

On the Improvement of E-Commerce Based Recommender Systems

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ABSTRACT

Recommender systems are essential for improving user experience in e-commerce by providing personalized product suggestions. However, traditional systems often struggle with the cold start problem, particularly for new users with minimal interaction history. This research proposes a Monte Carlo-based pagerank hybrid recommender system (MCPRHRec), which integrates Monte Carlo-based PageRank into the Multi-source Category Extended Historical Sequential Recommendation (MCE-HSPRec) System to enhance recommendation accuracy. By constructing a user-category graph, the system generates enriched user profiles and effectively mitigates the user cold start issue. Experimental results on an e-commerce dataset demonstrate significant improvements in recommendation performance, achieving a 97.09% increase in F1-score, 99.08% improvement in recall, 95.19% enhancement in precision, and 94.45% advancement in accuracy compared to existing methods. The proposed approach offers a scalable and efficient solution for personalized recommendations, providing a valuable contribution to the field of recommender systems.

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1. INTRODUCTION

In today's digital era, e-commerce has revolutionized how people shop by offering a wide range of products at their fingertips. The sheer volume of available choices can be overwhelming for customers, which can lead to customer dissatisfaction. E-commerce services have actively turned to Recommender systems to help users discover items that align with their needs, preferences and also improve sales volume of e-commerce [1]. Recommender systems provide suggestions of items to the users in different aspects of decision-making processes, such as what item to buy, what movie to watch, what music to listen to and what online news to read [2]. Recommender systems in e-commerce help to model the business process through analysis of customer requirements or purchase behavior [1]. The main recommender system techniques are content-based techniques, collaborative filtering techniques, knowledge-based recommender systems and hybrid techniques. The content-based recommender technique is concerned with the attribute information about users and items, such as a textual profile or relevant keywords. Collaborative filtering (CF) based recommender technique recommends an item for a particular user based on the items previously preferred by other users [3]. In a knowledge-based recommender technique, recommendations are based on explicitly specified user requirements [4]. Each recommender system technique has its own limitations; it is difficult to solve all issues with one method [5]. Therefore, hybrid recommender techniques emerged. Hybrid recommendation techniques combine two or more recommendation methods, such as content-based and Collaborative filtering-based techniques, in order to avoid certain limitations, such as the cold start problem, while improving RS performance [3].

The study [6] introduced a Multi-source Category Extended Historical Sequential Recommendation (MCE-HSPRec) system, which is an extended category-based collaborative filtering algorithm to make recommendations. The system generates a rich user-item preference matrix through sequential pattern mining in the user click and purchase click sequence database. They compute user preference to a category from the

user-item matrix, user-category and Category Co-occurrence graph (CCG) and then apply collaborative filtering to make a final recommendation. They address the problem of new item recommendation by computing user preferences for individual categories. While the MCE-HSPRec system has improved item recommendations, especially for new products, it fails to address the user cold start problem, which affects recommendation quality for new users. This research addresses this gap by proposing the integration of a PageRank algorithm into MCE-HSPRec to build more accurate user profiles from limited data, thereby improving the overall recommendation performance.

2. LITERATURE REVIEW

A system called the Hybrid Online Product Recommendation (HOPE) system [7] combines collaborative filtering (CF) and Sequential Pattern Analysis (SPA) to recommend products. The system calculates user similarities using implicit ratings, predicts preferences based on neighbours' ratings, and derives sequential patterns from transactional data. However, the system only considers implicit ratings and sequential patterns, making it unsuitable for new items and users. Another system, HCR18 [8], is a recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. It uses ontology to improve the accuracy of recommendations in collaborative filtering and employs Singular Value Decomposition (SVD) to find the most similar items and users in each cluster. However, the system is unable to capture modifications in user purchasing behaviour.

A recommendation system, HPCRec18 [9], uses purchasing history patterns to improve the rating quality and quantity for the matrix [10]. It mines consequential information between clicks and purchases to enhance the rating quantity in the matrix, improving recommendation accuracy. However, it does not integrate sequential pattern analysis for the user-item matrix in order to capture changes in user purchase behaviour. A stacking ensemble e-commerce recommendation system (SEERS) integrates collaborative filtering and sequential pattern mining to predict users' next purchase. It trains purchase data to find the best minimum support for the sequential pattern algorithm, the best similar users for collaborative filtering, and the best weight for integrating the intermediate user item matrices. However, it lacks consideration of other important user item interactions, such as clickstream.

