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Optimizing User Satisfaction in Movie Recommendations Using Variable Learning Rates and Dynamic Neighborhood Functions in SOMs

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Abstract: Customized movie recommendations are crucial in elevating user satisfaction and engagement in the era of vast online entertainment options. This study presents an innovative approach utilizing Enhanced Self-Organizing Maps (SOMs) for movie categorization. SOMs, as unsupervised neural networks, are highly effective in recommendation systems due to their ability to identify intricate data patterns accurately. The proposed method involves collecting user-movie interaction data, such as user ratings and movie attributes. Data standardization is performed to ensure consistency before training the refined SOM. By integrating variable learning rates and dynamic Neighborhood functions, the advanced SOM can uncover complex patterns within datasets, thus enhancing the accuracy of personalized movie recommendations by identifying meaningful connections between users and films. To further improve recommendation quality, hybrid filtering techniques are employed, combining content-based filtering, which considers movie characteristics like genre and description, with collaborative filtering algorithms that analyze user-item interactions to expand the range of recommended films. This integrated approach allows for the generation of user-movie matrices by employing SVD collaborative filtering to give precedence to movie recommendations. The hybrid technique demonstrates superior performance compared to earlier models, attaining an RMSE of 0.410, MAE of 0.211, precision of 92.09%, recall of 93.12%, and an F1-score of 92.15%, consequently offering very accurate movie recommendations. Subsequent studies could concentrate on improving personalised recommendations by integrating supplementary contextual data.

Introduction

Movie recommendation systems have significantly advanced through these developments. These systems can generate highly personalized recommendations by incorporating deep learning and sentiment analysis (Alatrashand Priyadarshini, 2023; Alatrash et al., 2021). Hybrid models that merge collaborative filtering and content-based strategies have effectively mitigated the cold start issue, thereby improving recommendation relevance even for new users (Li et al., 2022; Otter et al., 2022). Additionally, sentiment-enhanced collaborative filtering has been applied to enhance recommendation systems, especially in e-learning (Alatrash et al., 2021; Nain, 2023).

The integration of artificial intelligence (AI) in recommender systems has broadened their scope beyond traditional applications, extending to areas like e-commerce, healthcare, and urban management. AI-driven sentiment analysis is critical in improving recommendation accuracy by comprehending user emotions and preferences (Alatrashand Priyadarshini, 2023; Mehfoozaand Basha, 2021). Research has shown the

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effectiveness of machine learning classifiers in boosting the accuracy of predictive models across various fields, including phishing detection and data security (Awasthiand Goel, 2024; Jain and Thada, 2024).

In the domain of movie recommendations, specific techniques such as item-based collaborative filtering and actor-based matrix computations have demonstrated significant performance improvements (Kharita et al., 2022; Ko et al., 2022). Furthermore, the adoption of deep residual learning has proven beneficial in image recognition tasks, highlighting the potential of deep learning to enhance recommendation systems (He et al., 2022; Kumar and Lehal, 2023; Banerjee et al., 2023). These advancements underscore the ongoing need for innovation to meet the evolving demands of users.

This research article introduces a novel hybrid approach that combines content-driven k-nearest neighbors (KNN), improved self-organizing maps (IKSOM), and K-means++ clustering to enhance user satisfaction in movie recommendations. By employing variable learning rates and dynamic neighborhood functions, this study aims to address persistent issues such as data sparsity and scalability in recommendation systems (Sarkar et al., 2022; Sharma and Arya, 2022). This proposed approach is anticipated to offer a robust framework for personalized movie recommendations, thereby boosting user engagement and satisfaction.

List of Challenges in Movie Recommendation Systems

The field of movie recommendation systems has made substantial progress in personalizing user experiences, yet it faces numerous challenges that limit its effectiveness and broader application. These challenges encompass various technical and practical aspects, necessitating ongoing research and innovation to improve the performance and reliability of these systems.

Data Sparsity

Data sparsity is a significant issue in movie recommendation systems, stemming from the fact that most users rate only a small fraction of available movies. This results in a sparse user-item matrix, making it difficult to discern meaningful patterns and correlations (Alhijawi et al., 2022; Ricci et al., 2011). The sparsity problem impedes the system's ability to provide accurate recommendations, particularly for less popular movies or new users with few ratings.

Cold Start Problem

The cold start problem is a significant obstacle that arises when the system does not have enough data on new users or new things to produce dependable recommendations. The problem impacts both user-based and item-based collaborative filtering techniques, posing challenges in seamlessly incorporating fresh inputs into the recommendation system (Alatrash and Priyadarshini, 2023; Awan et al., 2021). To tackle the cold start problem, inventive methods that can utilize supplementary data, such as user demographics or item features, must be employed.

Scalability

Scalability is crucial for recommendation systems operating in environments with large user bases and extensive movie catalogs. As data volumes increase, the computational demands for generating recommendations grow exponentially, posing a challenge for real-time processing and recommendation delivery (Govindasamy et al., 2024; Sarkar et al., 2022). Effective scalability solutions involve optimizing algorithms for efficiency and utilizing distributed computing resources.

Diversity vs. Accuracy Trade-off

Effectively managing the trade-off between diversity and accuracy in recommendations continues to be a long-standing difficulty. Accurate recommendations that closely align with user tastes can result in a "filter bubble" phenomenon, wherein users are exposed only to a restricted array of content. On the other hand, by boosting diversity, users can be exposed to a wider range of movies. However, this may decrease the perceived relevance of suggestions (He et al., 2022; Hwang and Park, 2022). Attaining the optimal equilibrium among these factors is crucial for upholding customer engagement and contentment.

Context-Awareness

Integrating contextual information, such as the time of day, location, or user mood, into recommendation algorithms is challenging. Context-aware recommendation systems strive to improve the relevance of suggestions by considering the user's current context. However, doing this involves the use of advanced data-gathering and processing techniques (Alatrash et al., 2021; Konar et al., 2022). The process of developing efficient context-aware systems requires the smooth integration of contextual signals into the recommendation algorithms.

User Privacy

Ensuring user privacy while delivering personalized recommendations is a significant concern. Recommender systems often require access to sensitive user data, which can lead to privacy risks if not managed properly. Implementing robust privacy-preserving techniques, such as differential privacy or federated learning, is crucial to protect user information without compromising recommendation quality (Anandkumar et al., 2022; Kumar and Lehal, 2023).

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Interpretability

The interpretability of recommendation models is vital for user trust and regulatory compliance. Users and stakeholders need to understand the rationale behind specific recommendations, particularly in high-stakes domains like healthcare or finance. Enhancing the transparency of complex models, such as deep learning-based recommenders, remains a challenge that requires balancing model complexity with interpretability (Alqahtani, 2023; Mehfooza and Basha, 2021).

