Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

PERSONALIZED RECOMMENDATION ON MOVIESMETADATA USING HYBRID APPROACH

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ABSTRACT **- Recommendation systems are a form of data filtering that plays a crucial role in helping users discover relevant content,based on their interests and needs. They have become an integral feature of numerous platforms, particularly in digital streaming services, where users often struggle with decision fatigue due to vast content. However, challenges such as the cold-start problem, data sparsity, and evolving user preferences require advanced approaches that balance accuracy and scalability.This study presents a hybrid movie recommendation system that integrates content-based filtering and collaborative filtering techniques to generate highly relevant suggestions. The content-based approach leverages metadata from the Movie_Metadata and TMDB datasets, incorporating movie popularity and other relevant features. Collaborative filtering analyzes user interactions and preferences from the Movie_Metadata ratings dataset. By combining these techniques, the system effectively mitigates individual limitations, resulting in a robust and efficient recommendation engine. Experimental results demonstrate that the hybrid model outperforms standalone methods in user satisfaction. This scalable solution addresses the growing demands of streaming platforms and highlights the broader potential of hybrid recommendation systems across various domains.**

Keywords - Movie recommendation system, hybrid filtering, content-based filtering, collaborative filtering, machine learning, personalized recommendations, cold-start problem, data sparsity, user interaction data, scalability.

I. INTRODUCTION

In the era of digital transformation, the exponential growth of streaming services and online media platforms has revolutionized the way users consume entertainment. While this has enriched the user experience by offering an extensive array of choices, it has also introduced challenges in content discovery. Users often face decision fatigue when navigating vast libraries of movies and shows, leading to the necessity of intelligent systems that can assist in making personalized and efficient choices. Recommendation systems, powered by machine learning, have emerged as indispensable tools to bridge this gap by curating tailored content suggestions that align with user preferences and behaviors.

A recommendation system, or recommendation engine, is an information filtering paradigm that predicts user preferences based on historical interactions and offers suggestions accordingly. These systems have found widespread application across industries, including books, music, e-commerce, and movies. In the domain of movies, recommendation systems analyze various attributes such as genres, language, directors, release years, and user reviews to make relevant suggestions. Traditional recommendation systems include content-based filtering, which uses item properties, and collaborative filtering, which examines user interactions. However, these methods frequently have limits. Content-based filtering is restricted by domain-specific knowledge, while collaborative filtering is hindered by The cold-start problem occurs when there is inadequate data on new users or items, which might influence accuracy.

To address these challenges, this study proposes a hybrid movie recommendation system. The hybrid system ensures more accurate and personalized recommendations, effectively mitigating their individual limitations. The system leverages data from movies_metadata.csv, including the popularity and vote_average and vote_cout fields (which reflect user reviews), alongside data from ratings_small.csv(which represents user interaction data) such as individual user ratings, to refine its predictions. Additionally, the scalable design of the system ensures consistent performance under varying loads, making it adaptable to real-world applications. This project not only enhances the user experience by simplifying the decision-making process but also contributes to the broader field of recommendation systems by demonstrating the potential of hybrid approaches to deliver impactful solutions.

II. PROBLEM STATEMENT

In today's digital streaming landscape, users face a significant challenge of information overload when selecting movies to watch. With thousands of titles available across genres, languages, and formats, users often experience decision paralysis, which can lead to decreased satisfaction and engagement with streaming services. The vast volume of content has highlighted the urgent need for sophisticated personalized recommendation systems. While users have access to more content than ever before, finding movies that align with their tastes and preferences has become increasingly difficult. Traditional browsing and search methods are often ineffective, especially when users are unsure of what they want to watch or wish to explore new genres.

III. LITERATURE REVIEW

Recommendation systems have become crucial components of modern digital platforms,designed to alleviate information overload by delivering personalized suggestions [1]**.** Since their emergence in the mid-1990s, these systems have evolved considerably, employing advanced algorithms to analyze user preferences and behaviors. Broadly categorized into content-based filtering, collaborative filtering, and hybrid approaches, these systems tailor recommendations to individual user needs.