The historical sequential pattern recommendation (HSPRecSys) [11] discovers frequent historical sequential patterns from click and purchase data. The system uses the SHOD algorithm to discover daily, weekly, and monthly sequential patterns, enhancing the user-item purchase frequency matrix. However, it only considers habitual consumer behaviour, neglecting new users and price/quantity information. A Product Recommendation System Based on Multi-source Implicit Feedback (MuSIF) [12] creates a user's item frequency matrix from past interaction information and adds weights to each action. However, it may struggle with users having limited interaction history or items with sparse data.

The Semantics Embedded Sequential Recommendation for e-commerce products (SEMSREC) [13] integrates item semantics and sequential information from purchase history to calculate item similarity scores. However, it fails to incorporate user similarities, leading to a user cold start. A hybrid recommender system [14] concurrently processes user and item metadata to address data sparsity in e-commerce platforms. Their model combines probabilistic matrix factorization with convolutional neural networks to extract semantic features from textual data, enhancing recommendation accuracy. Evaluations on three real-world datasets demonstrated superior performance over existing methods. However, the model's reliance on extensive metadata and computational resources may limit its scalability in resource-constrained environments.

The High Utility Sequential Pattern Recommendation System (HUSRec) [15] extends the HSPRec19 system. The system generates a high-utility sequential database and mines high-utility sequential patterns using the Prefix Span algorithm. However, it neglects multiple data sources for overall user recommendations. A dynamic e-commerce recommendation system [16] models user behaviour across multiple interaction types (views, likes, dislikes, ratings, and purchases) rather than treating all actions equally. Their User-Item Behaviour-Based (UIBB) approach uses statistical analysis to adapt to evolving preferences and outperforms traditional collaborative filtering methods. The model highlights the value of behaviour differentiation in addressing user cold-start and sparsity issues, but neglects the problem of Item cold start, which can degrade the system's performance.

The DeepIDRS system [17] is a hierarchical recommendation system that integrates item metadata and user reviews through a text encoder and an attention-based sequential model. It achieved over 10% improvement compared to baseline methods. However, the model's reliance on high-quality, well-structured textual data limits its effectiveness in domains with sparse or noisy review content. The Multi-source Category Extended Historical Sequential Recommendation (MCE-HSPRec) system generates a rich user-item preference matrix through sequential pattern mining and computes user preferences to individual categories. However, the system overlooks the user cold start problem, focusing only on item cold start.

Despite the advancements demonstrated by the reviewed recommendation systems, the user cold start and Item cold start problems remain inadequately addressed in a single system. While a few systems attempt to mitigate either item cold start or user cold start, many failed to accommodate the two problems together, which significantly impacts the system's ability to provide personalized and relevant recommendations.

3. PROPOSED METHODOLOGY

In this section, an E-Commerce-based Recommender System (ECBRS) is presented. The general scheme for the research study flowchart is depicted in Figure 1.

