STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **15**, February 2026, pp 1433–1444.
Published online in International Academic Press (www.IAPress.org)

Multi-Objective Immune Optimization for Diversity–Novelty Trade-offs in Recommender Systems

Fatima Ezzahra Zaizi*, Sara Qassimi, Said Rakrak

L2IS, Computer Science, FSTG, Cadi Ayyad University, Marrakesh, Morocco

Abstract Recommender systems have become indispensable in digital platforms, driving user engagement and commercial success. Yet, achieving a balance between accuracy, diversity, and novelty remains a persistent challenge, as improvements in one objective often degrade the others. This work introduces a hybrid immune-inspired multi-objective optimization framework designed to address these conflicting goals. By integrating latent factor modeling with evolutionary immune mechanisms, the approach effectively captures user preferences while maintaining diversity and novelty in the recommendation lists. Extensive experimental evaluation shows that the proposed method consistently achieves superior trade-offs compared to traditional algorithms, offering a robust pathway toward more balanced and engaging recommender systems. The findings highlight the potential of immune-inspired optimization to advance recommendation quality and improve overall user satisfaction in commercial environments.

Keywords Recommender systems, Multi-objective optimization, Multi-Objective Evolutionary algorithms, MOIA Algorithm, Commercial, Collaborative filtering

DOI: 10.19139/soic-2310-5070-2768

1. Introduction

Recommender systems (RS) are now integral to e-commerce, streaming, and digital services, significantly shaping consumer behavior and company revenues. These systems assist users in filtering large amounts of information and selecting the most relevant products or services [1]. By tailoring suggestions to individual preferences, RS improve user satisfaction and engagement, with industry leaders such as Netflix, YouTube, Amazon, and Spotify attributing a substantial share of their revenues to personalized recommendations [2].

Despite these successes, modern RS face persistent challenges, especially in balancing multiple and often conflicting objectives such as accuracy, diversity, and novelty [3, 4]. Accuracy remains the cornerstone, measuring the relevance of recommendations to user preferences. However, excessive focus on accuracy risks overspecialization, reinforcing “filter bubbles” and limiting the discovery of new content. In contrast, diversity broadens the recommendation space by ensuring exposure to different item categories, while novelty introduces unexpected but potentially appealing items, enriching user experiences and fostering long-term engagement. The trade-off among these objectives forms a complex optimization problem that cannot be solved by optimizing a single metric.

This has motivated the use of *multi-objective optimization* (MOO) in recommender systems, which explicitly considers accuracy alongside non-accuracy metrics such as diversity and novelty [19, 6]. Bio-inspired meta-heuristics, particularly Multi-Objective Evolutionary Algorithms (MOEAs), have shown

*Correspondence to: Fatima Ezzahra Zaizi (Email: f.zaizi.ced@uca.ac.ma). L2IS, Computer Science, FSTG, Cadi Ayyad University, Marrakesh, Morocco.

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

strong capabilities in navigating high-dimensional solution spaces and achieving Pareto-optimal trade-offs [20, 7]. Among these, the Multi-Objective Immune Algorithm (MOIA) has emerged as a promising technique, inspired by the immune system's adaptability and clonal selection mechanisms, and has recently been extended to recommender systems [8, 9]. Parallel to this, advances in deep learning and hybrid methods (e.g., Neural Matrix Factorization, deep reinforcement learning) have highlighted the importance of integrating modern techniques with multi-objective paradigms to improve both scalability and personalization.

To address these challenges, this paper proposes a hybrid method—**SVD-MOIA**—that combines Singular Value Decomposition (SVD) with MOIA to balance accuracy, diversity, and novelty in commercial RS. SVD efficiently captures latent structures in sparse user–item interactions, providing a strong initialization, while MOIA iteratively refines solutions through immune-inspired operators to optimize multiple objectives simultaneously.

The main contributions of this paper are as follows:

- We formulate recommendation as a multi-objective optimization problem explicitly addressing accuracy, diversity, and novelty in commercial settings.
- We introduce a hybrid framework (SVD-MOIA) that leverages SVD for accurate initialization and MOIA for immune-inspired evolutionary optimization.
- We provide detailed algorithmic design, including formal definitions of the objective functions and description of immune operators (cloning, crossover, mutation).
- We conduct extensive experiments on three benchmark datasets (Amazon, Book-Crossing, IMDb), including ablation studies, comparisons against traditional and modern baselines (e.g., NSGA-II, MOEA/D), and sensitivity analyses.
- We discuss computational aspects, scalability, and the practical applicability of SVD-MOIA for real-world recommender systems.

The remainder of this paper is organized as follows. Section 2 reviews related work in multi-objective optimization for recommendation systems. Section 3 formalizes the problem. Section 4 presents the proposed framework in detail. Section 5 reports experimental results and analysis. Finally, Section 6 concludes with implications and future research directions.

2. Related Work

The evolution of recommender systems has been shaped by advances in Collaborative Filtering (CF), Matrix Factorization techniques, and the integration of Multi-Objective Optimization (MOO). More recently, bio-inspired algorithms such as the Multi-Objective Immune Algorithm (MOIA) have been introduced as promising solutions for balancing conflicting objectives. This section reviews these contributions and highlights their impact on commercial recommendation systems.