Content-based filtering suggests products that are comparable to those a user has previously favoured, based on qualities like genre, director, and popularity [1]. Collaborative filtering identifies trends in user interactions and is characterized as user-based or item-based techniques, depending on whether recommendations are derived from user similarities or item similarities [2], [3]. Hybrid systems integrate multiple techniques to overcome individual limitations, such as the cold-start problem and data sparsity, thereby achieving higher accuracy and relevance in recommendations [4]. The effectiveness of these systems is commonly evaluated using precision, recall, and root mean square error (RMSE).

Initial recommendation systems relied on rule-based methods and basic collaborative filtering techniques [5]. The introduction of matrix factorization methods, such as Singular Value Decomposition (SVD), significantly improved recommendation accuracy by identifying latent factors in user-item interactions [6]. The rise of deep learning in the 2010s further enabled the modeling of complex user-item relationships, resulting in more nuanced and highly personalized recommendations [7].

Recent advancements, including self-attention mechanisms and knowledge graphs, have improved contextual understanding and sequential recommendations [8], [9]. Additionally, reinforcement learning has enhanced recommendation systems by allowing real-time adaptability to evolving user preferences, addressing dynamic user behaviors and feedback loops [10]. These innovations have not only improved accuracy and scalability but also made recommendation systems more adaptive and efficient in handling large-scale datasets.

IV. EXISTING SYSTEM


Industrial Engineering Journal
ISSN: 0970-2555
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Movie recommendation systems play a pivotal role in content discovery on streaming platforms, each employing unique strategies to enhance user experience. Netflix combines collaborative and content-based filtering to analyze user behavior and viewing history, offering highly personalized suggestions with features like "Because you watched." Amazon Prime Video integrates viewing history with shopping patterns, creating a comprehensive user profile but occasionally prioritizing commercial factors. IMDB primarily relies on content-based filtering, using movie metadata like genres and directors for recommendations but lacks real-time adaptability. While these systems excel in personalization and multi-factor analysis, they face challenges like cold-start problems, over-reliance on popular content, and limited context awareness. Netflix leads in accuracy, Amazon Prime Video excels in cross-platform integration, and IMDB provides strong metadata-based recommendations, highlighting the diversity in recommendation strategies.

V. PROPOSED SYSTEM

A. Dataset:

The Movie Recommender System was trained and tested on datasets sourced from TMDB and Movie_Metadata. The TMDB datasets, encompassing movie metadata, cast, crew, and keywords, contain information on thousands of movies. This data ensures the model learns comprehensive movie characteristics and relationships, enabling content-based recommendations. User ratings were obtained from the Movie_Metadata datasets, including millions of ratings across thousands of movies, ensuring diverse user preferences are captured for collaborative filtering. Variety of movies: The datasets contain movies spanning diverse genres, release dates, and popularity levels, ensuring exposure to a wide range of movie characteristics. Multiple data points per movie: Each movie is associated with various metadata features (title, overview, tagline, genres, release date, popularity, cast, crew, and keywords), providing the model with a multi-faceted understanding of each film. To prepare the datasets for training the model: Movie metadata was pre-processed to handle missing values, convert data types, and extract relevant information like director and lead actors for content-based filtering. User ratings were filtered and formatted for compatibility with the collaborative filtering algorithms used in the Surprise library. The Movie_Metadata Links dataset was used to map movie IDs between TMDB and Movie_Metadata, enabling the integration of data from both sources.

B. Model Description This intelligent movie recommendation engine incorporates four distinct approaches for enhanced personalized discovery: **Simple Recommender:** This baseline model employs a popularity-based approach, ranking movies based on their overall ratings and vote counts. It provides a generic recommendation list for all users, highlighting widely appreciated films.

Content-Based Recommender: This model leverages movie metadata, including textual descriptions, cast, crew, genre, and keywords, to identify movies with similar characteristics. It employs similarity measures to recommend films related to a user's preferred content.

Collaborative Filtering: This approach utilizes user-item interaction data to identify patterns in user preferences. It leverages collaborative filtering algorithms to predict user ratings for unseen movies based on the preferences of similar users.

Hybrid Recommender: This model combines the advantages of content-based and collaborative filtering approaches. It uses content information to build a set of candidate recommendations, which are subsequently personalized using collaborative filtering based on expected user preferences. This hybrid technique seeks to improve suggestion accuracy while also addressing the cold start problem for new users.