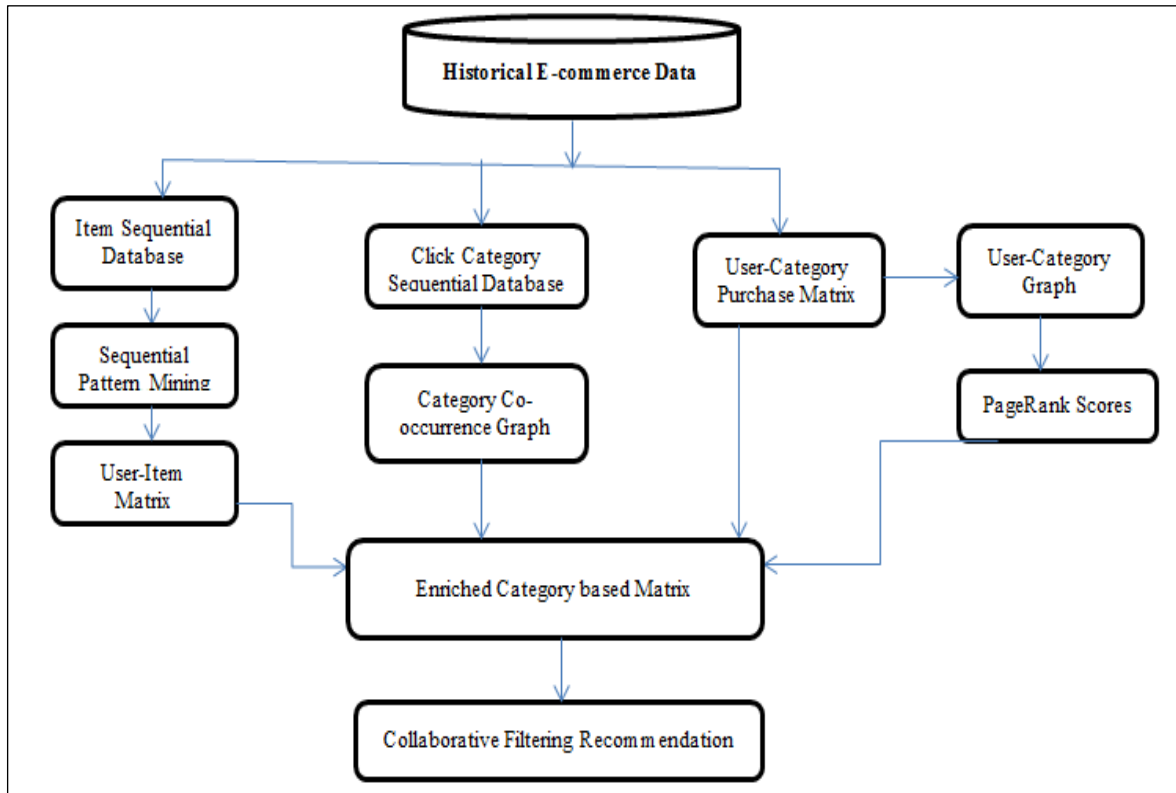


Figure 1. Schematic Diagram of the Research Dataflow

3.1. HSPRec Module

The HSPRec module has five components as described in Table 1.

Table 1. HSPRec Module

S. No	Component	Description	Details/Example
1.	Sequential Pattern Mining	Applies algorithms like GSP to discover frequent item sequences from user interactions	<ul style="list-style-type: none"> Click Sequences: Track items clicked before purchases. Purchase Sequences: Analyze order of item purchases. Consequential Rules: Establish links between clicks and purchases to improve recommendations
2.	User-Item Purchase Frequency Matrix	Matrix showing how often each user interacts (purchases) with items.	<ul style="list-style-type: none"> Used to represent the raw interaction data between users and items.

3.	Sequential Rule Generation	Generates "if-then" rules from mined patterns to predict missing data in the matrix.	<ul style="list-style-type: none"> If User U3 clicked I3 and I5 → Likely to purchase I4
4.	Click-Purchase Similarity	Measures how closely a user's click pattern matches their purchase behaviour to inform recommendations.	<ul style="list-style-type: none"> Sequence Similarity: Pattern match between click and purchase sequences. Frequency Similarity: How often clicks precede purchases. Example: User U1 clicked (I5, I3, I1, I3, I4, I5) → Purchased (I4, I3, I1) → I5 is strongly recommended
5.	Weighted Frequent Purchase Pattern Miner	Uses weighted mining to prioritize frequently bought items.	<ul style="list-style-type: none"> Items with higher support count get higher weights, making them more likely to be recommended.

3.2. MCE-HSPRec Module

This module consists of a user category purchase matrix and a category co-occurrence graph, as explained below:

3.2.1. User Category Matrix Module

The User-Category Module constructs a User-Category Preference Matrix that quantifies a user's preference for a category based on purchase frequency. It translates individual item interactions into category-level insights, enabling a broader perspective on user preferences. This matrix is crucial for overcoming the new item cold start problem, as recommendations can be generated based on shared categories.

3.2.2. CCG Module

The Category Co-occurrence Graph (CCG) Module models category relationships by analyzing their co-occurrence in user sessions. Nodes represent categories, and edges are weighted based on co-occurrence frequency. This graph structure is leveraged to enhance recommendations by extending user-category preferences to related categories, ensuring better coverage and diversity [18]. Equation 1 shows how the frequency of two connected nodes is calculated.

$$Fs_{(x,y)} = 1/d(x,y) \quad (1)$$

Given that x and y represent two categories, Fs is the frequency of co-occurrence in a sequence s, and d is the distance between the two categories x and y.