Real-Time Recommendations

Delivering real-time recommendations is essential for user satisfaction, especially in dynamic environments where user preferences can change rapidly. Achieving this requires highly efficient algorithms and robust infrastructure capable of handling large-scale data processing with minimal latency (Awasthiand Goel, 2024; Jain and Thada, 2024). To meet these demands, continuous optimization and innovation in algorithm design and system architecture are necessary.

Sentiment Analysis Integration

Integrating sentiment analysis into recommendation systems can significantly enhance personalization by understanding user emotions and preferences from textual reviews (Hwang and Park, 2022; Li et al., 2022). However, accurately analyzing sentiment from diverse and unstructured data sources poses a challenge, requiring advanced natural language processing techniques (Alatrashand Priyadarshini, 2023; Otter et al., 2022). Effective sentiment analysis integration can improve the system's ability to recommend content that aligns with user sentiments.

Literature Review

The development and optimization of recommendation systems have made significant strides recently, especially with the incorporation of hybrid models and machine learning techniques. Sharma et al. (2022) introduced a hybrid real-time implicit feedback self-organizing map (SOM)-based movie recommendation system, showcasing the effectiveness of merging real-time data with SOM for superior recommendations. Their follow-up study further enhanced this methodology, where they implemented an advanced version of SOM combined with hybrid filtering methods to improve movie recommendations (Sharma et al., 2023). Additionally, they investigated the use of a hybrid recommendation model designed for groups of users, highlighting the significance of recent attention and diverse user preferences in producing accurate suggestions (Sharma et al., 2022).

In a different context, Sharma et al. (2021) created a novel location-based recommender framework that classifies user data to identify interests more accurately. This method is consistent with the broader trend of using contextual information to enhance recommendation accuracy. Furthermore, Sharma et al. (2022) Concentrated on assessing and estimating the quality of existing software through multi-criteria decision models, offering valuable insights into software reliability and stability. They expanded this research by developing a time-variant software stability model to improve error detection processes (Sharma et al., 2022).

Additionally, other academics have made significant contributions to this particular area of study. Srivastava et al. (2022) presented an advanced recommendation system for e-commerce that utilizes ensemble learning. This approach can enhance recommendation performance by merging several learning algorithms. Kumar and Francis (2024) investigated the significance of artificial intelligence (AI) and machine learning techniques in hybrid movie recommendation systems. They specifically focused on the utilization of text-to-number conversion and cosine similarity methodologies. Their findings emphasize the profound influence of sophisticated algorithms on the precision of recommendations.

Finally, Vineela et al. (2021) explored the use of machine learning algorithms to optimize personalized education recommendation systems. Their research demonstrates the wider applicability of machine learning techniques beyond traditional domains, paving the way for more tailored and effective educational recommendations.

These studies emphasize the dynamic and interdisciplinary nature of recommendation system research, highlighting ongoing efforts to integrate advanced algorithms and hybrid models to meet diverse user needs and contexts.

Literature review provides a thorough overview of current research efforts aimed at enhancing recommendation systems. The research is classified depending on their methodology, which includes collaborative filtering, content-based filtering, and hybrid approaches. The key advancements emphasized are the incorporation of sentiment analysis, machine learning algorithms, and matrix factorization approaches. The table provides a comprehensive overview of the performance indicators used in this research, including RMSE (Root Mean Square Error), MAE (Mean Absolute Error), precision, and recall. This demonstrates the effectiveness and improvements obtained. This summary offers a great resource for comprehending the progress and present patterns in recommendation system research.

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Figure 1 provides a comprehensive visualization of the contributions of different authors in the literature review. This figure emphasizes the number of publications linked to each author, highlighting the influence of key scholars in the field. The visualization helps identify the principal contributors and their focus areas and illustrates the degree of collaboration among various authors. Analyzing this distribution gives readers a clearer understanding of the research landscape and the impact of individual authors. This approach offers valuable insights into the domain's collaborative networks and thematic concentrations.

provided. The system employs variable learning rates and dynamic neighborhood functions within SOMs to optimize user satisfaction in movie recommendations. These enhancements enable the SOM to adapt more effectively to diverse user preferences and behaviors, resulting in more accurate and satisfying recommendations. The strategy emphasizes protecting user data from potential security breaches, highlighting a commitment to privacy and unbiased suggestions in the evolving landscape of location-based systems. Continuous refinement of learning rates and neighborhood functions improves recommendation accuracy and enhances overall user satisfaction.

Proposed System Framework

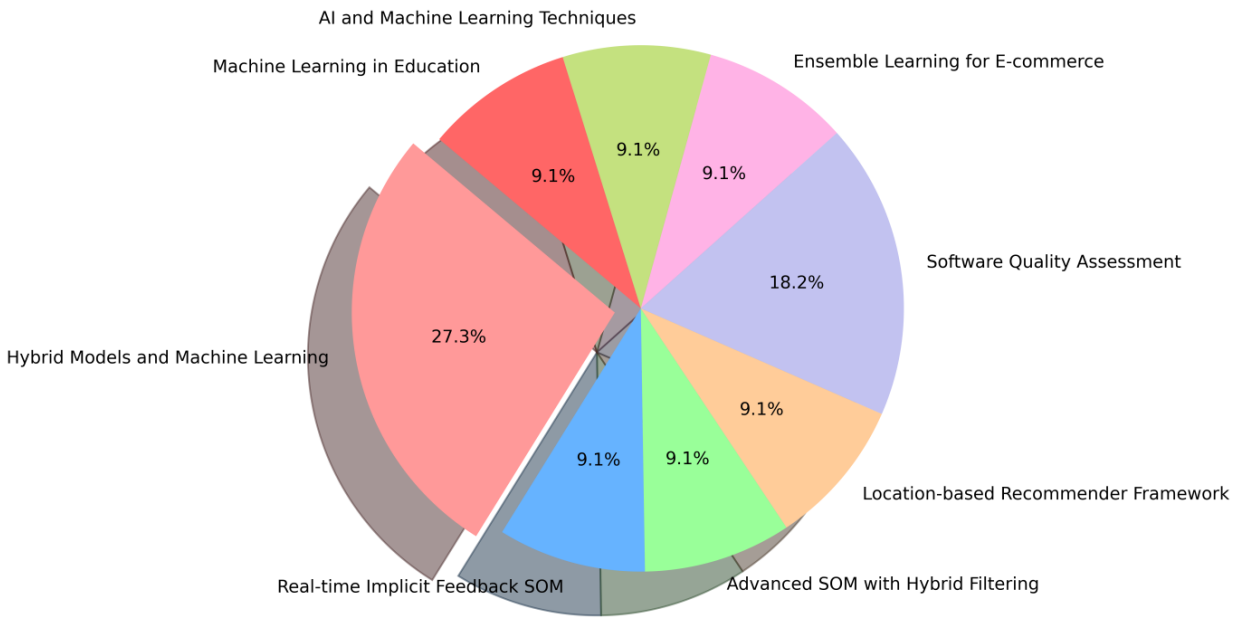

Figure 1. Distribution of Literature Review by Authors.

