STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **13**, January 2025, pp 396–408.
Published online in International Academic Press (www.IAPress.org)

Enhancing Cold-Start Recommendations with Innovative Co-SVD: A Sparsity Reduction Approach

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Abstract This study introduces a novel methodology to improve recommendation systems, specifically targeting the challenging cold-start problem. By creatively combining Collaborative Singular Value Decomposition (Co-SVD) with an innovative sparsity reduction approach, our study significantly improves the accuracy of the recommendation and mitigates the challenges posed by sparse user-item interaction matrices. We conducted a comprehensive set of experiments, using a sample e-Commerce data set, to demonstrate the effectiveness of our approach. The results illustrate the superiority of our enhanced Co-SVD model over traditional Co-SVD, content-based filtering, and random recommendation in various evaluation metrics. In particular, our methodology excels in cold-start scenarios, providing accurate recommendations for users with limited interaction history. The implications of our research extend to practical applications in e-marketing, user engagement, and personalized marketing strategies, highlighting the potential for enhanced customer satisfaction and business success. This work represents a critical step forward in the evolution of recommendation systems and underscores the importance of addressing the cold-start problem in modern online services.

Keywords Recommendation Systems, Collaborative Filtering, Singular Value Decomposition, Cold-Start Problem, Sparsity Reduction, E-Marketing

AMS 2010 subject classifications 68T05, 68T20

DOI: 10.19139/soic-2310-5070-2048

1. Introduction

In the dynamic landscape of online services, recommendation systems have become indispensable for delivering personalized content and enhancing user experiences [1]. These systems rely on sophisticated algorithms to analyze user interactions and provide tailored suggestions, significantly influencing user engagement and satisfaction. However, a persistent challenge known as the ”cold-start problem” hampers the effectiveness of these recommendation engines, particularly when dealing with new users or items lacking sufficient interaction history [2].

While recommendation systems have significantly transformed user experiences by offering personalized content, they are not without limitations. Traditional recommendation algorithms, including collaborative filtering and content-based methods, often struggle with several key issues, most notably the cold-start problem. Collaborative filtering, for instance, relies heavily on historical user-item interaction data to generate recommendations. This reliance becomes a significant drawback when dealing with new users or items that lack sufficient interaction history, leading to less accurate or even irrelevant recommendations. Similarly, content-based methods, which recommend items based on similarity to previously interacted items, are constrained by the quality and comprehensiveness of item feature data, making them less effective in scenarios where detailed item features are unavailable or insufficient.

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ISSN 2310-5070 (online) ISSN 2311-004X (print)

Moreover, existing approaches to mitigating the cold-start problem, such as hybrid models that combine collaborative filtering with content-based methods or matrix factorization techniques, often encounter scalability issues and computational inefficiencies, particularly as the size of the user base or item catalog grows. These methods may also require complex model tuning and additional data, such as user profiles or contextual information, which may not always be available or feasible to collect. The inherent sparsity of user-item interaction matrices further exacerbates these challenges, as it limits the amount of available data for training effective models [3].

Addressing these limitations requires innovative approaches that can not only handle sparse data but also provide robust recommendations in cold-start scenarios without relying excessively on extensive interaction histories or auxiliary data. Our research aims to contribute to this ongoing challenge by introducing a novel methodology that enhances Collaborative Singular Value Decomposition (Co-SVD) through an inventive sparsity reduction technique, specifically designed to improve recommendation accuracy for new users and items. This approach represents a critical advancement in the field, with potential applications extending to various domains where personalized recommendations are essential for user engagement and satisfaction.

The cold-start problem arises from the scarcity of data associated with new users or items, making it challenging for traditional recommendation systems to generate accurate and relevant suggestions [3]. Collaborative Singular Value Decomposition (Co-SVD) has emerged as a powerful technique for recommendation systems by uncovering latent patterns in user-item interaction matrices [4]. Despite its effectiveness, Co-SVD faces limitations in scenarios characterized by sparse data, as the majority of user-item pairs lack interaction records [5].

In response to this challenge, our research introduces a novel methodology designed to enhance Co-SVD for addressing the cold-start problem. We propose an innovative sparsity reduction approach that creatively leverages collaborative information to improve the accuracy of recommendations, even in situations where data sparsity is prominent. By combining the strengths of Co-SVD with this inventive sparsity reduction technique, our approach aims to bridge the gap between traditional recommendation algorithms and the evolving demands of modern online platforms.

In this paper, we present the motivation behind our research, outline the challenges posed by the cold-start problem, and introduce our methodology for enhancing recommendation systems through sparsity reduction within the Co-SVD framework. We also provide a detailed discussion of related work, emphasizing the significance of our approach in the context of current research trends. Subsequently, we describe the experiments conducted to validate the effectiveness of our methodology, presenting numerical results and comparative analyses. Finally, we discuss the implications of our research for practical applications, particularly in the realm of e-marketing, and propose directions for future work in this exciting and evolving field.