2.1. Collaborative Filtering and Matrix Factorization

Collaborative Filtering (CF) has long served as the foundation for recommendation, inferring user preferences from patterns of past interactions. Among matrix factorization approaches, Singular Value Decomposition (SVD) has proven particularly effective in addressing data sparsity and uncovering latent features in user–item interactions [10]. Applications include improving movie recommendations with bias-aware SVD models [10], music playlist generation that adapts to user preferences [11], and personalized news feeds [12]. More recent extensions combine SVD with deep learning to scale to large, dynamic environments, underscoring its continued importance in recommender systems research.

2.2. Multi-Objective Optimization in Recommendation

Recommender systems increasingly consider objectives beyond accuracy, including diversity, novelty, and fairness, to improve long-term user engagement [18]. Multi-Objective Optimization (MOO) provides a principled framework for these trade-offs. Evolutionary algorithms such as NSGA-II, NSGA-III, and MOEA/D have been successfully applied in recommendation scenarios [21], often balancing accuracy with diversity or novelty. While these methods have shown effectiveness, they remain computationally demanding and can struggle with preserving diversity in large-scale optimization [28, 27].

2.3. Immune-Inspired Optimization for Recommender Systems

Inspired by the adaptive mechanisms of biological immune systems, the Multi-Objective Immune Algorithm (MOIA) introduces cloning, mutation, and diversity-preserving operators to explore Pareto-optimal solutions. MOIA has been applied to enhance diversity and accuracy in movie recommendations [13], provide personalized location-based suggestions that account for both similarity and geography [14], and support Pareto ranking in service recommendations [15]. Recent surveys confirm MOIA's strong potential for multi-objective problems [9], although its adoption in recommender systems remains less explored compared to evolutionary algorithms such as NSGA-II or MOEA/D.

This body of work shows the trajectory from CF and SVD to modern multi-objective formulations and bio-inspired optimization. The next section builds upon these foundations by formally presenting the mathematical formulation of a Multi-Objective Recommendation System (MORS), which directly motivates the hybrid SVD-MOIA framework.

3. Multi-Objective Recommendation System (MORS) Formulation

Recommender systems aim to filter large volumes of data to provide personalized suggestions tailored to user preferences and behaviors [17, 16]. Formally, the core task can be expressed as a prediction function:

$$f : U \times I \to S,$$

where U is the set of users, I the set of items, and S the set of possible scores (e.g., ratings). The goal is to estimate the unknown score s_{ui} for each pair (u, i), thereby producing a ranked recommendation list for user u.

Traditionally, recommender systems focused primarily on accuracy, i.e., maximizing the relevance of recommended items. However, this single-objective perspective often leads to over-specialization, reducing the variety of items and limiting discovery [18]. Recent works highlight the importance of optimizing *multiple conflicting objectives*—including accuracy, diversity, and novelty—to ensure both short-term satisfaction and long-term engagement.

3.1. Multi-Objective Formulation

Let N be the recommendation list generated for user u. We define three key objectives:

1. **Accuracy ($O_{\mathbf{acc}}$)**: Ensures recommendations are relevant to the user's preferences:
$$O_{\text{acc}}(u, N) = \frac{1}{|N|} \sum_{i \in N} \text{rel}(u, i).$$
2. **Diversity ($O_{\mathbf{div}}$)**: Promotes dissimilarity among recommended items to avoid redundancy:
$$O_{\text{div}}(N) = \frac{2}{|N|(|N| - 1)} \sum_{i \neq j,\, i,j \in N} \text{dissim}(i, j).$$

3. **Novelty ($O_{\mathbf{nov}}$)**: Encourages inclusion of unfamiliar but potentially interesting items:

$$O_{\text{nov}}(u,N) = \frac{1}{|N|}\sum_{i\in N} \text{novelty}(u,i).$$

These objectives can be expressed in vectorized form as:

$$\max F(N) = \big(O_{\text{acc}}(u,N),\ O_{\text{div}}(N),\ O_{\text{nov}}(u,N)\big).$$

The optimization aims to identify a set of non-dominated recommendation lists that lie on the Pareto front:

$$N^* \in \mathcal{P} \quad \Leftrightarrow \quad \nexists N' \text{ s.t. } O_k(N') \geq O_k(N^*) \ \forall k \in \{acc, div, nov\}, \text{ and strict for at least one } k.$$

This formulation reflects the inherent trade-offs: improving accuracy often reduces novelty, while maximizing diversity may compromise precision. Finding an optimal compromise is NP-hard due to the exponential number of candidate lists and the complexity of evaluating joint objectives.

3.2. Motivation for Hybrid Optimization

Most existing multi-objective recommendation approaches address only pairs of objectives (e.g., accuracy–diversity or accuracy–novelty). By contrast, our formulation explicitly integrates three objectives within a unified optimization framework. This provides a more holistic perspective of user satisfaction, balancing short-term accuracy with long-term discovery.