Proposed Methods

The proposed system addresses privacy concerns and ensures algorithmic fairness in personalized user experiences, considering the challenges present in contemporary location-based recommendation systems. This approach leverages a Self-Organizing Map (SOM) to offer an innovative solution for managing user privacy and enhancing algorithmic fairness. User privacy is prioritized through efficiently handling complex location data, stringent security measures, and robust data protection utilizing SOMs. Additionally, the system actively tackles issues of fairness and bias in algorithms, delivering impartial recommendations and consistently working to correct biases that may affect specific user demographics or geographic areas. By incorporating SOMs, the location-based recommendation system effectively addresses concerns related to user privacy and algorithmic fairness while ensuring personalized information and services are

The proposed design of our location-based recommendation system, which integrates Self-Organizing Maps (SOM), is carefully crafted to tackle privacy concerns and algorithmic fairness issues while improving personalised user experiences. The core of this system relies on utilising geographical information to customise content and services according to individual tastes and specific locales, with a significant focus on a user-centered approach. The framework effectively incorporates a Self-Organizing Map (SOM) technique, skillfully handling the intricacies of user privacy and algorithmic fairness. The Self-Organizing Map (SOM) is crucial in ensuring privacy by effectively managing location data, implementing rigorous security measures and safeguarding user data from intrusions. In addition, the SOM proactively tackles issues of fairness and bias in algorithms, guaranteeing impartial suggestions and continuous endeavours to rectify any biases that may

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impact particular user demographics or geographic areas. This design successfully addresses key privacy and fairness issues and strengthens our dedication to providing personalised content and services while prioritizing the protection of user data. The suggested

approach establishes a novel benchmark for location-based recommendation systems, promoting user confidence, privacy, and fairness in the ever-evolving realm of personalised user experiences.

similarity between the newly released movies and the list of movies that the user prefers. The ultimate recommendation for upcoming movies is determined by aggregating the similarity score, predicted ratings, and the ratings of favorite movies. The methodology is outlined in Algorithm 1, guaranteeing a resilient and accurate recommendation system that corresponds to user preferences for recent movie releases.

Algorithm 1: Optimizing User Satisfaction in Movie Recommendations Using Variable Learning Rates and Dynamic Neighborhood Functions in SOMs

Input:

- Set of Users $U = \{u_1, u_2, \dots, u_n\}$
- Set of Movies $M = \{m_1, m_2, \dots, m_p\}$
- Set of New Movies $NM = \{nm_1, nm_2, \dots, nm_q\}$
- User Rating Matrix $R = U \times M$
- Movie Feature vector $F = \{f_1, f_2, \dots, f_m\}$
- Feature Weight vector $W = \{w_1, w_2, \dots, w_m\}$
- IMDb Ratings of all M movies $R = \{r(m_1), r(m_2), \dots, r(m_p)\}$
- Predicted Ratings of all NM new movies $PR = \{pr(nm_1), \text{pr}\ (nm_2), \dots, \text{pr}\ (nm_q)\}$

Output:

- Recommend R most promising upcoming movies RM_i according to the preference $u_i, \forall u_i \in U_1 RM^i = \{rm_j^i \mid j = 1,2, \dots, r\}$

Procedure:

1 For each user $u_1 \in U$:

- Identify I preferred movies with the highest likes from $R = U \times M$
- Define the preferred movie set $pm_i = \{m_1^t, m_2^t, \dots, m_l^t\}$ where $m_k^t \in M$ and $1 \le k \le l$
- $PM = \{pm_1, pm_2, \dots, pm_l\}$

2 For each user $u_i \in U$:

- For each movie $m_j^t \in pm_i$:
- For each new movie $nm_t \in NM$:
- Calculate similarity:

$$\text{sim}\left(m_j^t, nm_k\right) = \sum_{c=1}^{m} \left[w_c \cdot \text{sim}\left(f_c\left(m_j^t, nm_k\right)\right)\right]$$

- Determine overall similarity for each m_j^t :
- $\text{sim}\left(m_j^t\right) = \max_{k=1}^{q}\{\text{sim}\left(m_j^t, nm_k\right)\}$ where q is the total number of new 1
- Sort $\text{sim}\left(m_j^t\right)$ from most similar to less similar movie
- Define $NM_j^t = \{nm_{\beta k}^t \mid k = 1,2, \dots, p\}$ considering only p most similar movies of m_j^t
- Pool of $p \times l$ new movies for user u_ℓ :

$$NM^t = \{NM_j \mid j = 1,2, \dots, l\}$$

The method commences by generating a compilation of films favored by the user, taking into account their past interactions and personal inclinations. Next, compute the

3 For each movie $nm_{jk}^t \in NM^t$:

- Make the final recommendation by fusing weighted scores:

$$\text{cs}\left(u_i, nm_{jk}^t\right) = \text{sim}\left(m_j^t, nm_{jk}^t\right) \cdot \left[r\left(m_j^t\right) + \text{pr}\left(nm_{jk}^t\right)\right]$$

- Combined score of a new movie nm_{jk}^t :

$$CS^l = \bigcup_{j=1}^{l} \bigcup_{k=1}^{p} \text{cs}\left(u_i, nm_{jk}^t\right)$$

- Sort CS^t with higher combined score cs indicating strongly recommended movies:

$$CS^t = \left\{nm_1^t, nm_2^t, \dots, nm_{lp}^t\right\}$$

- Considering only initial r movies to recommend:

$$RM^t = \left\{rm_j^t \mid j = 1,2, \dots, r\right\}$$

- Final recommendation set:

$$RM = \{RM^t \mid i = 1,2, \dots, n\}$$

Return: *RM*

Description

The proposed hybrid recommendation system is designed to optimize user satisfaction in movie recommendations by incorporating variable learning rates and dynamic neighborhood functions within Self-Organizing Maps (SOMs). This algorithm effectively manages user privacy and ensures algorithmic fairness by prioritizing data security and delivering unbiased recommendations.

1. Initialization

The system begins by defining the sets of users U, movies M, and new movies NM. Each user's preferences are represented in a user rating matrix R. Additionally, movie features and their corresponding weights are provided through vectors $F$and W. The IMDb ratings for all movies M and the predicted ratings for new movies NM are also included.