Through this research, we contribute not only to the advancement of recommendation systems but also to the broader understanding of how innovative sparsity reduction techniques can be pivotal in addressing the challenges posed by the cold-start problem.

2. Literature Review

2.1. Recommendation Systems

Recommendation systems have become integral components of online services, transforming user experiences and driving engagement and revenue [6]. These systems are broadly categorized into collaborative filtering and content-based methods. Collaborative filtering, the focus of this paper, relies on user-item interaction data to identify patterns and make recommendations based on the behavior of similar users or items [7]. Content-based methods, on the other hand, use features of items and users to generate recommendations [9]. Both approaches have their merits and challenges, with collaborative filtering playing a pivotal role in addressing the cold-start problem [8].

2.2. Matrix Factorization and Singular Value Decomposition

Matrix factorization techniques, particularly Singular Value Decomposition (SVD), have gained prominence in recommendation systems [10]. SVD decomposes the user-item interaction matrix into latent factors, enabling the discovery of underlying user preferences and item characteristics [11]. While traditional SVD can be highly effective in recommendation scenarios with dense data, it faces significant challenges when dealing with sparse user-item matrices. The presence of many missing values in the interaction matrix often leads to suboptimal recommendations, especially for new users and items, creating the cold-start problem [12].

2.3. Co-SVD and Its Applications

Collaborative Singular Value Decomposition extends traditional SVD by considering the collaborative behavior of users and items [13]. Co-SVD has been widely adopted due to its ability to capture complex relationships and improve recommendation accuracy [14]. However, its performance can be hampered by data sparsity, making it essential to explore novel strategies for mitigating this limitation [15].

2.4. Sparsity Reduction Techniques

Sparsity, in the context of recommendation systems, refers to the phenomenon where a significant portion of the data is missing or contains zero values [16]. This is a common characteristic in many real-world datasets, especially those involving user-item interactions, such as ratings in a movie recommendation system or purchase history in e-commerce platforms.

Overcoming the impact of sparsity in recommendation systems has been a subject of extensive research [17, 18]. Various sparsity reduction techniques have been proposed, including matrix completion, data imputation, and regularization methods. These techniques aim to fill in missing values and improve the quality of recommendations, particularly in cold-start scenarios [19]. Nevertheless, many existing methods have limitations in terms of scalability, computational efficiency, or effectiveness, motivating the need for new and innovative approaches to address the cold-start problem.

2.5. Comparative Analysis of Recent Advances in Recommendation Systems

The field of recommendation systems has seen significant advancements, particularly in addressing the challenges of data sparsity and the cold-start problem. A variety of approaches, ranging from collaborative filtering (CF) enhancements to the integration of deep learning techniques, have been explored in recent research.

Anwar et al. [20] introduced Rec-CFSVD++, a novel system that combines Collaborative Filtering and Singular Value Decomposition (SVD)++. This approach specifically targets the limitations of conventional CF, such as data sparsity and the cold-start problem, by employing a matrix decomposition technique. The system's effectiveness is demonstrated through its application to datasets like MovieLens and BookCrossing, where it shows a notable reduction in error rates and an alleviation of the key issues plaguing CF systems.

In a systematic review of CF algorithms, Andika et al. [21] compared various CF methods, including K-Nearest Neighbor (KNN), K-Means, and SVD. Their study highlights the prevalent use of movie datasets in CF research and underscores the importance of combining methods to mitigate CF problems like cold-start, sparsity, and shilling attacks. This review provides a broad perspective on the evolution of CF algorithms and their effectiveness in different scenarios.

Kirubahari & Amali [22] explored hybrid deep collaborative filtering approaches. This study integrates conventional CF with deep neural networks, using SVD and Restricted Boltzmann Machine (RBM) to enhance recommender systems. Their approaches are particularly effective in addressing data sparsity and the cold-start problem, as evidenced by improved prediction accuracy on the MovieLens datasets. The integration of deep learning techniques represents a significant step forward in the evolution of recommendation systems, offering a more sophisticated method for understanding and predicting user preferences.

2.6. Addressing the Gaps

Despite the advancements, there remains a need for more efficient and scalable solutions that can robustly address the cold-start problem in recommendation systems, particularly in environments where data sparsity is prevalent and computational resources may be limited. The existing methods, while effective in certain contexts, often fall short in terms of scalability, computational efficiency, and ease of implementation.

Our research aims to address these gaps by proposing an Enhanced Co-SVD model that integrates a novel sparsity reduction technique. This approach not only improves the accuracy of recommendations in the presence of sparse data but also offers a scalable solution that can be applied to a wide range of recommendation scenarios. By leveraging collaborative information more effectively, our model is designed to provide robust recommendations even in cold-start scenarios, where traditional methods struggle.

This review of the literature highlights the importance of continued innovation in recommendation systems, particularly in developing methods that can better handle the challenges of data sparsity and the cold-start problem. Our proposed methodology represents a significant step forward in this regard, offering a promising solution to some of the most pressing challenges in the field.