To address this complex optimization challenge, our study introduces a hybrid solution: SVD is used to construct an initial recommendation matrix, ensuring accuracy and robustness under sparse conditions, while the Multi-Objective Immune Algorithm (MOIA) is employed to refine the results toward Pareto-optimal solutions that also maximize diversity and novelty. This joint formulation directly underpins the framework described in Section 4.

4. Framework of the Proposed Approach

The proposed approach, SVD-MOIA, enhances commercial recommender systems by integrating Singular Value Decomposition (SVD) with the Multi-Objective Immune Algorithm (MOIA). Unlike conventional methods such as NSGA-II, NSGA-III, and MOEA/D, which have shown effectiveness in balancing conflicting objectives [21], our framework leverages SVD for efficient latent factor modeling and MOIA for evolutionary refinement. This integration provides a unique trade-off between accuracy, diversity, and novelty, addressing both sparsity and over-specialization issues that limit baseline methods. The high-level architecture of the framework is illustrated in Figure 1, which highlights the modular flow from input preprocessing to final recommendation generation.

4.1. Singular Value Decomposition for Recommendation

The first stage applies SVD [22] to the user–item interaction matrix R. By decomposing R into three lower-dimensional matrices,

$$R_{m\times n} \approx U_{m\times r}\Sigma_{r\times r}V_{r\times n}^T,$$

latent user preferences (U) and item attributes (V) are uncovered, while Σ holds the strength of latent features. SVD generates an initial recommendation matrix by predicting missing entries, thereby addressing sparsity and ensuring accuracy-oriented recommendations before refinement.

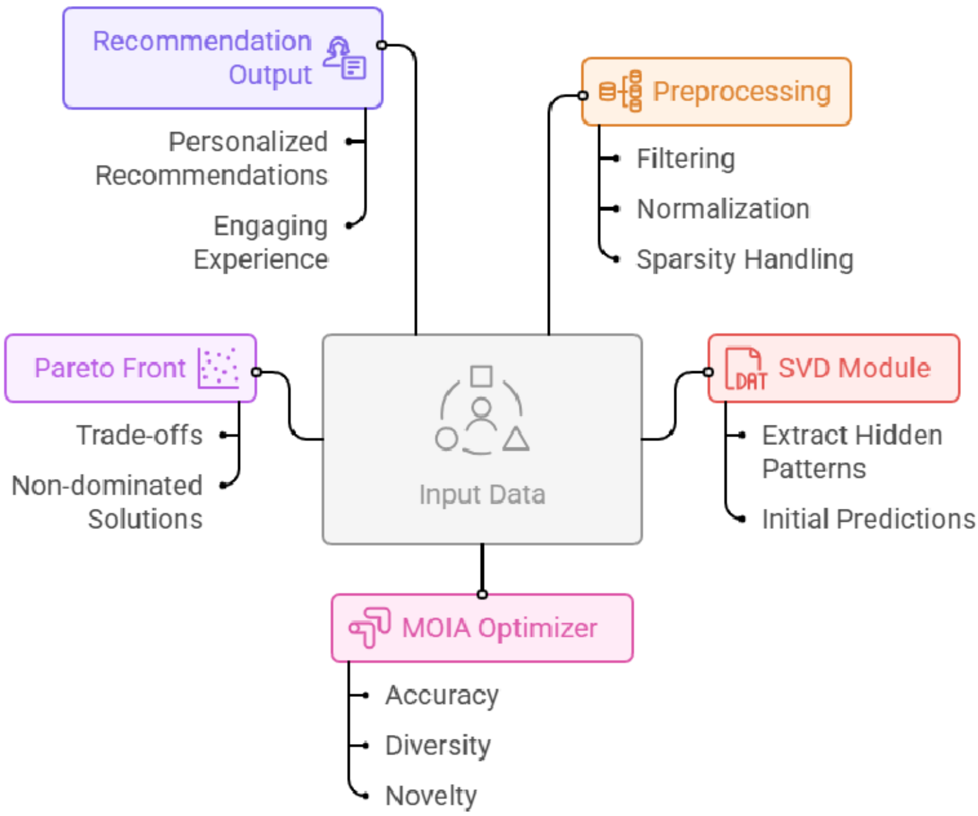

Figure 1. System architecture of the proposed SVD-MOIA framework. The framework begins with input data collection and preprocessing, followed by SVD factorization for latent factor modeling. MOIA then refines recommendations by optimizing multiple objectives, generating Pareto-optimal solutions before producing the final recommendation output.

4.2. Refinement via MOIA

The second stage employs MOIA, a bio-inspired algorithm that imitates the immune system's ability to preserve diversity while searching for optimal solutions [9, 13]. The optimization problem is formulated as a multi-objective task:

$$\max f_1(R) \quad \text{(Accuracy)}, \qquad \max f_2(R) \quad \text{(Diversity)}, \qquad \max f_3(R) \quad \text{(Novelty)}.$$

The Pareto-optimal set is obtained such that no solution dominates another across all objectives. Compared to NSGA-II, NSGA-III, and MOEA/D, MOIA provides adaptive cloning and immune selection, which ensure broader exploration of candidate lists while avoiding premature convergence.