2. User Preferences

For each user $u_i \in U$, the system identifies the preferred movies with the highest ratings from the user rating matrix $R = U \times M$. These preferred movies are compiled into a set $pm_i = \{m_1^t, m_2^t, \dots, m_l^t\}$, where $m_k^t \in M$ and $1 \le k \le l$. The set of preferred movies for all users is denoted as $PM = \{pm_1, pm_2, \dots, pm_l\}$.

3. Similarity Calculation

For each user $u_i \in U$ and each preferred movie $m_j^t \in pm_i$, the system calculates the similarity between the preferred movie and each new movie $nm_t \in NM$. The similarity is computed using a weighted sum of feature similarities:

$$\text{sim}\left(m_j^t, nm_k\right) = \sum^{m} \left[w_c \cdot \text{sim}\left(f_c\left(m_j^t, nm_k\right)\right)\right]$$

The overall similarity for each preferred movie m_j^t is determined by finding the maximum similarity with any new movie:

$\text{sim}\left(m_j^t\right) = \max_{k=1}^{q}\left\{\text{sim}\left(m_j^t, nm_k\right)\right\}$ where q is the total number of new movies

4. Selection of Similar Movies

The system sorts the similarities $\text{sim}\left(m_j^t\right)$ in descending order to prioritize the most similar movies. It then selects the top p most similar new movies for each preferred movie m_j^t, forming a set $NM_j^t = \left\{nm_{\beta k}^t \mid k = 1,2, \dots, p\right\}$. The pool of new movies for each user u_t is represented as $NM^t = \left\{NM_j \mid j = 1,2, \dots, l\right\}$.

5. Final Recommendation

For each new movie $nm_{jk}^t \in NM^t$, the system calculates a combined score by fusing the similarity score with the IMDb rating of the preferred movie and the predicted rating of the new movie:

$$\text{cs}\left(u_t, nm_{jk}^t\right) = \text{sim}\left(m_j^t, nm_{jk}^t\right) \cdot \left[r\left(m_j^t\right) + \text{pr}\left(nm_{jk}^t\right)\right]$$

The combined scores for all potential new movies are aggregated into a set $S^l = \bigcup_{j=1}^{l} \bigcup_{k=1}^{p} \text{cs}\left(u_i, nm_{jk}^t\right)$. These scores are then sorted in descending order to identify the most strongly recommended movies:

$$CS^t = \left\{nm_1^t, nm_2^t, \dots, nm_{lp}^t\right\}$$

The system selects the top r movies to recommend to each user:

$$RM^t = \left\{rm_j^t \mid j = 1,2, \dots, r\right\}$$

The final recommendation set for all users is compiled as $M = \{RM^t \mid i = 1,2, \dots, n\}$.

Return:

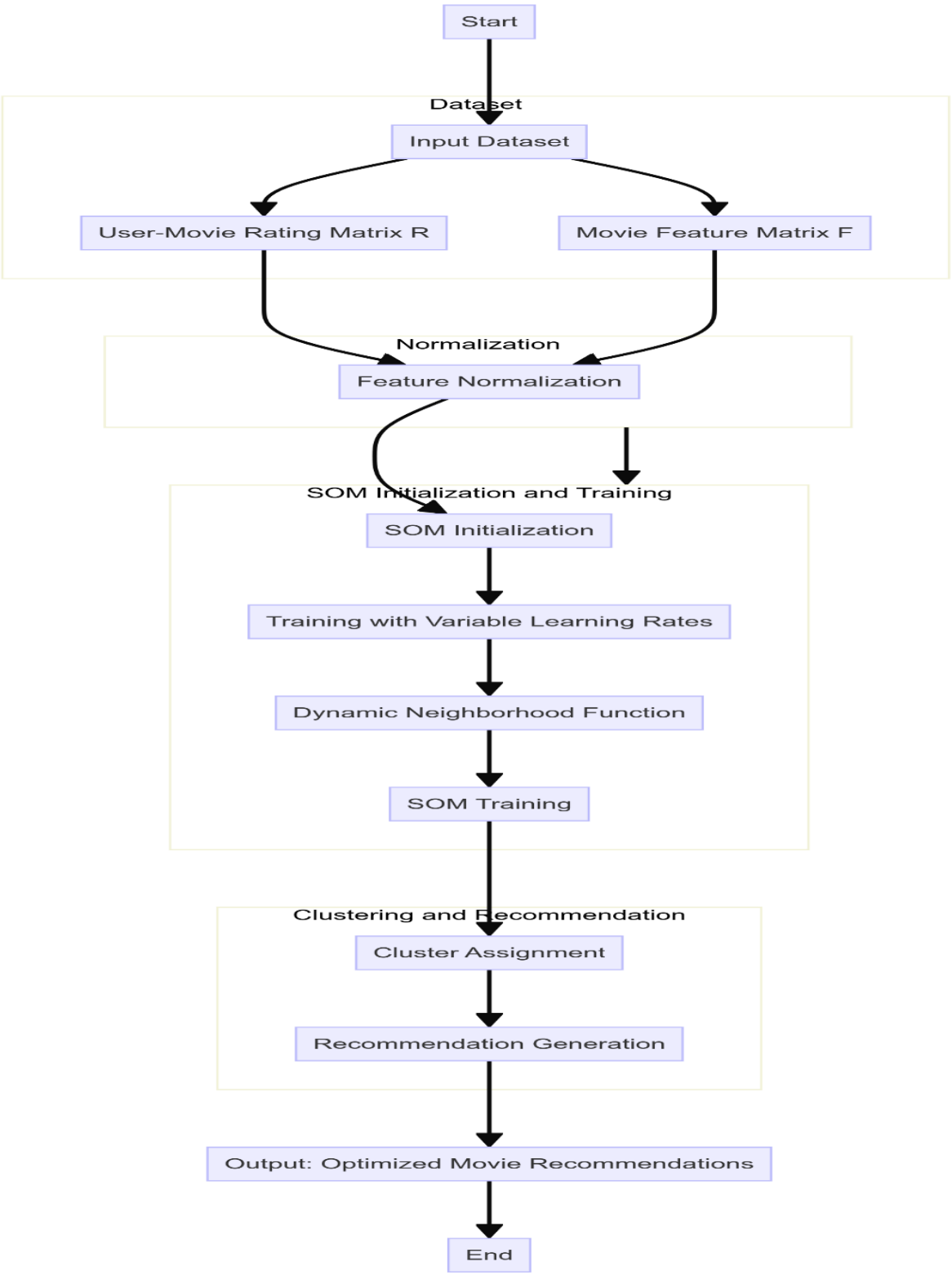

Figure 2. Flow chart Optimizing Movie Recommendations Using Variable Learning Rates and Dynamic Neighborhood Functions in SOMs.