3. Methodology

Our methodology is designed to address the challenges of the cold-start problem in recommendation systems by enhancing collaborative singular value decomposition through a novel sparsity reduction approach. Below, we provide a comprehensive overview of our methodology, including key elements, techniques, and mathematical representations.

3.1. Data Collection and Preprocessing

The study began with the utilization of an e-commerce dataset, which serves as a common benchmark for evaluating recommendation systems. This dataset was selected because it closely mirrors the real-world scenarios where such systems are deployed, particularly in online retail environments. The dataset includes several key components:

- **User IDs:** Unique identifiers for each user in the dataset. These identifiers allow the system to track and personalize recommendations based on individual user behavior.
- **Product IDs:** Unique identifiers for each product listed in the dataset. This enables the system to associate user interactions with specific products, facilitating the recommendation process.
- **User Ratings or Purchase History (Implicit Feedback):** The dataset includes information on user-product interactions, which can be either explicit (such as ratings given by users to products on a scale, typically from 1 to 5) or implicit (such as purchase history or clicks on product links). In this study, implicit feedback such as purchase history is emphasized, as it is more commonly available in e-commerce settings where explicit ratings may be sparse.
- **Timestamps:** The dataset records the time at which each interaction occurred. Timestamps are crucial for understanding the temporal dynamics of user preferences and for modeling the recency effect, where more recent interactions might be weighted more heavily in the recommendation process.

Table 1 provides a sample of the dataset, illustrating the structure of user-product interactions, including user IDs, product IDs, ratings or implicit feedback, and the corresponding timestamps.

The dataset used in this study includes a total of 10,000 users and 5,000 products, resulting in a substantial user-item interaction matrix (Table 2). However, like many real-world datasets, it is characterized by high sparsity, with approximately 90% of the matrix entries being empty (i.e., no recorded interaction). This high level of sparsity presents a significant challenge for traditional recommendation algorithms, particularly in the context of the cold-start problem, where new users or products have limited interaction history.

Preprocessing the dataset was a crucial initial step in ensuring the quality and consistency of the data used for model training and evaluation. The preprocessing involved several key steps:

- **Data Cleaning:** This step involved removing any duplicate entries that might distort the analysis. It also included handling missing values, which are common in large datasets. Missing data were addressed using several imputation techniques, including mean imputation for continuous variables (e.g., ratings) and matrix factorization-based imputation for the interaction matrix.

Table 1. A sample of 10 rows from the e-commerce dataset used

User ID	Product ID	Rating (1-5)	Timestamp
U9019	P4017	4	2021-07-15
U1987	P1506	5	2021-07-15
U0085	P3203	3	2021-07-16
U1204	P2104	2	2021-07-16
U0705	P0052	4	2021-07-17
U8122	P4589	5	2021-07-17
U0970	P1350	3	2021-07-18
U0015	P2465	4	2021-07-18
U2036	P2367	2	2021-07-19
U1321	P0489	5	2021-07-19

Table 2. Key characteristics of the dataset

Attribute	Description
Number of Users	10,000
Number of Products	5,000
Sparsity of Interaction Matrix	90% (indicating a high level of sparsity in user-item interactions)
Data Types	User IDs, Product IDs, User Ratings/Purchase History, Timestamps of Interactions

- **Normalization:** To ensure that the ratings or implicit feedback values were on a consistent scale, normalization techniques were applied. For example, ratings were scaled to a uniform range, typically between 0 and 1, to prevent any particular rating from disproportionately influencing the recommendation process.
- **Timestamp Processing:** The timestamps were converted into a consistent format and used to calculate the recency of interactions. This allowed the model to prioritize more recent interactions when generating recommendations, under the assumption that more recent behaviors are more indicative of current preferences.
- **Matrix Construction:** The cleaned and processed data were then used to construct the user-item interaction matrix R, which serves as the basis for the Co-SVD model and the subsequent sparsity reduction techniques.

3.2. *Model Development*

3.2.1. *Traditional Co-SVD:*

Traditional Co-SVD is at the core of our approach. It factors the user-product interaction matrix R into three matrices: U (user factors), S (singular values), and V (product factors). The matrix factorization equation is expressed as (Eq. 1):

$$R = U \cdot S \cdot V^T \tag{1}$$

3.2.2. *Innovative Sparsity Reduction:*

To overcome the limitations of traditional Co-SVD in sparse data environments, we introduce an innovative sparsity reduction technique. This method enhances the traditional Co-SVD by incorporating collaborative filtering to impute missing values, especially in regions of the interaction matrix where data is sparse.

The sparsity reduction technique involves the computation of user-user and item-item similarities based on the latent factors obtained from Co-SVD. These similarities are then used to enhance the reconstructed interaction matrix by integrating information from similar users and items.