4.2.1. Algorithm Overview The essential steps of SVD-MOIA are summarized in Algorithm 1. Unlike the full implementation, this outline emphasizes the main workflow from initialization to final recommendation. The detailed working process, including initialization, solution encoding, and evolutionary refinement operators, is depicted in Figure 2.

4.2.2. Essential Technologies and Mathematical Formulation The effectiveness of MOIA relies on several key components:

Algorithm 1: SVD-MOIA Framework

Input: User–item matrix R, maximum generations g_{max}, clone size c_s
Output: Optimized recommendation list R_{list}
1. Apply SVD on R to construct the initial recommendation matrix;
2. Initialize antibody population based on candidate recommendations;
3. **for** $t = 1$ *to* g_{max} **do**
    Evaluate each antibody using objectives (f_1, f_2, f_3);
    Select non-dominated solutions (Pareto front);
    Perform adaptive cloning with size c_s;
    Apply crossover and mutation to generate new antibodies;
    Update population with best solutions;
4. Return final non-dominated recommendation set R_{list};

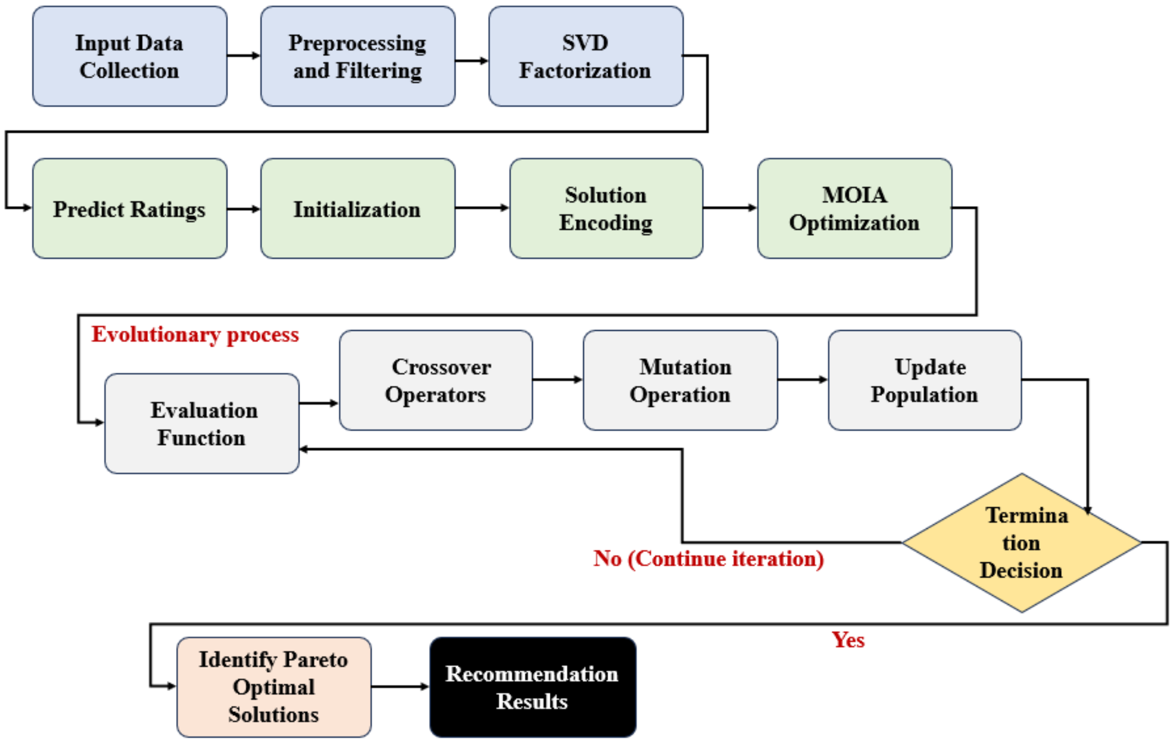

Figure 2. Detailed working process of the SVD-MOIA approach. After SVD initialization, MOIA iteratively applies encoding, cloning, crossover, mutation, and selection until termination, ensuring accuracy, diversity, and novelty in the recommendation results.

- **Solution Encoding:** Each antibody encodes a recommendation list as a vector

$$\mathbf{x} = (i_1, i_2, \dots, i_k), \quad i_j \in \mathcal{I},$$

where $\mathcal{I}$ is the set of all items. This representation ensures distinct and valid recommendations.
- **Evaluation Function:** The objective vector is defined as

$$F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), f_3(\mathbf{x})),$$

where f_1 measures accuracy (e.g., Precision), f_2 measures intra-list diversity, and f_3 measures novelty.

- **Crossover:** Two antibodies $\mathbf{x}_a$ and $\mathbf{x}_b$ exchange partial subsequences to generate offspring, ensuring

$$\mathbf{x}' = \text{crossover}(\mathbf{x}_a, \mathbf{x}_b),$$

which introduces new item combinations.