These models represent a diverse set of recommendation strategies, each addressing different aspects of movie discovery. The simple recommender provides a baseline for general movie preferences, while content-based and collaborative filtering models offer personalized recommendations. The hybrid recommender integrates these approaches to further enhance personalization and recommendation quality.

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ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

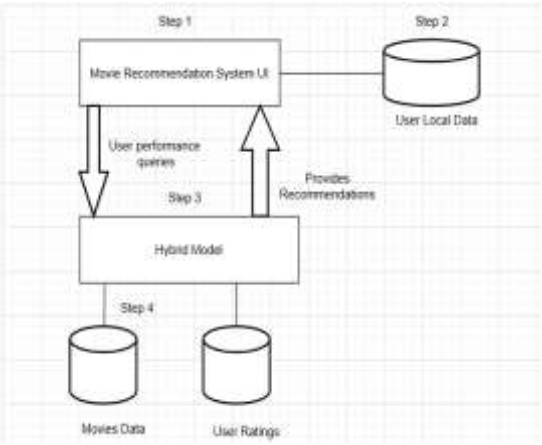

Figure 1: System Architecture Diagram

C. **Implementation**

1. Importing Libraries:

The project utilized essential libraries such as Pandas, NumPy, Scikit-learn, and Surprise for data manipulation, model building, and evaluation. Libraries for visualization, such as Matplotlib and Seaborn, were also employed. Additionally, a web framework like Streamlit could be used for front-end development.

2. Data Preparation:

Movie metadata, including titles, overviews, taglines, genres, release dates, and popularity scores, was obtained from The Movie Database (TMDB). Cast and crew information, along with movie keywords, were also extracted from TMDB to enhance content-based recommendations. User ratings were sourced from the Movie_Metadata datasets provided by GroupLens Research, enabling collaborative filtering techniques. Finally, the Movie_Metadata Links dataset facilitated integrating data from TMDB and Movie_Metadata by mapping their respective movie IDs. These datasets underwent preprocessing steps such as cleaning, filtering, handling missing values, data type conversions, and feature engineering to prepare them for model training.

3. Data Splitting:

To ensure reliable performance evaluation, the datasets were split into training and validation sets. This division allows for training the models on a portion of the data and assessing their performance on unseen data to avoid overfitting and obtain a realistic estimate of their generalization capabilities.

4. Model Architecture

Four distinct recommendation models were developed:

(a) Simple Recommender, using IMDB's weighted rating formula for popularity-based recommendations.

$$\text{Weighted Rating (WR)} = \left(\frac{v}{v+m}.R\right) + \left(\frac{m}{v+m}.C\right)$$

where,

- The number of votes for the movie is denoted by "v."
- The minimum number of votes needed to be on the chart is denoted as m.
- R represents the movie's average rating.
- C represents the average vote across the report.

(b) Content-Based Recommender, employing cosine similarity to identify similar movies based on textual descriptions and metadata;

4.1 Cosine Similarity:

Cosine similarity is used to measure the similarity between movies based on their descriptions or metadata. It works by transforming movie descriptions or metadata (like cast, crew, keywords, and genre) into numerical vectors using CountVectorizer. Then, the cosine similarity between these vectors is calculated using linear_kernel or cosine_similarity from sklearn.

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Formula:

$$Cosine(\theta) = \frac{A.B}{||A||.||B||}$$

Where:

- A and B are vector representations of two movies.
- A.B is the dot product
- ||A|| and ||B|| are vector magnitudes.

The cosine similarity score, ranging from 0 to 1, represents the similarity between two movies, with higher scores indicating greater similarity. This score is then used to recommend movies similar to a given movie, with higher similarity scores leading to higher recommendations. To improve the quality of recommendations, additional factors like movie popularity and ratings are also considered in the final recommendation process, ensuring that highly similar and well-rated movies are recommended.
(c) Collaborative Filtering, utilizing the Surprise library's SVD algorithm to predict user ratings based on the preferences of similar users;

4.2 Singular Value Decomposition (SVD):

Singular Value Decomposition (SVD) is a matrix factorization technique used to reduce the dimensionality of a matrix and extract latent features. In collaborative filtering, it's employed to uncover underlying relationships between users and items (movies in this case) based on their ratings.