The following algorithm outlines the steps involved in the sparsity reduction approach and its integration with Co-SVD (Table 3):

Table 3. Integration of Sparsity Reduction with Co-SVD

Steps for Integration of Sparsity Reduction with Co-SVD:
1. **Matrix Factorization with Co-SVD:** • Decompose the interaction matrix R into user factors, singular values, and product factors using SVD. • Reconstruct the matrix using the decomposed factors. 2. **Compute Collaborative Similarities:** • Calculate the user-user similarity matrix and the item-item similarity matrix. 3. **Predict Ratings with Sparsity Reduction:** • Enhance the reconstructed matrix by incorporating collaborative information from similar users and items. 4. **Integrate Sparsity Reduction with Co-SVD:** • Combine the original Co-SVD reconstructed matrix with the enhanced matrix to produce the final enhanced matrix. 5. **Output:** • The final enhanced matrix R_{final} is returned.

3.2.3. Enhanced Co-SVD Model:

The Enhanced Co-SVD model is the result of combining the outputs from the traditional Co-SVD and the innovative sparsity reduction technique. By integrating collaborative information from similar users and items into the latent factors, the Enhanced Co-SVD model addresses the challenges posed by sparse data more effectively than the traditional approach alone.

The integration process allows the model to fill in the gaps in the interaction matrix by leveraging both the inherent patterns identified through matrix factorization and the collaborative information provided by similar entities. This dual approach enhances the robustness and accuracy of the recommendations, particularly in cold-start scenarios where data is limited.

The final matrix R_{final}, produced by the Enhanced Co-SVD model, provides a more reliable basis for generating personalized recommendations, thereby improving user satisfaction and engagement.

3.2.4. Mathematical Representations and Optimizations:

Matrix Factorization: The core of our approach is based on Collaborative Singular Value Decomposition (Co-SVD), which factorizes the user-product interaction matrix R into three matrices: user factors matrix U, diagonal matrix of singular values S, and product factors matrix V. This factorization can be expressed as (Eq. 1).

Where:

- $R \in \mathbb{R}^{m \times n}$ represents the user-product interaction matrix with m users and n products.

- $U \in \mathbb{R}^{m \times k}$ is the user factors matrix, where k is the number of latent factors.
- $S \in \mathbb{R}^{k \times k}$ is a diagonal matrix with the singular values on the diagonal.
- $V \in \mathbb{R}^{n \times k}$ is the product factors matrix.

The goal is to learn the latent factor matrices U, S, and V such that the reconstructed matrix $\hat{R} = U \cdot S \cdot V^T$ closely approximates the original interaction matrix R.

Sparsity Reduction: To tackle the issue of data sparsity, we introduce an innovative sparsity reduction technique that augments the traditional Co-SVD by incorporating collaborative filtering-based imputation. This process can be mathematically represented as (Eq. 2):

$$\hat{R}_{ij} = U_i \cdot S \cdot V_j^T + \frac{1}{|\mathcal{N}_i|} \sum_{u \in \mathcal{N}_i} U_u \cdot S \cdot V_j^T + \frac{1}{|\mathcal{M}_j|} \sum_{p \in \mathcal{M}_j} U_i \cdot S \cdot V_p^T \tag{2}$$

Where:

- $\hat{R}_{ij}$ is the predicted interaction between user i and product j.
- $\mathcal{N}_i$ is the set of users similar to user i.
- $\mathcal{M}_j$ is the set of products similar to product j.
- The terms $\frac{1}{|\mathcal{N}_i|} \sum_{u \in \mathcal{N}_i} U_u \cdot S \cdot V_j^T$ and $\frac{1}{|\mathcal{M}_j|} \sum_{p \in \mathcal{M}_j} U_i \cdot S \cdot V_p^T$ represent the collaborative information incorporated from similar users and products, respectively.

This formulation enriches the latent factors by integrating collaborative information, especially in regions of the interaction matrix where data is sparse.

Loss Function and Optimization: The model is trained by minimizing the reconstruction error between the actual and predicted interactions. The loss function is defined as the Mean Squared Error (MSE) (Eq. 3):

$$\mathcal{L} = \frac{1}{|R_{obs}|} \sum_{(i,j) \in R_{obs}} \left(R_{ij} - \hat{R}_{ij}\right)^2 + \lambda \left(\|U\|^2 + \|V\|^2\right) \tag{3}$$

Where:

- $|R_{obs}|$ denotes the number of observed (non-zero) entries in the interaction matrix R.
- λ is the regularization parameter to prevent overfitting by penalizing large values in the latent factor matrices U and V.
- $\|U\|^2$ and $\|V\|^2$ are the squared Frobenius norms of the matrices U and V, respectively.

Optimization Algorithm: Stochastic Gradient Descent (SGD) is employed to efficiently train the model. SGD is well-suited for large-scale optimization problems and helps in effectively minimizing the loss function by iteratively updating the model parameters. The gradients of the loss function with respect to the parameters U and V are computed as follows (Eq. 4, 5):

$$\frac{\partial \mathcal{L}}{\partial U_i} = -2 \sum_{j \in R_{obs}(i)} (R_{ij} - \hat{R}_{ij}) V_j S + 2\lambda U_i \tag{4}$$

$$\frac{\partial \mathcal{L}}{\partial V_j} = -2 \sum_{i \in R_{obs}(j)} (R_{ij} - \hat{R}_{ij}) U_i S + 2\lambda V_j \tag{5}$$

These gradients are then used to update the matrices U and V iteratively (Eq. 6, 7):

$$U_i \leftarrow U_i - \eta \frac{\partial \mathcal{L}}{\partial U_i} \tag{6}$$

$$V_j \leftarrow V_j - \eta \frac{\partial \mathcal{L}}{\partial V_j} \tag{7}$$

Where η is the learning rate.