3.3. UCG Module

The User Category Graph (UCG) module constructs a bipartite graph from the User Category purchase frequency matrix, where Users and categories represent nodes, and edges represent the relationship between them. The graph is used to get the pagerank scores of the nodes [19]. Equation 2 inspired and shows the formula used to capture the preference scores.

$$PR(v) = \frac{(1-a)}{n} + a * \left(\sum_{n=1} (\text{walk length}) a^i * \frac{1}{\text{number of walks}} \right) \quad (2)$$

Where a is the teleportation factor set to 0.85, n is the number of nodes in the graph, number of walks is the random walks, and i is the length of the walk.

3.4. MCPRHRec Module

This module extends MCE-HSPRec by incorporating pagerank scores into the user category graph. It combines: The User-Category Matrix and the Category Co-occurrence Graph (from MCE-HSPRec), the PageRank scores and the User-Item Frequency Matrix (from HSPRec). The matrix is then normalized, and collaborative filtering (CF) is used to generate relevant recommendations.

4. RESULTS AND DISCUSSION

In this section, the results of the evaluation of both MCE-HSPRec and MCPRHRec are presented. A set of new users was added to the testing data to assess the models' ability to generalize to users with limited interactions, simulating a cold start scenario in a collaborative filtering framework. The Kaggle E-commerce Datasets are used with a neighbourhood size of $K=20$ for both MCE-HSPRec and MCPRHRec [20]. The results for accuracy, precision, recall and F1-Score are taken into consideration during the experiments and presented as follows:

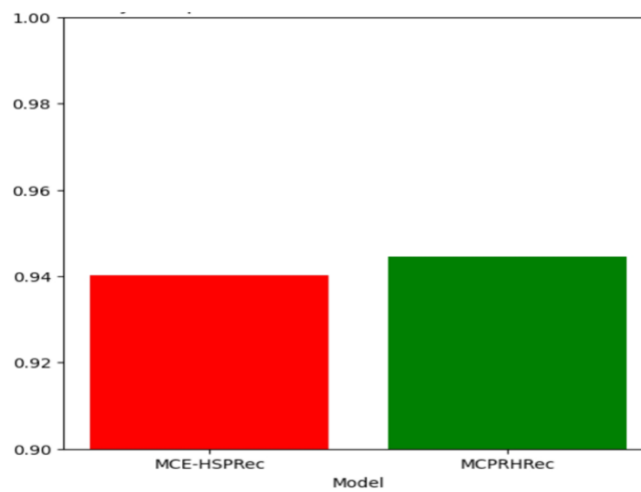


Figure 2. Accuracy Performance Evaluation Result at $K=20$

In Figure 2, the proposed model achieves an accuracy of 94.45%, which surpasses the existing systems' accuracy of 94.03%.

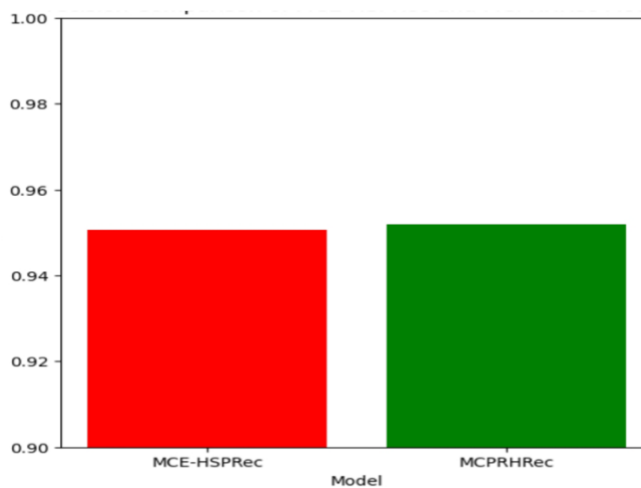


Figure 3. Precision Performance Evaluation Results

In Figure 3, the proposed model achieves a precision of 95.19%, outperforming the existing model, which achieves 95.05%. The proposed model demonstrates a clear improvement, reducing the number of false positives.