Working of SVD in collaborative filtering:

1. **Rating Matrix:** The input is a user-item rating matrix, where rows represent users, columns represent movies, and cells contain the ratings given by users to movies.

$$\mathbf{A = U\Sigma V^T}$$

2. **Decomposition:** SVD decomposes the rating matrix into three matrices:

U: Represents user features or preferences.
Σ: Represents the singular values, indicating the importance of latent features.
V: Represents movie features or characteristics.

3. **Dimensionality Reduction:** By selecting a smaller number of singular values (latent features) from Σ, we can reduce the dimensionality of the original rating matrix while preserving the most important information. These singular values represent the importance of the corresponding latent factors, which are hidden dimensions capturing underlying user preferences and item characteristics. By retaining only the largest singular values, we focus on the most significant latent factors that contribute most to the observed user-item interactions.

4. **Prediction:** Using the reduced matrices, we can predict the rating a user might give to a movie they haven't seen before. The prediction process involves using the trained SVD model to estimate the rating a user would give to an item based on learned patterns of user preferences and item characteristics. This prediction is achieved by applying the prediction formula, which combines various factors to produce the final rating estimate.

Prediction Formula:

r̂_ui = μ + b_u + b_i + p_u^T q_i

- **r̂_ui:** The predicted rating of user u for item i.
- **μ:** The overall average rating across all users and items.
- **b_u:** The user bias, representing how much user u tends to rate items higher or lower than the average.
- **b_i:** The item bias, representing how much item i tends to be rated higher or lower than the average.
- **p_u:** The user latent factor vector, representing user u's preferences for different latent factors.
- **q_i:** The item latent factor vector, representing item i's relationship to different latent factors.
- **p_u^T:** The transpose of the user latent factor vector.

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ISSN: 0970-2555
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We obtain a trained SVD model capable of predicting user ratings for unrated movies based on learned user preferences and movie features.
(d) Hybrid Recommender, combining content-based and collaborative filtering techniques to generate personalized recommendations.

5. Training:
Movie recommendations are generated using a hybrid approach that combines the strengths of content-based and collaborative filtering. Content-based filtering relies on calculating cosine similarity between numerical representations of movies based on their features, including descriptions, taglines, cast, crew, genres, and keywords. Collaborative filtering, on the other hand, employs Singular Value Decomposition (SVD) is used to extract latent components describing user preferences and movie attributes from user-item rating data. These factors are then used to predict user ratings for unseen movies.

Hybrid Recommendation Algorithm:

Input:

User ID (userId): Unique identifier of the user.

Step 1: Content-Based Filtering

Convert Movie Metadata into Numerical Representations

- Movie descriptions are transformed into numerical vectors using Count Vectorizer.
- Count Vectorization is a technique that converts movie descriptions and metadata into numerical vectors by counting word occurrences.
- Each unique word in the description forms a column, while each row represents a movie.

Compute Cosine Similarity Between Movies

- Cosine Similarity is applied to measure how similar two movie vectors are based on their metadata.
- It is calculated as the dot product of two vectors divided by the product of their magnitudes.
- The vectors represent movies in a multi-dimensional space, where each dimension corresponds to a unique word from the metadata.
- Higher similarity scores indicate stronger relationships between movies.

Construct the Similarity Matrix

- A matrix is formed where each value represents the similarity score between two movies.
- The diagonal values are always 1, as each movie is identical to itself.

Retrieve Similar Movies

- For the input movie, similarity scores are sorted in descending order.
- Movies with the highest similarity scores are selected as most relevant recommendations.

Step 2: Collaborative Filtering

Construct the User-Item Rating Matrix

- A matrix is created where rows represent users and columns represent movies.
- Each cell contains a rating given by a user to a specific movie.
- Missing ratings are handled using matrix completion techniques to fill gaps in user preferences.

Apply Singular Value Decomposition (SVD)

- The user-item matrix is decomposed into three smaller matrices (U, Σ, and V^T).
- U (User matrix) captures user preferences.
- Σ (Singular values matrix) highlights key latent features.
- V^T (Item matrix) represents movie characteristics.