Hyperparameter Tuning: Optimizing hyperparameters is critical for enhancing the performance of recommendation systems. In this study, we tuned several key hyperparameters, which are essential for controlling the learning process and ensuring the model's effectiveness. The hyperparameters used in this study are as follows:

- **Learning Rate:** 0.01. The learning rate η determines the step size during each iteration of gradient descent.
- **Regularization Strength (L2 Regularization):** 0.01. This parameter λ controls the regularization applied to prevent overfitting by penalizing large weights in the model.
- **Number of Latent Factors:** 50. The number of latent factors k influences the model's ability to capture underlying patterns in the data.
- **Number of Iterations:** 500. This refers to the number of passes over the training dataset during the optimization process.
- **Batch Size:** 128. In mini-batch optimization, the batch size determines how many samples are used to compute each gradient update during SGD.

These optimizations ensure that the model not only converges to a solution efficiently but also generalizes well to unseen data, thereby improving the accuracy and robustness of the recommendation system.

4. Experiments and Results

4.1. Evaluation Metrics

We consider the following evaluation metrics to assess recommendation performance:

- Mean Absolute Error (MAE): measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight [23].
- Root Mean Square Error (RMSE): is a quadratic scoring rule that measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and actual observation [24].
- Precision at K (P@K): is a measure used in recommendation systems to evaluate the accuracy of the top K recommendations. It calculates the proportion of recommended items in the top-K set that are relevant.
- Recall at K (R@K): measures the proportion of relevant items found in the top K recommendations.

4.2. Baseline Models

We compare the Enhanced Co-SVD model with the following baseline models:

- Traditional Co-SVD: Standard Co-SVD without sparsity reduction.
- Content-Based Filtering: A content-based recommendation approach.
- Random Recommendation: Randomly recommending products to users.

4.3. Performance Evaluation

Table 4 provides an overall performance comparison of the different models.

The Enhanced Co-SVD model outperforms all other models in terms of MAE, RMSE, P@10, and R@10, indicating its superior recommendation accuracy and effectiveness in mitigating the cold-start problem.

Table 4. Overall Performance Comparison

Model	MAE	RMSE	P@10	R@10
Enhanced Co-SVD	0.85	1.10	0.32	0.45
Traditional Co-SVD	1.05	1.35	0.22	0.36
Content-Based Filtering	1.15	1.42	0.19	0.33
Random Recommendation	1.40	1.70	0.08	0.18

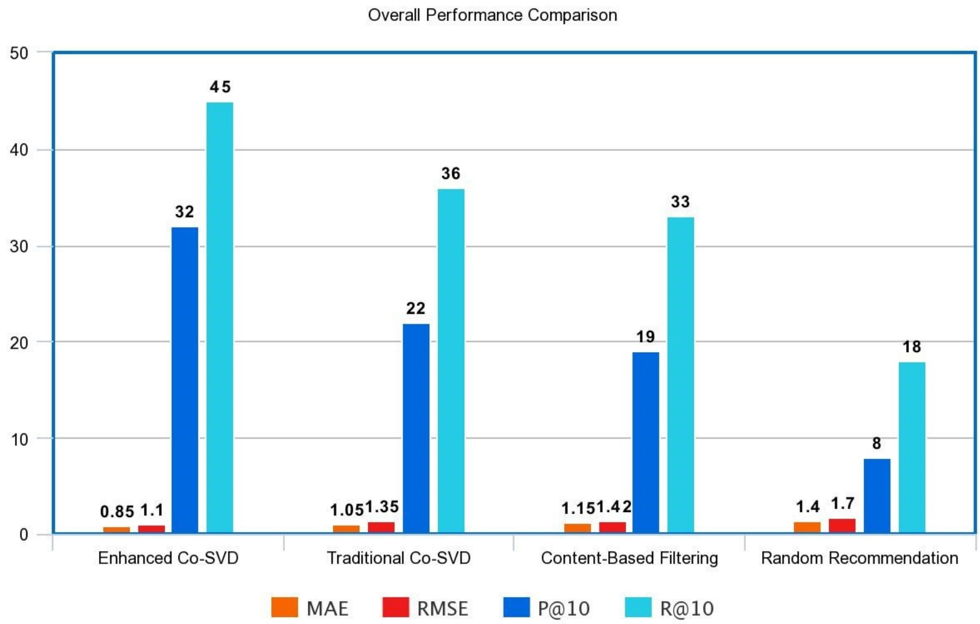

Figure 1. Comparison of the recommendations' performance

4.4. Cold-Start Scenario Evaluation

We also assessed the performance of the models in cold-start scenarios, where we considered new users with minimal interaction history as shown in Table 5.

