the research is to prepare the dataset. The dataset format used is a Comma Separated Value (CSV). The dataset is then preprocessed. The preprocessing stage is an essential step because it can affect model performance. The next step is splitting the data into training, validation, and testing.

Furthermore, the training process uses the NNCF algorithm to make recommendations. After that, validation was carried out using data validation and testing using data testing to calculate the mean reciprocal ratings (MRR) and normalized discount cumulative gain (NDCG) values. The final stage of this study was analyzed by comparing accuracy based on previous studies. The flowchart of the methods is shown in Figure 1.

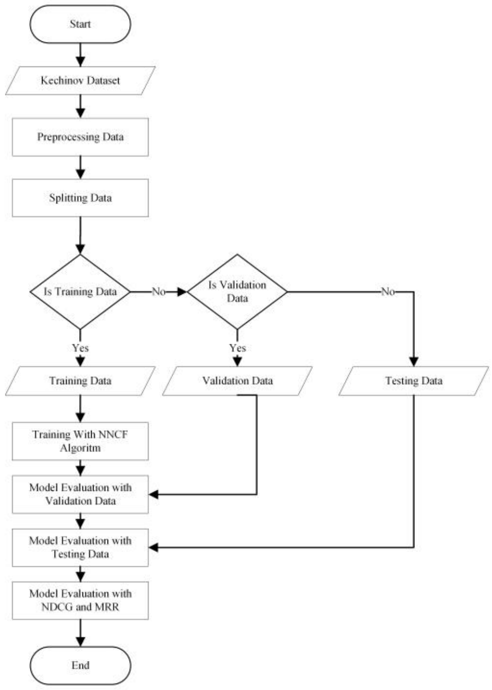

Figure 1. Flowchart of methods

Dataset

The dataset used is the "eCommerce Event History in Cosmetics Shop" from Kaggle, containing 8,738,120 rows and nine columns. It is used for unsupervised recommendation system trials and does not use labelled data for training. The dataset's features are listed in Table 1. The variety of event data types helps explore the predictability of purchasing events across different online platforms [28]. All cosmetic products in the dataset were included in the study.

Preprocessing Data

After collecting data, the next stage is preprocessing, which involves preparing the data for analysis by removing unnecessary parts to save resources [29]. Steps include data cleaning (checking for missing values), combining data from five separate files into one, filtering relevant data, converting data into atomic files, splitting the data, and evaluating it.

Table 1. Feature on Dataset

Feature	Description
event_time	The user's interaction time with the product
event_type	The type of interaction that occurs
product_id	ID of the product
category_id	ID category of product
category_code	Product categories
Brand	The brand name of the product
Price	Product prices are in float form.
user_id	ID of user
user_session	Temporary user session ID

Data reduction helps eliminate irrelevant data and improves accuracy, setting the data up for model training.

Dataset Loading

Dataset Loading is the stage for making datasets preprocessing results from atomic files into data in the form of interactions that will be included in the algorithm for training. Interaction is data formed from user interaction with the product.

Splitting Data

The splitting data is divided based on the interaction dataset into three parts: training data, validation data, and testing data, 70%, 15%, and 15%, respectively.

Modeling NNCF

This stage develops an NNCF model for the recommendation system, which extends matrix factorization with a multi-layer perceptron to capture user-item interactions. Testing on real-world datasets shows that NNCF significantly outperforms existing techniques. The results indicate that using deeper neural network layers enhances recommendation performance. Figure 2 illustrates the NNCF model [30].

Evaluation of Model

The primary purpose of the recommendation system is to recommend items according to the characteristics and wishes of users, so it is necessary to evaluate the recommendation system built [31]. The study uses NDCG and MRR metrics to evaluate the relevance of recommendation results. Both metrics range from 0 to 1, with higher values indicating better performance. An NDCG of 1 means perfect ranking, while 0 means no correlation with item relevance. NDCG values above 0.9 are excellent, and below 0.5 are poor. For MRR, 1 means the top-ranked item is always relevant, while 0 means the top-ranked item is never relevant. MRR values above 0.5 are good, and below 0.2 are poor.

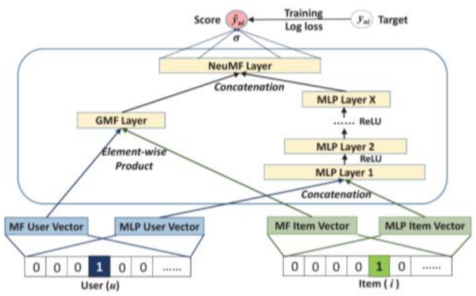

Figure 2. Architecture of Neural Network Collaborative Filtering

The simplest way to measure recommendation results is with Cumulative Gain (CG), which can be calculated by (1).

$$\mathrm{CG_k} = \sum_{i=1}^{k} \mathrm{rel_i} \tag{1}$$

$$\mathrm{DCG_k} = \sum_{i=1}^{k} \frac{2^{\mathrm{rel_i}-1}}{\log_2(i+1)} \tag{2}$$

$$\mathrm{IDCG_k} = \sum_{i=1}^{|\mathrm{rel_k}|} \frac{2^{\mathrm{rel_i}}-1}{\log_2(i+1)} \tag{3}$$

$$\mathrm{NDCG_k} = \frac{\mathrm{DCG_k}}{\mathrm{IDCG_k}} \tag{4}$$

The value of k k represents the maximum ranking, i i is the item's position in the ranking, and rel_i rel i is the relevance value of the item at position i i. Cumulative Gain (CG) sums item values without considering their positions, which is then improved to Discounted Cumulative Gain (DCG), which accounts for item positions (see (2)). Higher DCG values indicate more highly ranked items. However, DCG struggles to compare different recommendations, so Normalized Discounted Cumulative Gain (NDCG) is used (see (4)), utilizing Ideal DCG (IDCG) as a constant for comparison. The Mean Reciprocal Rank (MRR) is calculated as shown in (5).

$$\mathrm{MRR@K} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\mathrm{Rank_i}} \tag{5}$$

Where i is the ith query, $|Q|$ is the number of queries performed, and $\mathrm{rank_i}$ the ranking position of the first relevant item from the ith query.