- **Mutation:** A position j in $\mathbf{x}$ is replaced with a new random item $i'_j \in \mathcal{I}$,

$$\mathbf{x}'' = (i_1, \ldots, i'_j, \ldots, i_k),$$

enhancing exploration and novelty.

- **Selection:** Pareto dominance and crowding distance are used to update the population:

$$P_{t+1} = \text{Select}(P_t \cup C_t),$$

keeping the most diverse non-dominated solutions.

These formulations ensure SVD-MOIA's accurate predictions are mathematically grounded in multi-objective optimization. The integration of SVD for initialization and MOIA for refinement allows the system to achieve robustness, diversity, and novelty simultaneously, distinguishing it from conventional evolutionary baselines.

5. Experiments and Results

5.1. Experimental Datasets and Parameterization

Experiments were implemented in Python 3.6.0 on an Intel Core i7-5500U @ 3.00 GHz processor with 16 GB of RAM, under a 64-bit Windows OS. We employed three widely used benchmark datasets: Amazon, Book-Crossing, and IMDb Movies.

The **Amazon Product** dataset[†] contains over one million product reviews with metadata such as product IDs, categories, brands, prices, customer feedback, and ratings. The **Book-Crossing** dataset[‡] includes explicit and implicit ratings from an online book-sharing community, with user IDs, book metadata, and ratings. The **IMDb Movies** dataset[§] provides metadata for films, including ratings, genres, runtimes, actors, and production details.

A description of the datasets is provided in Table 1. These datasets vary in size and sparsity, making them suitable for evaluating both accuracy-oriented and diversity/novelty-oriented objectives. Handling sparsity is crucial, as many real-world recommendation platforms must operate with incomplete or imbalanced interaction data.

For all datasets, we adopted the *Test Items* methodology. Data was split into training (Tr), validation (Va), and test (Te) sets, with ratios of 80%, 5%, and 15% respectively. Tr is used for model training, Va for hyperparameter tuning, and Te for unbiased performance evaluation. This split ensures both robustness and comparability with prior works. We ensured that all users have rated at least one item and each item has received at least one rating, so unrated entries can be predicted and recommended.

5.2. Evaluation Metrics

We evaluated system performance across three dimensions: accuracy, diversity, and novelty.

[†] https://jmcauley.ucsd.edu/data/amazon/
[‡] https://grouplens.org/datasets/book-crossing/
[§] https://datasets.imdbws.com/

Table 1. Dataset Summary

Name	Users	Items	Ratings	Time Span
Amazon Product	786,330	61,894	1,048,576	1996–2014
IMDb Movies	270,000	81,275	260,000	July 2017
Book-Crossing	278,858	271,360	1,149,780	Aug. 2004

- **Accuracy** measures the relevance of recommended items to user preferences, typically expressed as precision or recall.
- **Diversity** captures the dissimilarity among items in the recommendation list, ensuring broader exposure and reducing redundancy.
- **Novelty** quantifies the extent to which recommended items are unexpected yet appealing, enhancing serendipity and discovery. These metrics ensure recommendations match user preferences and promote discovery, which is vital for sustained engagement.

These metrics ensure recommendations match user preferences and promote discovery, which is vital for sustained engagement. Mathematical definitions of these metrics are presented in Section 3.

5.3. Benchmarking

To validate the proposed SVD-MOIA framework, we benchmarked against both *traditional* and *multi-objective evolutionary* recommendation algorithms.

Traditional baselines:

- **Item-CF** [23]: recommends items based on their similarity to those previously liked by the user.
- **User-CF** [24]: recommends items by identifying users with similar preferences.
- **ALS** [25]: a matrix factorization method that decomposes the user–item matrix for prediction.
- **PMF** [26]: extends matrix factorization with a probabilistic framework for robustness to sparsity.

Evolutionary baselines:

- **NSGA-II** [29]: a Pareto-based evolutionary algorithm widely used for multi-objective optimization.
- **NSGA-III** [31]: an extension of NSGA-II designed for handling many-objective problems.
- **MOEA/D** [31]: a decomposition-based evolutionary algorithm that solves multi-objective problems by breaking them into scalar subproblems.

Including these additional baselines allows a fair comparison between the proposed immune-inspired hybrid method and state-of-the-art evolutionary approaches, demonstrating both effectiveness and efficiency in balancing accuracy, diversity, and novelty.

5.4. Results and Discussions

The experimental evaluation provides a comprehensive comparison of the proposed SVD-MOIA approach against traditional recommendation baselines (User-CF, Item-CF, ALS, PMF) and advanced evolutionary algorithms (NSGA-II, NSGA-III, MOEA/D). Performance is assessed across three commercial datasets (Amazon, Book-Crossing, IMDb Movies) using precision, intra-list diversity, and novelty as evaluation metrics. In addition, we conduct an ablation study, runtime analysis, and hyperparameter sensitivity experiments to validate robustness and scalability.