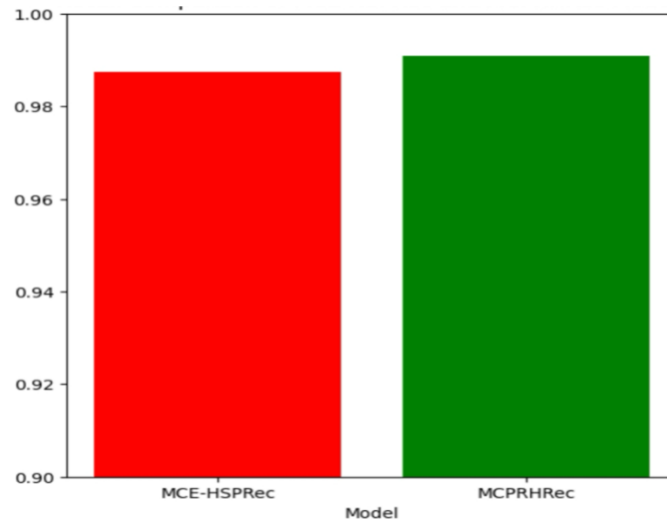


Figure 4. Recall Performance Evaluation Results

In Figure 4, the proposed model approach achieves a higher recall of 99.08% indicating a better ability to recommend relevant items to new users.

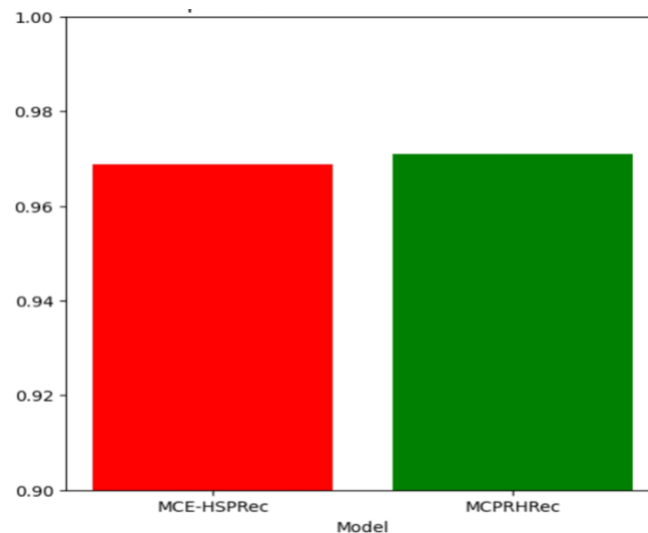


Figure 5. F1-Score Performance Evaluation Results

Figure 5: The MCPRHRec demonstrates superior performance compared to the existing system, achieving a higher F1-score of 97.09% versus 96.88%.

Table 2. Performance Evaluation

Models	Accuracy	Precision	Recall	F1-Score
MCPRHRec	94.45%	95.19%	99.08%	97.09%
MCE-HSPRec	94.03%	95.09%	98.73%	96.88%

The Accuracy, Precision, Recall and F1-score of MCE-HSPRec at K=20 using 5-fold cross-validation are 0.9403, 0.9509, 0.9873 and 0.9688, respectively, while those of the proposed MCPRHRec are 0.9445, 0.9519, 0.9908 and 0.9709. From Table 2 above, it is clear that the proposed MCPRHRec has outperformed the MCE-HSPRec in terms of relevance to new users and also enhanced personalization.

5. CONCLUSION

This research introduces an improved E-Commerce-based Recommender System that integrates PageRank (PR) with User Category Graphs (UCG) to enhance recommendation performance. By addressing the cold start problem for new users, MCPRHRec generates a richer preference matrix through global category-level insights rather than relying solely on item-based interactions. The integration of Monte Carlo-based PageRank (MCPR) in UCG with Collaborative Filtering significantly improves Precision, Recall, and F1-score, outperforming the existing model (MCE-HSPRec) across various evaluation points (K=20, K=50). The system effectively leverages global category relationships and user-item interactions to provide personalized and relevant recommendations, demonstrating superior accuracy and efficiency in e-commerce recommendations. As future work, the study will attempt to explore the integration of Monte Carlo-based PageRank with the User Category Graph in other recommendation domains such as education and agriculture.

DATA AVAILABILITY STATEMENT

The original data presented in the study are openly available at <https://www.kaggle.com/mkechinov/e-commerce-events-history-in-electronics-store>

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest in this work.

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