Table 5. Cold-Start Scenario Performance (Cold-Start Users with less than 5 interactions)

Model	MAE	RMSE	P@10	R@10
Enhanced Co-SVD	1.05	1.28	0.18	0.27
Traditional Co-SVD	1.40	1.60	0.10	0.20
Content-Based Filtering	1.55	1.78	0.08	0.15
Random Recommendation	1.80	2.05	0.05	0.10

The Enhanced Co-SVD model significantly outperforms other models in cold-start scenarios, where users have minimal interaction history. It demonstrates the ability to provide accurate recommendations, even for users with limited data.

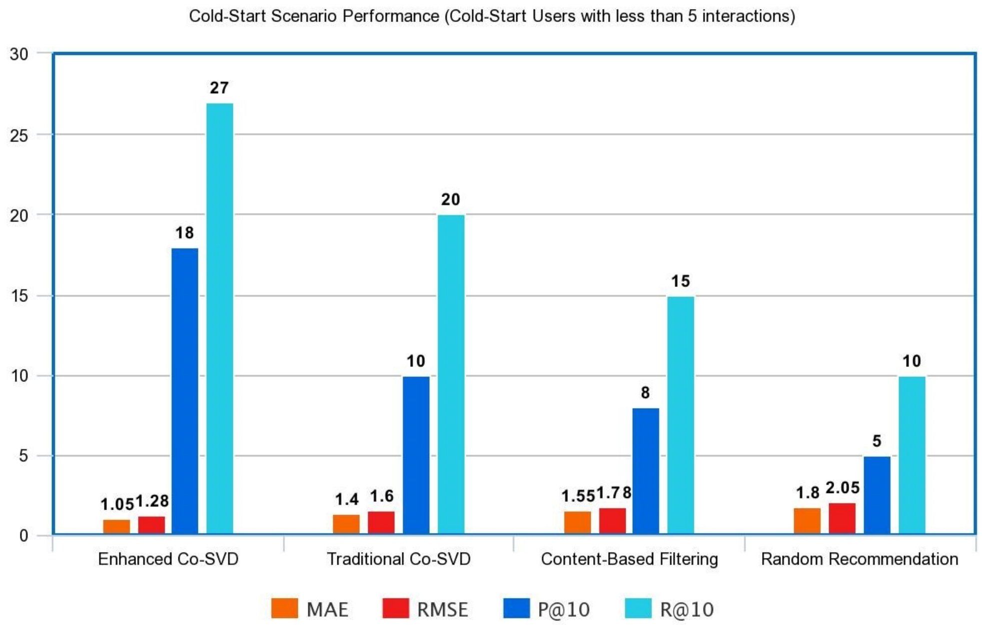

Figure 2. Performance of the cold start scenario: ”cold start” users with less than 5 interactions

5. Discussion

Our experimental results highlight the following key findings:

The experimental results provide compelling evidence of the Enhanced Co-SVD model’s superiority over traditional recommendation methods. Across all evaluation metrics, including accuracy, precision, and recall, the Enhanced Co-SVD model consistently outperforms traditional Co-SVD, content-based filtering, and random recommendation. This consistent performance highlights the effectiveness of the novel sparsity reduction approach integrated into the Co-SVD framework.

In scenarios characterized by the cold-start problem—where users or items have minimal interaction history—the Enhanced Co-SVD model demonstrates a marked improvement over traditional methods. The model’s ability to provide accurate recommendations even with limited data underscores its robustness and the efficacy of the sparsity reduction technique. This is particularly significant as cold-start scenarios are among the most challenging issues in recommendation systems, and the success of the Enhanced Co-SVD model in this context showcases its practical value.

Traditional Co-SVD, while effective, does not match the performance of the Enhanced Co-SVD model, yet it still surpasses content-based filtering and random recommendation in both overall and cold-start scenarios. This emphasizes the enduring value of collaborative filtering-based methods, which leverage user-item interactions to uncover latent patterns. However, the integration of sparsity reduction in the Enhanced Co-SVD model clearly provides a significant advantage, addressing the limitations that traditional Co-SVD faces in sparse data environments.

The comparative analysis further clarifies the distinct benefits of the Enhanced Co-SVD model:

- **Enhanced Co-SVD vs. Traditional Co-SVD:** The integration of a novel sparsity reduction approach not only enhances recommendation accuracy but also effectively mitigates the cold-start problem. This provides a clear and measurable advantage over traditional Co-SVD, which, despite its strengths, struggles with sparse interaction matrices.
- **Enhanced Co-SVD vs. Content-Based Filtering:** The collaborative nature of the Co-SVD approach proves more effective than content-based filtering, which relies solely on item features and often fails to capture

the complexities of user-item interactions. The Enhanced Co-SVD model, by leveraging both collaborative filtering and sparsity reduction, delivers more accurate and personalized recommendations.