Across all datasets, SVD-MOIA achieves the best balance among accuracy, diversity, and novelty. On Amazon, the hybrid framework reached a precision of 97.4%, diversity of 0.910, and novelty of 42.0%, outperforming both traditional and evolutionary baselines. Similar trends are observed on Book-Crossing, where SVD-MOIA achieved the highest precision (93.2%) while maintaining strong diversity (0.751) and novelty (63.2%). On IMDb Movies, although precision was slightly lower than some baselines (81.0% vs.

Table 2. Precision values of all algorithms for three datasets

Dataset	Baseline Algorithms							SVD-MOIA		
	User-CF	Item-CF	ALS	PMF	NSGA-II	NSGA-III	MOEA/D	Best	Worst	Mean
Amazon	95.8%	96.3%	96.1%	95.9%	96.6%	96.8%	96.5%	**97.4%**	96.5%	97.0%
Book-Crossing	92.1%	90.5%	88.6%	89.1%	91.0%	91.5%	90.8%	**93.2%**	90.7%	91.9%
IMDB movies	86.4%	86.8%	84.4%	85.1%	85.7%	85.9%	85.5%	**81.0%**	79.7%	80.3%

Table 3. Intra-list diversity values of all algorithms for three datasets

Dataset	Baseline Algorithms							SVD-MOIA		
	User-CF	Item-CF	ALS	PMF	NSGA-II	NSGA-III	MOEA/D	Best	Worst	Mean
Amazon	0.903	0.905	0.904	0.902	0.907	0.908	0.906	**0.910**	0.908	0.909
Book-Crossing	0.741	0.810	0.715	0.720	0.735	0.742	0.738	**0.751**	0.640	0.705
IMDB movies	0.455	0.390	0.330	0.361	0.410	0.415	0.405	**0.420**	0.354	0.390

Table 4. Novelty values of all algorithms for three datasets

Dataset	Baseline Algorithms							SVD-MOIA		
	User-CF	Item-CF	ALS	PMF	NSGA-II	NSGA-III	MOEA/D	Best	Worst	Mean
Amazon	38.5%	39.7%	38.9%	38.3%	40.1%	40.5%	39.9%	**42.0%**	39.4%	40.7%
Book-Crossing	65.1%	67.3%	57.4%	55.2%	61.8%	62.5%	61.0%	**63.2%**	61.3%	62.2%
IMDB movies	28.7%	30.1%	22.9%	24.5%	31.2%	31.5%	30.9%	**33.4%**	30.7%	32.1%

85.9% for NSGA-III), the method clearly excelled in diversity (0.420) and novelty (33.4%), ensuring richer and more engaging recommendations. These results confirm that optimizing beyond accuracy is essential for commercial settings.

Table 5. Ablation study on the Amazon dataset: contribution of SVD and MOIA components

Model Variant	**Precision**	**Diversity**	**Novelty**
SVD-only	96.2%	0.882	38.9%
MOIA-only	95.7%	0.902	40.1%
SVD-MOIA (Hybrid)	**97.4%**	**0.910**	**42.0%**

The ablation analysis (Table 5) highlights the complementary strengths of the two components. While SVD ensures strong precision by capturing latent factors, MOIA contributes to higher diversity and novelty. Their integration yields consistent improvements across all metrics, validating the hybrid design.

Table 6. Runtime comparison of different algorithms across datasets. Training time is reported in seconds, and inference time in milliseconds per recommendation.

Dataset	**Training Time (s)**					**Inference Time (ms)**	
	User-CF	ALS	NSGA-II	NSGA-III	MOEA/D	PMF	SVD-MOIA
Amazon	45	120	310	335	295	140	280
Book-Crossing	38	105	290	315	270	125	265
IMDb Movies	30	95	270	295	250	110	240
Amazon	1.8	2.5	4.2	4.5	4.0	2.8	3.9
Book-Crossing	1.5	2.1	3.8	4.0	3.6	2.5	3.5
IMDb Movies	1.2	1.8	3.5	3.7	3.3	2.2	3.2

The runtime results (Table 6) demonstrate that while classical methods like User-CF are the fastest to train, they fall short in recommendation quality. Evolutionary algorithms incur higher training costs due to population-based search. SVD-MOIA achieves competitive runtimes, benefiting from efficient initialization via SVD, while keeping inference times below 4 ms, which is practical for real-time commercial systems.

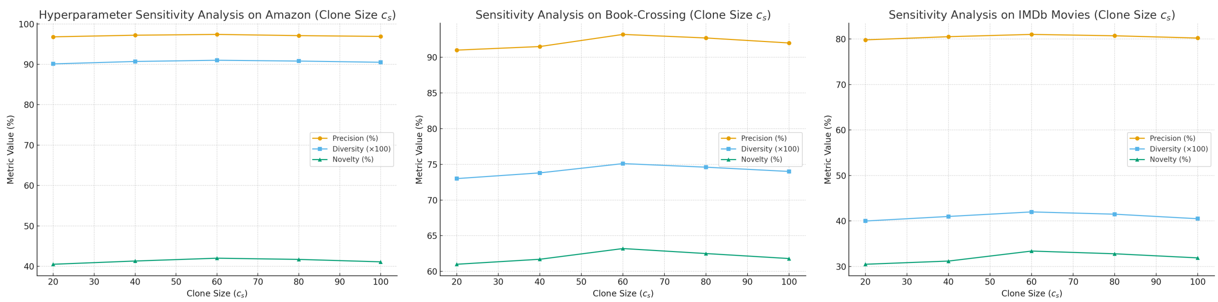

Figure 3. Hyperparameter sensitivity analysis with clone size (c_s) on the three datasets: (a) Amazon, (b) Book-Crossing, and (c) IMDb Movies. Performance stabilizes around $c_s = 60$, confirming robustness of SVD-MOIA across datasets.