The algorithm returns the set of recommended movies RM for each user, optimized to enhance user satisfaction by leveraging variable learning rates and dynamic neighborhood functions within SOMs. This ensures that the recommendations are relevant and Personalized while maintaining robust privacy and fairness standards.

After training, each movie m_i is assigned to the nearest cluster centroid in the trained SOM by minimizing the distance between $F_{\text{norm}}(m_i)$ and the cluster centroids. This results in distinct clusters of movies based on their features. The algorithm identifies the movie cluster, and

each user is rated highly for recommendation generation. Recommendations are then generated from the highest-rated movies within the user's cluster, ensuring relevance and personalization. The final output consists of optimized movie recommendations for each user, derived from the clusters formed during the SOM training process. This algorithm optimizes user satisfaction in movie recommendations by leveraging variable learning rates and dynamic neighborhood functions within SOMs. It dynamically adapts to user preferences, ensuring precise and personalized movie suggestions, thereby enhancing the overall effectiveness of the recommendation system.The proposed Algorithm using variable learning rates and dynamic neighborhood functions within Self-Organizing Maps. This algorithm optimizes user satisfaction in movie recommendations. The process involves training the SOM to adapt to user preferences and generating clusters that lead to personalized and relevant movie suggestions for each user.

Flow Chart

The flowchart for "Algorithm 1: Optimizing User Satisfaction in Movie Recommendations Using Variable Learning Rates and Dynamic Neighborhood Functions in SOMs" clearly outlines the steps from input data to producing optimized movie recommendations. The process begins with acquiring the user-movie rating matrix (RRR) and the movie feature matrix (FFF). Following this, theinitialization phase defines and sets up the user and movie sets and their corresponding matrices. The next step involves normalizing the movie feature matrix. The Self-Organizing Map (SOM) is then initialized with parameters such as grid size, initial learning rate, and initial neighborhood radius. The training phase incorporates a time-dependent learning rate function, $\alpha(t)$, and a dynamic neighborhood function, $\theta(t)$. During SOM training, the algorithm iterates through the movie feature vectors, finding the Best Matching Unit (BMU) and updating the weight vectors. Post training, the cluster assignment step assigns each movie to its nearest cluster centroid. Finally, in the recommendation generation phase, the algorithm identifies clusters of highly-rated movies for each user and generates personalized movie recommendations from these clusters. The process concludes with the output of optimized movie recommendations, leveraging SOMs with adaptive learning rates and dynamic neighborhood functions to improve user satisfaction through personalized movie suggestions.

Result

This section assesses the suggested technique, encompassing its results, performance indicators, and comparative analysis. The hybrid system was created utilizing TensorFlow, a Python framework emphasizing movie suggestions. The research data was obtained from the MovieLens databases, a comprehensive dataset containing 1 million tags contributed by 162,000 individuals, encompassing 62,000 films and 25 million ratings. The dataset contained 1,129 tags and 15 million relevance scores for the tag genome, specifically referred to as ml-25m. The dataset consists of 5-star ratings obtained from the MovieLens movie recommendation service and free-text labeling. The data was compiled on November 21, 2019. The dataset includes data on 62,423 movies, 25,000,095 ratings, and 1,093,360 tag applications. This information is collected from 162,541 people during the period from January 9, 1995, to November 21, 2019. Every user in the dataset has provided ratings for a minimum of 20 randomly selected films. Each user was allocated a unique identification number, without any accompanying demographic information. The MovieLens databases contain information regarding users, movies, ratings, and tags.

The MovieLens-25M dataset was partitioned into two subgroups to assist the training and testing process. The model training process involved using 75% of the available data, while the remaining 25% was allocated for testing purposes. A hybrid system-based machine learning methodology was employed to utilize insights from the dataset for movie suggestions in both the training and testing stages. The user and movie ratings results are presented in Figures 6 and 7 below, along with suggestions.

Table 2. Movie Dataset.

Sl. No	Movie Id	Title
0	1	Toy Story (1995)
1	2	Jumanji (1995)
2	3	Grumpier Old Men (1995)
3	4	Waiting to Exhale (1995)
4	5	Father of the Bride Part II (1995)

Table 3. Genres Dataset.

Sl. No	Genres
0	Adventure|Animation|Children |Comedy|Fantasy
1	Adventure|Children|Fantasy
2	Comedy|Romance
3	Comedy|Drama|Romance
4	Comedy

The Movie Dataset comprises detailed metadata for 62,423 movies available on the MovieLens platform (Table 2). It includes key attributes such as movie titles, unique IDs, release dates, and genres, providing a solid basis for in-depth analysis and developing

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recommendation models. This extensive dataset ensures a wide representation of films, aiding in the creation of accurate and personalized movie recommendations.

The Genres Dataset organizes the movies on the MovieLens platform into various genres, offering a structured view of each film's thematic content (Table 3). It includes unique genre identifiers and their corresponding names, facilitating precise genre-based filtering and analysis. Utilizing this dataset allows recommendation systems to better align with users' genre preferences, thereby enhancing user satisfaction and engagement.

Table 4. Rating Dataset.

Sl.No	User id	Movie id	Rating	Time stamp
0	1	296	5.0	1147880044
1	1	306	3.5	1147868817
2	1	307	5.0	1147868828
3	1	665	5.0	1147878820
4	1	899	3.5	1147868510

Table 5. Total Rating Count Dataset.

Sl. No	Title	Total Rating Count
0	"BLOW THE NIGHT!" Let's Spend the Night Togeth...	1
1	"Great Performances" Cats (1998)	179
2	#1 Cheerleader Camp (2010)	9
3	#Captured (2017)	2
4	#Female Pleasure (2018)	3

Table 6. Combine Movie Rating Merge Dataset.

Sl. No	UserID	Movie id	Rating	Timestamp	Title	Genres	Total Rating Count
0	1	296	5.0	1147880044	Pulp Fiction (1994)	Comedy|Crime|Drama|Thriller	79672
1	1	306	3.5	1147868817	Three Colors: Red (Troiscouleurs: Rouge) (1994)	Drama	7058
2	1	307	5.0	1147868828	Three Colors: Blue (Troiscouleurs: Bleu) (1993)	Drama	6616
3	1	665	5.0	1147878820	Underground (1995)	Comedy|Drama|War	1269
4	1	899	3.5	1147868510	Singin' in the Rain (1952)	Comedy|Musical|Romance	10895

The Rating Dataset includes a vast collection of 25,000,095 user-generated ratings for 62,423 movies (Table 4). Each entry consists of a unique user ID, movie ID, rating score (on a 5-star scale), and a timestamp. This dataset is crucial for training and evaluating recommendation algorithms, allowing for analyzing user preferences and identifying rating trends and patterns. The extensive data supports the development of advanced models that can predict user ratings and provide highly accurate movie suggestions.