RESULTS AND DISCUSSION

Result

The collected dataset undergoes preprocessing to handle missing values, which can inflate data size but leave it incomplete. Missing values are identified using pandas library functions isna() and sum(). After determining the missing values in the category_code column for each month, data without missing values in this column are retained. The filtered monthly data results are summarized in Table 2.

Table 2. Amount of Data for Each Category Code Without Missing Values

Months	Count
October	67,477
November	75,748
December	58,465
January	74,719
February	77,185

After the monthly data without missing values in the category_code column is obtained, the next step is to combine all the separated data into one file. The next stage is reducing the amount of data based on the value in a particular column. In this study, the reduction was done by removing data based on the event_type column with the value "remove_from_cart".

After data reduction, the data is converted into atomic files for use with the Recbole library in Python. The first step creates a file of user-product interactions in a .inter format, and the second step creates product-related files in a .item format. The atomic file data is then converted into interaction data for algorithm training, representing user-product interactions. This preprocessing resulted in 223,791 interactions, grouped by user and sorted by timestamp, differing from the initial 315,136 interactions before grouping.

Table 3 shows the amount of each data split into training, validation, and testing data. The amount of validation data and testing data does not have the same number, even though the percentage of validation data and testing data is the same, which is 0.15%. This happens because the data is divided based on the timestamp so that data in one session is still in the same series and cannot be split to avoid losing context.

The training and evaluation process is carried out based on the Top-K and Evaluation Model, where K is the number of top candidates. In the training process, the data used are training data and validation data. The data evaluation process is used to test data. Figure 3 and Figure 4 evaluate model-based MRR and NDGC. Based on Figure 3, it's evident that the MRR values show a steady rise with successive iterations, stabilizing around the 15th iteration. Similarly, Figure 4 illustrates that the NDGC values also exhibit incremental growth with each iteration, stabilizing approximately by the 20th iteration.

Table 3. Amount of Each Splitting Data

Data Split	**Amount of Interaction**
Training data	154,636
Validation data	30,367
Testing data	38,788

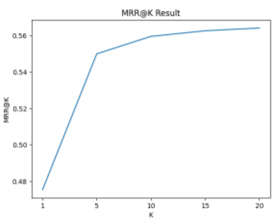

Figure 3. MRR Evaluation model based TOP-K

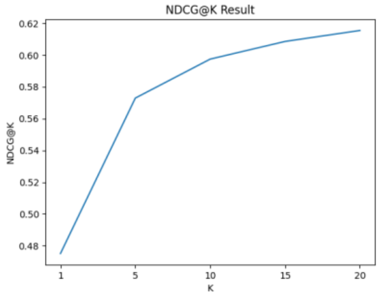

Figure 4. NDGC Evaluation model based TOP-K

Discussion

Furthermore, the research obtained better results than previous studies. Results comparing this study with previous studies are shown in Table 4. The results of the evaluation metrics in this study using MRR and NDCG were 0.56 and 0.60, respectively, which were higher than those of [33], who obtained an average MRR of 0.31 and NDCG 0.32 using the same e-commerce dataset. The method used is NNCF with Data Reduction. In his research, he received suggestions to use other features besides product ID and user_id to get better results. Therefore, this research utilized the product's features and performed data reduction in the preprocessing section.

This study also obtained better results than the research conducted by Delianidi et al. [32], who used the HSP and RIC models and obtained an MRR of 0.24. In his study, the model was trained by predicting the next item based on the sequence, while in this study, the model was introduced by masking the NNCF algorithm in the sequence. The dataset used in the research by Delianidi et al. uses a dataset with the same object, namely E-commerce [32].

Table 4. Accuracy Comparison with Previous Research

No.	**Research Methods**	**Object**	**Accuracy**
[27]	Deep Neural Network with Optimizer Adam	Dataset Kechinov 'eCommerce Events History in Cosmetics Shop'	Recall 0.31
[32]	Hierarchical Sequence Probability and Recurrent Item Co-occurrence with Graph Modelling	Dataset Kechinov eCommerce	MRR 0.24
[33]	BERT4REC for sequential recommendation	Ecommerce Dataset Amazon Beauty	MRR 0.31 NDCG 0.32
Proposed Method	NNCF with Data Reduction	Dataset Kechinov 'eCommerce Events History in Cosmetics Shop'	MRR 0.56, NDCG 0.60 Recall 0.74

The results of this study also obtained better results than those of research conducted by Szabo [27] with the same dataset. Although the research focuses on measuring the value of MRR and NDCG, this study also calculates Recall. Szabó and Genge's research [27] obtained a Recall value of 0.31, while this study received a Recall of 0.74. In this study, the same preprocessing was applied to the research conducted by Szabo and Genge [27], namely data reduction and the conversion method of user interaction event types with products into a single UX value. In contrast, the algorithm used in this study differs from his research, namely NNCF.

CONCLUSION

This study focuses on implementing NNCF in e-commerce to overcome the cold start problem so that we can continue to provide product recommendations to users without referring to user preferences. The results of the metric evaluation using NDCG, MRR, and Recall in this study were better than those of other studies, namely 0.60, 0.56, and 0.74. In future research, this can be done by using more data and trying different distribution percentages to improve accuracy.

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