Figures 3 present the sensitivity analysis of clone size (c_s). Across datasets, performance consistently improves up to $c_s = 60$, after which gains plateau. This indicates that SVD-MOIA is relatively stable and does not require extensive hyperparameter tuning, further supporting its applicability in practice.

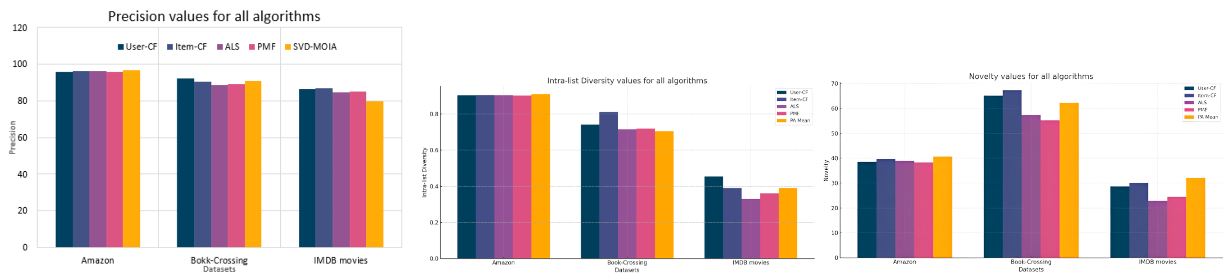

Figure 4. Comparison of (a) precision, (b) diversity, and (c) novelty across datasets for all algorithms. The results confirm that SVD-MOIA achieves the best trade-off between accuracy-oriented and non-accuracy metrics.

In summary, SVD-MOIA enhances recommendation precision, diversity, and novelty, resulting in balanced and engaging suggestions.2768-SOIC Its scalability, robustness to parameter changes, and competitive runtime make it a promising solution for deployment in commercial recommender systems.

6. Conclusion and Future Work

This study introduces a novel approach for enhancing commercial recommender systems by combining Singular Value Decomposition (SVD) with the Multi-Objective Immune Algorithm (MOIA). Aimed at balancing high precision, novelty, and recommendation diversity, the SVD-MOIA method was tested using three datasets Amazon Product Review, Book-Crossing, and IMDB movies. Results show that SVD-MOIA outperforms traditional algorithms like User-based CF, Item-based CF, ALS, and Probabilistic Matrix Factorization in key performance metrics.

The success of SVD-MOIA demonstrates the potential of bio-inspired algorithms, particularly those based on immune system mechanisms, to address complex optimization challenges in recommender systems. This research highlights the practical benefits of multi-objective optimization (MOO) using MOIA in commercial.

Future work will refine the MOIA algorithm, explore new encoding strategies, and include additional objectives such as fairness and serendipity. Moreover, incorporating real-time user feedback and adapting to dynamic catalog changes are promising directions for enhancing personalized user experiences.