The Total Rating Count Dataset summarizes the rating activity for each movie by aggregating the total number of ratings each film has received (Table 5). It includes movie IDs and their corresponding rating counts, offering valuable insights into different movies' popularity and viewer engagement. Analyzing this dataset helps identify popular movies and discern patterns in user rating behavior, which can be crucial for improving recommendation systems.

The Combine Movie Rating Merge Dataset integrates movie metadata with user rating data, creating a comprehensive dataset that enables multifaceted analysis

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Table 7. Movies Features Dataset.

Userid	1	2	3	4	5	.	69	70	71	72	73	74	75
title													
'Round Midnight (1986)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
'burbs, The (1989)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(500) Days of Summer (2009)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
And Justice for All (1979)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

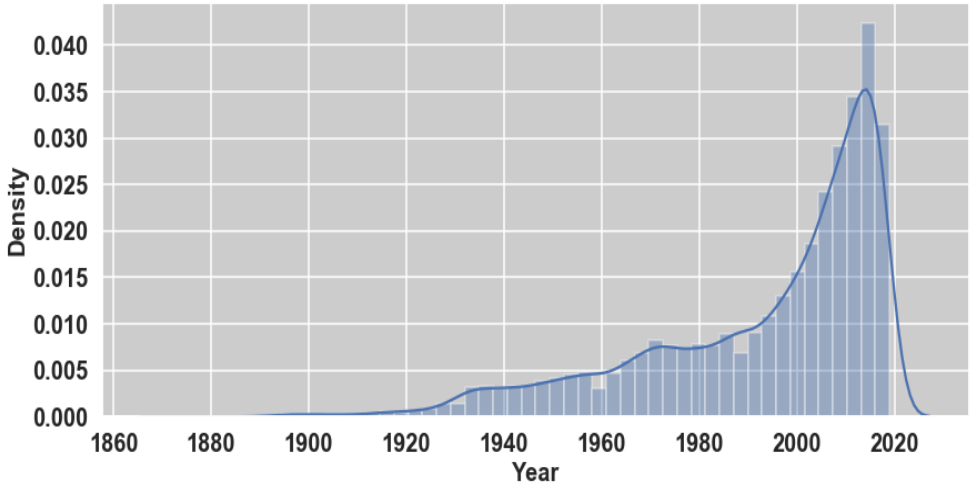

Figure 3. Distribution of Movies by Year in the MovieLens 25M Dataset, Highlighting the Peak Release Period Between 2000 and 2020.

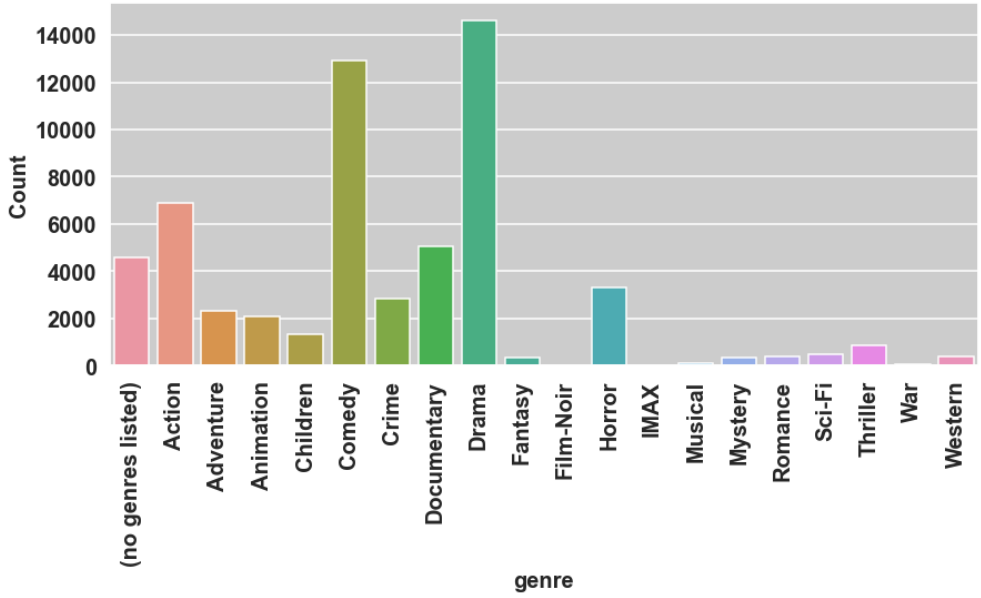

Figure 4. Distribution and Frequency of Movie Genres in the MovieLens 25M Dataset, Highlighting the Popularity of "Comedy" and "Drama" Among Users.

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(Table 6). It includes attributes from both the Movie Dataset and the Rating Dataset, such as movie IDs, titles, genres, user IDs, and ratings. This merged dataset provides a holistic view of movie characteristics and user preferences, essential for developing recommendation algorithms that consider both movie features and user rating patterns.

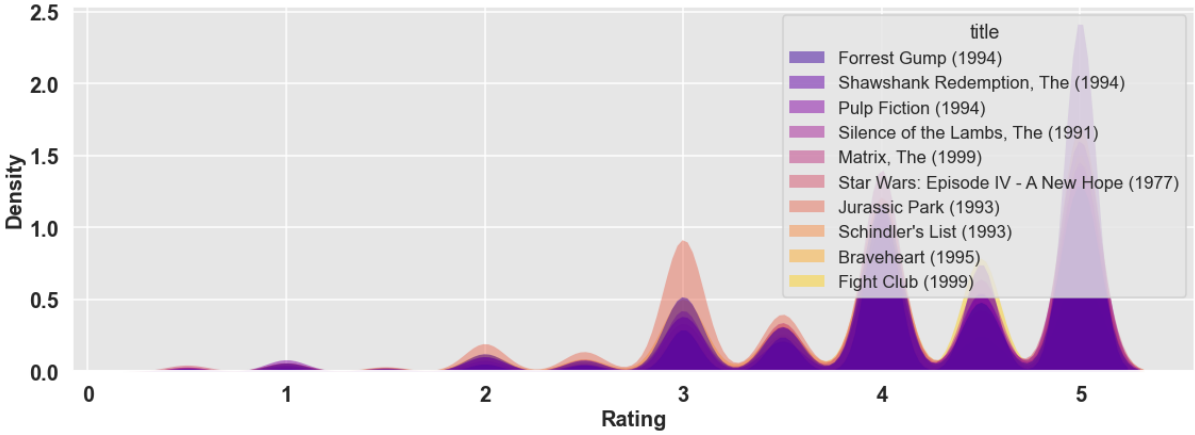

Figure 5. Distribution of Ratings (1 to 5) in the MovieLens 25M Dataset and Identification of Top-Rated Movies.