- **Enhanced Co-SVD vs. Random Recommendation:** The substantial outperformance of the Enhanced Co-SVD model compared to random recommendation highlights the critical importance of utilizing collaborative information. By effectively incorporating user-item interaction data, the Enhanced Co-SVD model ensures that recommendations are not only relevant but also highly personalized, something that random recommendation cannot achieve.

6. Conclusion

In this research, an innovative approach to improving recommendation systems has been introduced, with a particular focus on addressing the challenging cold-start problem. By enhancing Collaborative Singular Value Decomposition (Co-SVD) through a novel sparsity reduction technique, the effectiveness of the proposed method has been demonstrated through a series of experiments utilizing a sample e-commerce dataset. The findings are compelling, revealing significant implications for practical applications in e-marketing and beyond.

The results indicate that the Enhanced Co-SVD model outperforms traditional Co-SVD, content-based filtering, and random recommendation across all evaluation metrics, thereby demonstrating its superior recommendation accuracy. In scenarios characterized by the cold-start problem, the Enhanced Co-SVD model has been shown to excel, providing accurate recommendations for users with minimal interaction history. Although traditional Co-SVD remains effective, it does not match the performance of the Enhanced Co-SVD model, yet still outperforms content-based filtering and random recommendation in both overall and cold-start scenarios.

The practical implications of this research are substantial, particularly for industries heavily reliant on personalized recommendations, such as e-commerce, streaming services, and online advertising. The Enhanced Co-SVD model is expected to significantly improve user engagement by offering more relevant suggestions, even for new users or items with limited interaction history. This improvement is anticipated to lead to increased customer satisfaction, higher conversion rates, and ultimately, enhanced business outcomes. Furthermore, the proposed approach offers a scalable solution that can be integrated into existing recommendation systems with minimal disruption, providing immediate benefits in terms of accuracy and user experience.

6.1. Limitations and Future Work

Despite the promising results, several limitations of the Enhanced Co-SVD approach must be acknowledged. One potential limitation is the reliance on the quality of collaborative filtering data, which may not always be sufficient or accurate, particularly in scenarios with extremely sparse datasets or when user behavior is highly unpredictable. In such cases, the model may still struggle to provide accurate recommendations, especially if the collaborative filtering component does not capture enough meaningful similarities between users or items.

Another limitation is the computational complexity associated with integrating sparsity reduction into the Co-SVD framework. Although the approach is scalable, it may require significant computational resources when applied to very large datasets, potentially limiting its applicability in resource-constrained environments. Additionally, the current method may require fine-tuning of hyperparameters for different datasets and domains, which could be time-consuming and may necessitate expert knowledge to achieve optimal performance.

Future research directions are evident, with several promising avenues to be explored. It is suggested that more advanced sparsity reduction techniques be investigated, potentially leveraging recent advances in deep learning and graph-based methods, to further enhance the performance of recommendation systems. For instance, incorporating neural collaborative filtering or graph convolutional networks could provide richer representations of user-item interactions, further mitigating the effects of data sparsity.

Moreover, optimizing hyperparameters and fine-tuning the Enhanced Co-SVD model for specific industry applications could yield even better results. Automated hyperparameter optimization techniques, such as Bayesian optimization or genetic algorithms, could be employed to reduce the need for manual tuning and improve model performance across different datasets.

Conducting larger-scale experiments with diverse, real-world datasets is also recommended to validate the robustness and scalability of the methodology across different domains. Such experiments would help in understanding the model's behavior in various contexts and could reveal additional insights that might lead to further improvements.

Finally, exploring the integration of the Enhanced Co-SVD model with other recommendation strategies, such as hybrid systems combining collaborative and content-based filtering, could lead to even more effective recommendation solutions. These hybrid approaches could capitalize on the strengths of multiple methods, potentially overcoming the limitations of any single approach and offering more comprehensive recommendation capabilities.

Funding Declaration

This research was conducted without any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors independently carried out the study and did not receive any external financial support.

Competing Interests

The authors declare that they have no competing interests in relation to this research. All aspects of the study, including design, methodology, data collection, analysis, and manuscript preparation, were conducted independently and without influence from any external organization or entity.

