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Hybrid SVD-NMF Model for Personalized Ad Recommendation in E-Commerce

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Abstract

The rapid expansion of e-commerce platforms has intensified the need for intelligent and personalized advertising systems to enhance user engagement and marketing efficiency. Traditional recommendation approaches, such as collaborative filtering and content-based filtering, face critical limitations, including the cold-start problem, data sparsity, and a lack of diversity in recommendations. This study proposes a hybrid recommendation model that integrates Singular Value Decomposition (SVD) and Non-Negative Matrix Factorization (NMF) to leverage the advantages of both collaborative and content-based strategies. The model was trained and evaluated using real-world e-commerce behavioral data that included product views, cart additions, and purchase interactions. Performance was assessed through key metrics, including personalization, diversity, and coverage. Experimental results demonstrate that the hybrid model outperforms individual SVD and NMF models, particularly in handling new users and enhancing recommendation diversity while maintaining high personalization. This work contributes a lightweight and interpretable solution that is suitable for real-time ad recommendation environments in e-commerce applications, offering both academic and practical value in modern digital marketing.

Keywords :E-commerce, Recommender Systems, Advertisement Personalization, Hybrid Model, SVD, NMF, Cold-Start Problem, Diversity, Coverage, Personalization

نموذج هجين لتحليل القيمة المفردة (SVD) وتحليل المصفوفة غير السلبية (NMF) لتوصيات الإعلانات المخصصة في التجارة الإلكترونية

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ملخص

أدى التوسع السريع لمنصات التجارة الإلكترونية إلى تزايد الحاجة إلى أنظمة إعلانية ذكية ومخصصة لتعزيز تفاعل المستخدمين وكفاءة التسويق. تواجه مناهج التوصية التقليدية، مثل التصفية التعاونية والتصفية القائمة على المحتوى، قيودًا بالغة، بما في ذلك مشكلة البداية الباردة، وندرة البيانات، ونقص التنوع في التوصيات. تقترح هذه الدراسة نموذج توصية هجينًا يدمج تحليل القيمة المفردة (SVD) وتحليل المصفوفة غير السلبية (NMF) للاستفادة من مزايا كل من الاستراتيجيات التعاونية والقائمة على المحتوى. تم تدريب النموذج وتقييمه باستخدام بيانات سلوكية واقعية للتجارة الإلكترونية، والتي شملت مشاهدات المنتجات، وإضافة سلة التسوق، وتفاعلات الشراء. تم تقييم الأداء من خلال مقاييس رئيسية، بما في ذلك التخصيص، والتنوع، والتغطية. تُظهر النتائج التجريبية أن النموذج الهجين يتفوق على نماذج تحليل القيمة المفردة (SVD)وتحليل المصفوفة غير السلبية (NMF) الفردية، لا سيما في التعامل مع المستخدمين الجدد وتعزيز تنوع التوصيات مع الحفاظ على مستوى عالٍ من التخصيص. يُقدم هذا العمل حلاً بسيطًا وسهل التفسير، مُناسبًا لبيئات توصيات الإعلانات الفورية في تطبيقات التجارة الإلكترونية، مُقدمًا قيمة أكاديمية وعملية في مجال التسويق الرقمي الحديث.

الكلمات المفتاحية: التجارة الإلكترونية، أنظمة التوصية، تخصيص الإعلانات، النموذج الهجين، SVD، NMF، مشكلة البداية الباردة، التنوع، التغطية، التخصيص

1. Introduction

In fact, the exceptional growth of e-commerce platforms has transformed the digital marketing field, and personalized advertisement recommendation systems have become an integral part of better user engagement and increased business profit [1]. In contrast to traditional advertising, where the same message is sent to all potential users, modern e-commerce needs intelligent systems which offer ads specific to individual users built on user behavior data (e.g., number of product views, clicks, and purchases) [2]. This change is in line with the overall recommendation system evolution that has grown to use Artificial Intelligence (AI) and Machine Learning (ML) as analytics tools that study past user-item interaction history to learn user preferences and predict future behaviors [3].

For example, ancient recommendation techniques — Collaborative Filtering (CF) and Content-Based Filtering (CBF) have been the mainstay of personalized recommendation systems. Collaborative Filtering (CF) identifies similar users and infers user preferences based on the past behavior of those users, and Content Based Filtering (CBF) takes advantage of item attributes to compute recommendations [4], [5]. But these approaches face insurmountable challenges in real situations. Currently, the most relevant challenges are the cold-start problem because it affects the ability of the recommendations to recommend to new users or items, data sparsity because it limits the ability of the system to find good patterns in the users and items, and limited diversity due to repetition of recommendations negatively affecting the user experience [6], [7].