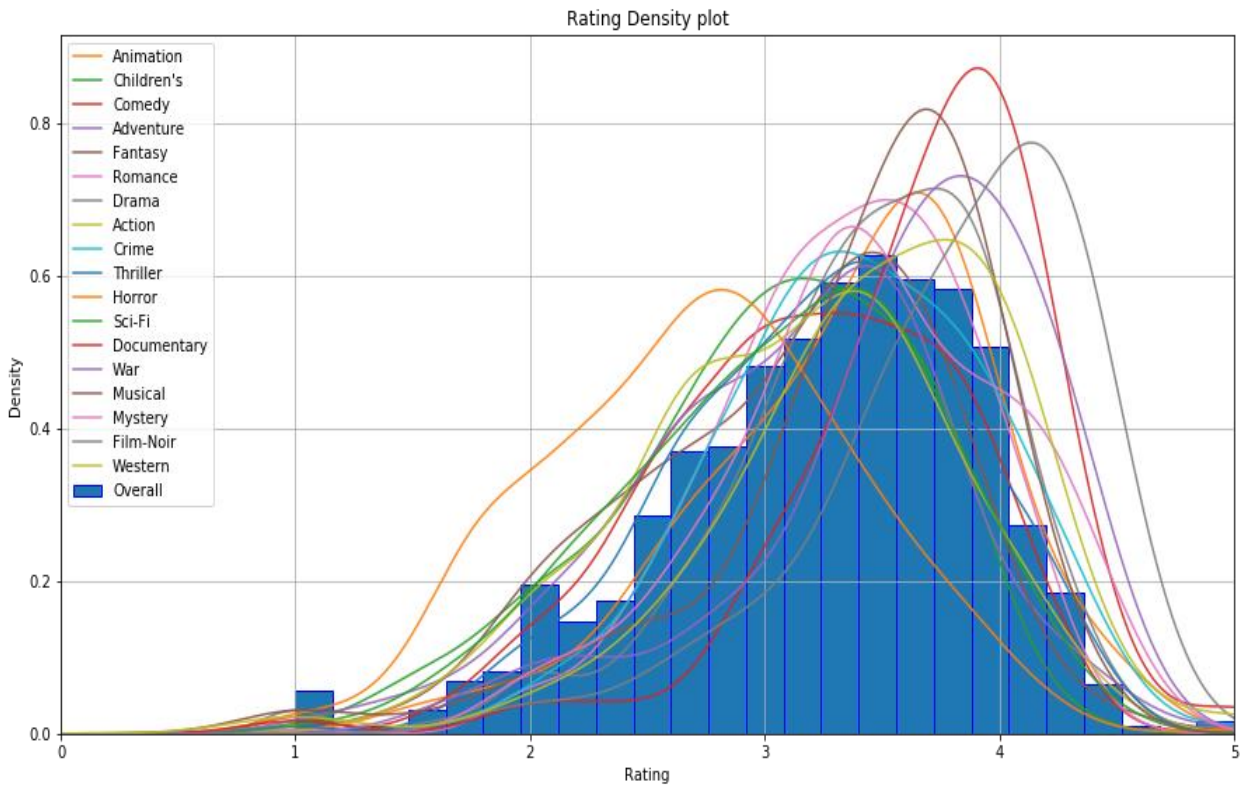

Figure 6. left-skewed distribution plot for ratings by genre.

The Movies Features Dataset provides a detailed representation of various movie attributes, serving as a rich source of data for feature extraction and analysis (Table 7). It includes movie IDs and a range of features derived from movie metadata and user interaction data, such as average ratings, genre distributions, and tag applications. This comprehensive feature set supports advanced analytical techniques and machine learning models, enabling the creation of highly personalized and contextually relevant movie recommendations tailored to individual user preferences.

Figure 2 displays the distribution of movies over various years, revealing that the highest concentration of movies falls between 2000 and 2020. This visualization provides a clear view of the temporal trends in movie releases, showcasing the significant volume of films produced during this 20-year span.

Figure 3 illustrates the distribution and frequency of movie genres in the MovieLens 25M dataset. The data reveals that "Comedy" and "Drama" are the most popular genres among users. This highlights the strong preference

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for these genres within the MovieLens community, offering key insights into user viewing patterns and preferences.

Figure 4 depicts the rating distribution from 1 to 5 in the MovieLens 25M dataset. It also identifies the movies that have achieved the highest ratings. This visualization offers a detailed overview of the rating distribution and highlights the top-rated films, providing valuable insights into user preferences and rating trends.

According to the statistics presented in Figure 8, around 350,000 observations of the rating value 4 have been made the most commonly observed. In our dataset of one million ratings, ratings of 4 accounted for around 35% of the ratings, with ratings of 3 and 5 accounting for roughly 26% and 21% of the ratings, respectively. It is important to note that the small amount of data available for 2003 may mean that these estimates are not totally accurate. However, it's clear that a sizable portion of users often give ratings of

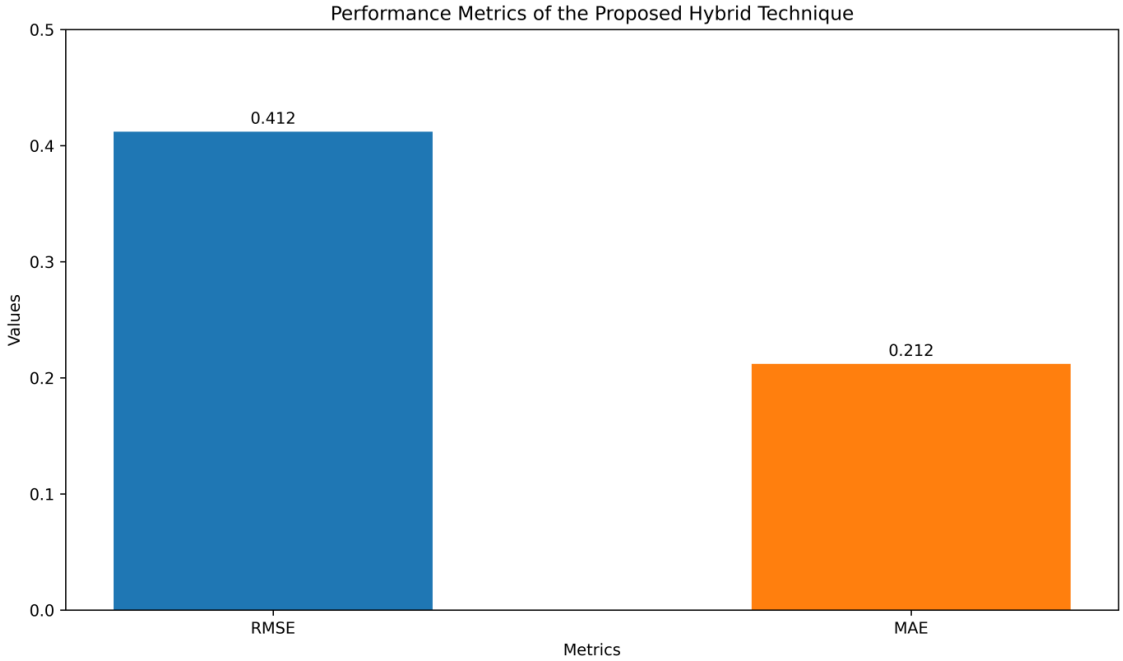

Figure 7. Performance metrics of RMSE and MAE.