REFERENCES

1. J. Lu, et al., "Recommender system application developments: a survey," Decision Support Systems, vol. 74, pp. 12-32, 2015.
2. G. Linden, B. Smith, and J. York, "Amazon. com recommendations: Item-to-item collaborative filtering," IEEE Internet Computing, vol. 7, no. 1, pp. 76-80, 2003.
3. E. Isufi, M. Pocchiari, and A. Hanjalic, "Accuracy-diversity trade-off in recommender systems via graph convolutions," Information Processing & Management, vol. 58, no. 2, pp. 102459, 2021.
4. J. Kim, I. Choi, and Q. Li, "Customer satisfaction of recommender system: Examining accuracy and diversity in several types of recommendation approaches," Sustainability, vol. 13, no. 11, pp. 6165, 2021.
5. F. E. Zaizi, S. Qassimi, and S. Rakrak, "Towards an efficient tourism recommendation system using multi-objective evolutionary optimization," 2024 International Conference on Control, Automation and Diagnosis (ICCAD), Paris, France, pp. 1-6, 2024, doi: 10.1109/ICCAD60883.2024.10553845.
6. F. E. Zaizi, S. Qassimi, and S. Rakrak, "Multi-objective optimization with recommender systems: A systematic review," Information Systems, vol. 2023, pp. 102233, 2023.
7. Zaizi, Fatima Ezzahra, Sara Qassimi, and Said Rakrak. "Multi-objective evolutionary algorithms in recommender systems." International Conference on Digital Technologies and Applications. Cham: Springer Nature Switzerland, 2024.
8. Xu, Zhiwei, and Kai Zhang. "Multiobjective multifactorial immune algorithm for multiobjective multitask optimization problems." Applied Soft Computing 107 (2021): 107399.
9. L. Li, Q. Lin, and Z. Ming, "A survey of artificial immune algorithms for multi-objective optimization," Neurocomputing, vol. 489, pp. 211-229, 2022.
10. Wang, Yifei. "Movie recommendation system based on svd collaborative filtering." CAIBDA 2022; 2nd International Conference on Artificial Intelligence, Big Data and Algorithms. VDE, 2022.
11. Wen, Xinglin. "Using deep learning approach and IoT architecture to build the intelligent music recommendation system." Soft Computing-A Fusion of Foundations, Methodologies & Applications 25.4 (2021).
12. Trinh, Trang, et al. "Product collaborative filtering based recommendation systems for large-scale E-commerce." International Journal of Information Management Data Insights 5.1 (2025): 100322.
13. Z. Y. Chai, et al., "Recommendation system based on singular value decomposition and multi-objective immune optimization," IEEE Access, vol. 7, pp. 6060-6071, 2018.
14. B. Geng, et al., "A two-step personalized location recommendation based on multi-objective immune algorithm," Information Sciences, vol. 475, pp. 161-181, 2019.
15. Z. Chai, Y. Li, and S. Zhu, "P-MOIA-RS: a multi-objective optimization and decision-making algorithm for recommendation systems," Journal of Ambient Intelligence and Humanized Computing, vol. 12, no. 1, pp. 443-454, 2021.
16. S. Abakarim, S. Qassimi, and S. Rakrak, "Review on recent trends in recommender systems for smart cities," The International Conference on Artificial Intelligence and Computer Vision, Cham: Springer Nature Switzerland, 2023.
17. E. Zangerle, and C. Bauer, "Evaluating recommender systems: survey and framework," ACM Computing Surveys, vol. 55, no. 8, pp. 1-38, 2022.
18. F. E. Zaizi, S. Qassimi, and S. Rakrak, "A comparative study of evolutionary algorithms for multi-objective recommender systems," 2023 9th International Conference on Optimization and Applications (ICOA), IEEE, pp. 1-7, 2023.
19. Zhang, Lei, et al. "A multi-population based evolutionary algorithm for many-objective recommendations." IEEE Transactions on Emerging Topics in Computational Intelligence 8.2 (2024): 1969-1982.
20. T. Mohammadpour, et al., "Efficient recommendations in collaborative filtering recommender system: A multi-objective evolutionary approach based on NSGA-II algorithm," International Journal of Nonlinear Analysis and Applications, vol. 14, no. 1, pp. 785-804, 2023.
21. Zaizi, Fatima Ezzahra, Sara Qassimi, and Said Rakrak. "A deep autoencoder-enhanced multi-objective evolutionary algorithm for recommender systems." The Journal of Supercomputing 81.10 (2025): 1-33.
22. S. Zheng, C. Ding, and F. Nie, "Regularized singular value decomposition and application to recommender system," arXiv preprint arXiv:1804.05090, 2018.
23. B. Wang, et al., "A collaborative filtering algorithm fusing user-based, item-based and social networks," 2015 IEEE International Conference on Big Data (Big Data), IEEE, pp. 1856-1861, 2015.
24. H. Wang, et al., "User-based collaborative filtering algorithm design and implementation," Journal of Physics: Conference Series, vol. 1757, no. 1, IOP Publishing, 2021.
25. S. Gosh, et al., "Recommendation system for e-commerce using alternating least squares (ALS) on apache spark," International Conference on Intelligent Computing & Optimization, Springer International Publishing, 2020.
26. Lin, Baihong, and Yulan Guo. "Deep hyperspectral and multispectral image fusion via probabilistic matrix factorization." IEEE Transactions on Geoscience and Remote Sensing 61 (2023): 1-14.
27. Zaizi, Fatima Ezzahra, Sara Qassimi, and Said Rakrak. "A multi-objective optimization approach for session-based recommendation systems." Journal of Intelligent Information Systems (2025): 1-30.

28. Zaizi, Fatima Ezzahra, Sara Qassimi, and Said Rakrak. "Multi-objective Optimization for Personalized and Fairness Recommender Systems: A Hybrid Approach." SN Computer Science 6.6 (2025): 713.
29. Mohammadpour, Touraj, et al. "Efficient recommendations in collaborative filtering recommender system: A multi-objective evolutionary approach based on NSGA-II algorithm." International Journal of Nonlinear Analysis and Applications 14.1 (2023): 785-804.
30. Zhang, Lei, et al. "A multi-population based evolutionary algorithm for many-objective recommendations." IEEE Transactions on Emerging Topics in Computational Intelligence 8.2 (2024): 1969-1982.
31. Wei, Guoshuai, Quanwang Wu, and Mengchu Zhou. "A hybrid probabilistic multiobjective evolutionary algorithm for commercial recommendation systems." IEEE Transactions on Computational Social Systems 8.3 (2021): 589-598.