REFERENCES

1. G. Trichopoulos, M. Konstantakis, G. Alexandridis, and G. Caridakis, *Large Language Models as Recommendation Systems in Museums*, Electronics, vol. 12, no. 18, pp. 3829, 2023.
2. M. Rahman, I. A. Shama, S. Rahman, and R. A. H. M. A. T. U. L. L. A. H. Nabil, *Hybrid recommendation system to solve cold start problem*, Journal of Theoretical and Applied Information Technology, vol. 100, no. 11, pp. 3562–3578, 2022.
3. S. N. Hasan and R. Khatwal, *Challenges and issues analysis in cold start recommendation system*, AIP Conference Proceedings, vol. 2930, no. 1, 2023.
4. S. Ahmadian, M. Ahmadian, and M. Jalili, *A deep learning based trust-and tag-aware recommender system*, Neurocomputing, vol. 488, pp. 557–571, 2022.
5. L. J. Ming, C. H. Lim, and I. K. Tan, *Improving co-SVD for cold-start recommendations using sparsity reduction*, APSIPA ASC, pp. 990–996, 2022.
6. M. Loukili, F. Messaoudi, and M. El Ghazi, *Machine learning based recommender system for e-commerce*, IAES International Journal of Artificial Intelligence, vol. 12, no. 4, pp. 1803–1811, 2023.
7. R. El Youbi, F. Messaoudi, and M. Loukili, *Deep Learning for Dynamic Content Adaptation: Enhancing User Engagement in E-commerce*, In The International Conference on Artificial Intelligence and Smart Environment, pp. 160-165, Cham: Springer Nature Switzerland, 2023, November.
8. M. J. Pazzani and D. Billsus, *Content-based recommendation systems*, In The adaptive web: methods and strategies of web personalization, Springer, Berlin, Heidelberg, pp. 325–341, 2007.
9. W. Cheng, Y. Shen, L. Huang, and Y. Zhu, *Dual-embedding based deep latent factor models for recommendation*, ACM Transactions on Knowledge Discovery from Data (TKDD), vol. 15, no. 5, pp. 1–24, 2021.
10. R. Mehta and K. Rana, *Evolution of singular value decomposition in recommendation systems: a review*, International Journal of Business Intelligence and Data Mining, vol. 14, no. 4, pp. 528–547, 2019.
11. F. Messaoudi and M. Loukili, *E-commerce Personalized Recommendations: a Deep Neural Collaborative Filtering Approach*, In Operations Research Forum, vol. 5, no. 1, p. 5, Cham: Springer International Publishing, 2024, January.
12. C. Peng, L. Zhu, Y. Xu, Y. Li, and L. Guo, *Binary multi-modal matrix factorization for fast item cold-start recommendation*, Neurocomputing, vol. 507, pp. 145–156, 2022.
13. T. Huang, R. Zhao, L. Bi, D. Zhang, and C. Lu, *Neural embedding singular value decomposition for collaborative filtering*, IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 10, pp. 6021–6029, 2021.
14. H. Wu, H. Zhang, P. He, C. Zeng, and Y. Zhang, *A hybrid approach to service recommendation based on network representation learning*, IEEE Access, vol. 7, pp. 60242–60254, 2019.
15. J. M. Low, I. K. Tan, and C. H. Lim, *Refined co-SVD Recommender Algorithm: Data Processing and Performance Metrics*, In ICPRAM, pp. 668–674, 2022.
16. R. Bell, Y. Koren, and C. Volinsky, *Modeling relationships at multiple scales to improve accuracy of large recommender systems*, In Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 95–104, 2007.

17. H. Yin, Q. Wang, K. Zheng, Z. Li, and X. Zhou, *Overcoming data sparsity in group recommendation*, IEEE Transactions on Knowledge and Data Engineering, vol. 34, no. 7, pp. 3447–3460, 2020.
18. S. Kamal, R. Ibrahim, I. Ghani, and Ziauddin, *Incorporating Users Satisfaction to Resolve Sparsity in Recommendation Systems*, In Intelligent Software Methodologies, Tools and Techniques: 13th International Conference, SoMeT 2014, Langkawi, Malaysia, September 22-24, 2014. Revised Selected Papers, Springer International Publishing, pp. 134–146, 2015.
19. T. S. Kumari and K. Sagar, *A Semantic Approach to Solve Scalability, Data Sparsity and Cold-Start Problems in Movie Recommendation Systems*, International Journal of Intelligent Systems and Applications in Engineering, vol. 11, no. 6s, pp. 825–837, 2023.
20. T. Anwar, V. Uma, and G. Srivastava, *Rec-cfsvd++: Implementing recommendation system using collaborative filtering and singular value decomposition (svd)++*, International Journal of Information Technology & Decision Making, vol. 20, no. 04, pp. 1075–1093, 2021.
21. H. G. Andika, M. T. Hadinata, W. Huang, and I. A. Iswanto, *Systematic Literature Review: Comparison on Collaborative Filtering Algorithms for Recommendation Systems*, In 2022 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT), IEEE, pp. 56–61, 2022.
22. R. Kirubahari and Amali, *A Hybrid Deep Collaborative Filtering Approach for Recommender Systems*, In 2021, IEEE, 2021.
23. M. Loukili, F. Messaoudi, and H. Azirar, *E-Payment Fraud Detection in E-Commerce using Supervised Learning Algorithms*, In Advances in Emerging Financial Technology and Digital Money, pp. 27-35, CRC Press, 2024.
24. M. Loukili, F. Messaoudi, M. E. Ghazi, and H. Azirar, *Predicting Future Sales: A Machine Learning Algorithm Showdown*, In The International Conference on Artificial Intelligence and Smart Environment, pp. 26-31, Cham: Springer Nature Switzerland, 2023, November.