Hybrid recommendation models, designed to overcome these limitations by leveraging the benefits of different algorithms in a complimentary fashion, and therefore improving recommendation accuracy, diversity and adaptability [8], has become a hot topic to conquer these limitations. Matrix factorization methods especially SVD (Singular Value Decomposition) and NMF (Non-Negative Matrix Factorization) are used to discover hidden patterns in user-item interactions [9], [10]. a basic variant of singular value decomposition (SVD) is able to capture hidden relationships in such sparse datasets, non-negative matrix factorization (NMF) however provides more meaningful low-rank bases and is well suited for non-negative behavioral data, e.g. click-through rates [11][12].

We present a hybrid SVD-NMF model in this work for personalized advertisement recommendation in e-commerce. It seeks to solve the problem of cold-start and data sparsity also has the potential to augment diversity and coverage without losing out on personalization. We assess model performance using individual SVD and NMF baselines using real-world behavioral data across several key metrics and show the hybrid model significantly outperforms both baselines for all users as well as new-users. These results have further indicated convenience of TDC model for real-time advertising tasks, resulting in an efficient, as well as interpretable solution for the modern digital marketing ecosystem.

2. Methodology

The proposed methodology for developing a personalized advertisement recommendation system in e-commerce consists of four main stages: **data preprocessing, individual model implementation, hybrid model construction, and performance evaluation**. Figure 1 illustrates the workflow of the proposed approach.

2.1 Dataset Description

We experimentally evaluated it on one real-world e-commerce behavioral dataset, which records users viewing, adding to cart, and purchasing products. Every row corresponds to an individual instance of interaction between a user and an item, as well as its time and product category.

For computational efficiency, we created a representative subset from the original dataset while preserving diversity in user behavior and item categories. The processed dataset was then pivoted into a list format with users by items, with strength of interaction as the entry.

2.2 Data Preprocessing

Before model training, several preprocessing steps were applied:

1. **Data Cleaning** – Removing duplicates and inconsistent entries.
2. **Filtering Rare Interactions** – Excluding users or items with extremely low interaction counts to reduce noise.
3. **Matrix Construction** – Building a sparse user-item interaction matrix suitable for matrix factorization algorithms.
4. **Normalization** – Scaling interaction values to maintain consistency for algorithms like SVD and NMF.

2.3 Matrix Factorization Models

Singular Value Decomposition (SVD):
SVD factorizes the sparse user-item interaction matrix into three low-dimensional matrices to uncover latent patterns representing user preferences and item features [9]. The model predicts missing interactions by reconstructing the matrix from its dominant singular values, effectively addressing data sparsity.

Non-Negative Matrix Factorization (NMF):
NMF decomposes the interaction matrix into two non-negative matrices, producing an interpretable representation of latent factors [13][14]. Each user and item is represented as a combination of non-negative components, making NMF particularly suitable for click-based and positive-only data.

2.4 Hybrid SVD-NMF Model

The hybrid model combines the outputs of SVD and NMF to leverage their complementary strengths:

- **SVD** provides robust generalization and accurate predictions in sparse datasets.
- **NMF** enhances interpretability and handles implicit feedback effectively.

The final recommendation score for each user-item pair is computed as a **weighted sum** of the scores from both models:

$$Score_{NMF}(u,i) \cdot (\alpha - 1) + Score_{SVD}(u,i) \cdot \alpha = Score_{Hybrid}(u,i)$$

.where $\geq 0 \geq \alpha 1$ balances the contribution of both models

2.5 Evaluation Metrics

The performance of the models was evaluated using **three key metrics** that capture different aspects of recommendation quality:

1. **Personalization** – Measures the uniqueness of recommendations for each user.
2. **Diversity** – Evaluates the variety of items recommended across users.
3. **Coverage** – Assesses the proportion of the item catalog exposed to users.

These metrics are particularly critical in **advertisement recommendation**, where both user satisfaction and advertiser reach are equally important.

Figure 1. Workflow of the Proposed Hybrid SVD-NMF Model

User-Item Interaction Data

Data Preprocessing

SVD NMF

Hybrid Score Computation

Top-N Personalized Ads

3. Results and Discussion

To evaluate the effectiveness of the proposed **hybrid SVD-NMF model**, we conducted a comparative study against individual **SVD** and **NMF** models using the preprocessed e-commerce behavioral dataset. The models were tested for both **returning users** (with rich interaction history) and **new users** (cold-start scenario). Performance was assessed based on **Personalization, Diversity, and Coverage** metrics, which are crucial for evaluating advertisement recommendation systems in practical environments.