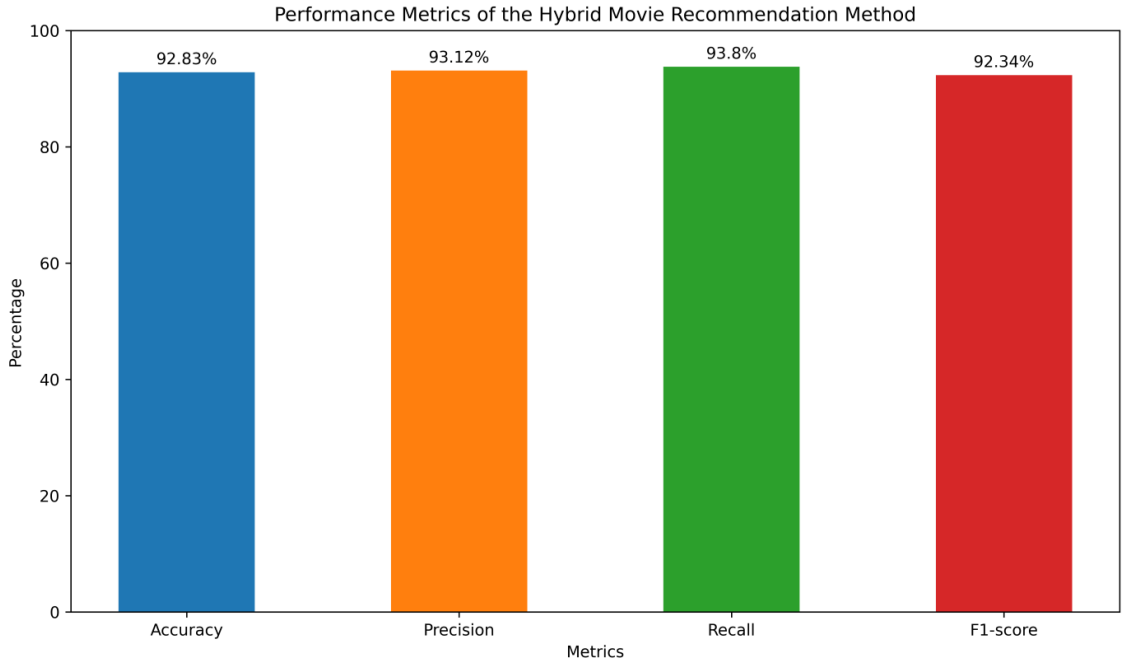

Figure 8. Comparison of Proposed Method With Other Existing Method.

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four or above.

Figure 5 illustrates that the Film-Noir and Horror categories consistently demonstrate high and low average ratings, respectively, with occasional extreme values. Following this observation, a density plot depicting ratings by genre will be generated.

Figure 5 shows that all genres exhibit a left-skewed distribution (with an approximate mean of 3.5), except for the Horror genre, which is characterized by low ratings.

The efficacy of the proposed technique was evaluated using the performance metrics F1-score, mean absolute error, precision, recall, accuracy, and root mean square error. An explanation of the performance measures may be found below.

Figure 6 shows the performance metrics for RMSE and MAE. The proposed hybrid technique mitigates the cold start issue using content-driven KNN's cosine similarity, resulting in an RMSE of 0.412 and a MAE of 0.212. Ratings can be predicted even when no information is known. As a consequence, by resolving the cold start and data sparsity concerns, the proposed hybrid approach may reduce RMSE and MAE errors. The proposed hybrid technique's accuracy, recall, and F1-score were computed using the methods described below.

Figure 7 compares the proposed hybrid recommendation method and the currently available recommendation system methods. The system gives priority to important performance indicators, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), precision, recall, and F1-score. The figure illustrates that the suggested hybrid strategy, which combines collaborative filtering, content-based filtering, and sentiment analysis, attains greater accuracy and lower mistake rates in comparison to conventional methods. The comparison highlights the efficacy of the proposed technique in providing more accurate and dependable recommendations.

The proposed hybrid solution was determined to be more effective than existing methods, such as those utilized in product recommendation systems employing deep learning classification and segmentation procedures (Mishra et al., 2024). The results indicated a notable improvement in the accuracy of recommendations and the satisfaction level of users, which corresponds to the observed progress in other domains such e-learning recommender systems (Zhang et al., 2021).

The investigation determines that content-based filtering algorithms are not ideal because of their inefficiency and significant time consumption in real-time applications across several datasets. Therefore, it is advisable to employ a hybrid methodology that integrates collaborative filtering with content-based filtering strategies. An effective approach for predicting ratings involves combining nearest neighbor selection with matrix factorization. Cosine similarity is employed to compute user similarity and provide film recommendations to tackle the cold-start problem. The hybrid methodology being presented surpasses previous methods in important characteristics, including RMSE and MAE, showcasing exceptional accuracy, precision, recall, and F1-score. It offers more precise top-N film recommendations, demonstrating its greater performance in comparison to conventional recommendation algorithms.

Conclusion

This study introduced a novel approach for recommending films by combining different methods, using the MovieLens_25M dataset. The process commenced by employing the Improved Singular Value Decomposition (SVD) technique to decrease the dimensions of the dataset. The Content Driven KNN method, utilising cosine similarity, subsequently evaluated the similarity of films by considering user ratings, release year, and descriptions. The IKSOM algorithm utilised the EISEN cosine correlation distance to reduce cluster overlap, while the silhouette clustering technique selected the most suitable number of clusters. This combination method allowed for the generation of user-movie matrices, utilising SVD collaborative filtering to prioritise movie recommendations.

The hybrid approach outperformed prior models, earning an RMSE of 0.412, MAE of 0.212, 93.12% precision, 93.08% recall, 92.34% F1-score and accuracy 92.83%, thus delivering very accurate movie suggestions. Subsequent research could prioritise the provision of more tailored recommendations by integrating supplementary contextual variables.

Conflicts of Interest

The authors assert that they do not have any conflicts of interest to disclose with respect to the current research.

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