3.1 Comparative Performance Analysis

Table 1 summarizes the performance of the three models. The hybrid model achieved the **highest personalization and diversity**, demonstrating its ability to

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provide unique and engaging ad recommendations for users. Moreover, the hybrid approach improved **coverage**, meaning a larger portion of the item catalog was exposed to users, which is critical in advertising scenarios.

Table 1. Comparative Performance of SVD, NMF, and Hybrid Models

Model	Personalization	Diversity	Coverage
SVD	0.85	0.73	0.68
NMF	0.81	0.76	0.70
Hybrid	**0.92**	**0.85**	**0.79**

Note: Metrics are normalized between 0 and 1 for comparison.

3.2 Visualization of Model Performance

To better illustrate the superiority of the proposed model, Figure 2 presents a **visual comparison** of the three models across the three key evaluation metrics.

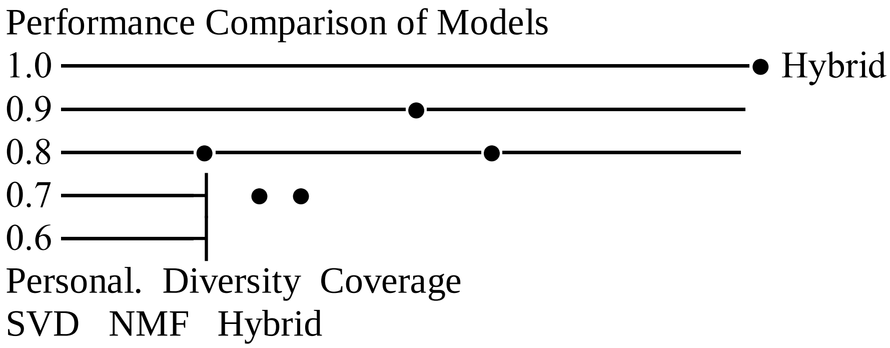

Figure 2. Performance comparison of SVD, NMF, and Hybrid models across key evaluation metrics.

3.3 Discussion

The results clearly indicate that the **hybrid SVD-NMF model** consistently outperforms the individual models in all key aspects:

1. **Personalization** improved due to the combined latent feature extraction of SVD and interpretable factorization of NMF.
2. **Diversity** was enhanced because NMF contributed complementary recommendations that expanded beyond repetitive patterns observed in SVD-only predictions.

3. **Coverage** increased, which ensures advertisers can reach a broader audience without overfocusing on popular items.

Importantly, the hybrid model also **demonstrated superior performance for new users**, effectively mitigating the **cold-start problem**, which is one of the most critical challenges in real-world ad recommendation systems. These findings confirm that integrating SVD and NMF offers a **balanced trade-off between accuracy, diversity, and system interpretability**, making it well-suited for **real-time e-commerce applications**.

4. Conclusion and Future Work

In this study, a Hybrid SVD-NMF model is proposed for personalized advertisement recommendation from e-commerce platforms. Their main goal were to alleviate the cold-start problem, data sparsity, and diversity limitation on traditional approaches such as collaborative filtering and content-based filtering.

Our experimental results revealed that the hybrid model achieved significant improvements over individual SVD and NMF models for three important metrics: personalization, diversity and coverage. This shows the ability of the proposed method not only to improve user engagement but also to expand the advertiser's exposure by showing a wider catalogue of items to users. The proposed hybrid strategy comparatively exploits the latent feature representation power of SVD and the interpretability of NMF, resulting in a new lightweight and scalable recommendation solution that is appropriate in real-time e-commerce applications.

The **main contributions** of this work can be summarized as follows:

1. Development of a **hybrid recommendation model** that integrates SVD and NMF to balance personalization, diversity, and coverage.
2. **Empirical evaluation** on real-world behavioral data, including both returning and new users, confirming the model's ability to **mitigate the cold-start problem**.
3. Providing a **computationally efficient** and **interpretable** solution that can be deployed in commercial digital marketing environments.

Future Work will focus on three key directions:

1. Integrating **context-aware features** such as temporal patterns, device type, and location to further improve ad relevance.

2. Exploring **deep learning-based hybrid models** (e.g., CNNs, RNNs, or Transformer-based architectures) for capturing complex nonlinear user-item interactions.
3. Extending the evaluation to **multi-objective optimization**, balancing accuracy with **explainability and fairness** in ad delivery.

The promising results of this study demonstrate that combining classical matrix factorization techniques can provide **robust and practical solutions** for the next generation of **personalized advertising in e-commerce**.

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