Train the SVD Model

- The three matrices are optimized to accurately reconstruct the original rating matrix.
- The model aims to minimise the discrepancy between actual and anticipated scores.
- The final trained matrices are stored for efficient future rating predictions**.**

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Step 3: Hybrid Recommendation Generation

- Extract the index of the input movie title from the metadata to identify its position in the dataset.
- Retrieve the corresponding movie IDs from multiple sources to ensure comprehensive matching.
- Compute the similarity scores between the input movie and all other movies using the Cosine Similarity Matrix, which measures the similarity based on the contextual representation of movie features.
- Identify the top N most similar movies by selecting those with the highest cosine similarity scores relative to the input movie.
- Utilize the trained Singular Value Decomposition (SVD) model to predict the user's rating for each of the N similar movies based on collaborative filtering techniques.
- Compute the hybrid recommendation score by combining the content similarity scores with the predicted ratings obtained from the SVD model.
- Rank the movies in descending order according to their hybrid recommendation scores to prioritize the most relevant recommendations.

Output:

- Return the top k movies as personalized recommendations for the user.

This hybrid technique combines the capabilities of content-based and collaborative filtering, allowing for personalised suggestions based on both movie content and user preferences.

6. Evaluation and Visualization:

- The model evaluation involved qualitative and quantitative analysis. Qualitative assessment focused on the relevance and coherence of recommendations generated by content-based methods. Quantitative analysis employed metrics like RMSE and MAE through cross-validation to evaluate collaborative filtering performance.

6.1 RMSE:

This metric calculates the average magnitude of errors between anticipated and actual values. A lower RMSE indicates improved model performance because the predictions are closer to the actual values.

$$RMSE = \sqrt{\Sigma(y_i - \hat{y}_i)^2 / n}$$

Where:

- y_i: represents the target variable's actual value for the i-th observation
- $\hat{y}_i$: The predicted value of the target variable for the i-th observation.
- **n:** The total number of observations.

6.2 MAE:

It calculates the mean absolute difference between expected and actual values. A lower MAE indicates greater model performance because the predictions are, on average, closer to the true values.

$$MAE = \Sigma|y_i - \hat{y}_i| / n$$

- y_i: The target variable's actual value at the i-th observation.
- $\hat{y}_i$: Predicted value for the i-th target variable.
- **n:** The total number of observations.

Personalization was examined by assessing the system's ability to tailor recommendations to individual user preferences. Visualization techniques were used to present evaluation results and gain insights into model performance.

VI. RESULTS

The hybrid recommendation system integrates content-based and collaborative filtering techniques, leveraging item similarity and user preferences to generate personalized movie recommendations. By incorporating personalized user ratings, the hybrid system provides tailored recommendations for different users, even when they request suggestions for the same movie, as demonstrated in the

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ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

figure. This integrated approach aims to enhance recommendation relevance and accuracy, ultimately improving user experience
and satisfaction.

	title	vote_count	vote_average	year	id	est
975	A Grand Day Out	199.0	7.4	1990.0	530	3.451813
3360	The Dish	62.0	6.6	2000.0	5257	3.361389
4804	Avalon	93.0	6.8	2001.0	10681	3.326523
6105	A Trip to the Moon	314.0	7.9	1902.0	775	3.306626
1898	A Simple Plan	191.0	6.9	1998.0	10223	3.280488
4643	Heaven Knows, Mr. Allison	27.0	6.8	1957.0	37103	3.115181
2059	The Matrix	9079.0	7.9	1999.0	603	3.064215
7587	The American	488.0	5.8	2010.0	27579	3.056044
7763	Hanna	1284.0	6.5	2011.0	50456	3.049994
3015	House Party 2	22.0	4.7	1991.0	16096	3.036212

Figure 2: Example of Personalized Movie Recommendations Generated by the Hybrid Model.

The evaluation results of the implemented recommendation systems are presented in this part of the study.

Model	RMSE	MAE	PRECISION
Collaborative (SVD)	0.89	0.68	0.59
Hybrid Model	0.82	0.59	0.61

The results highlight the performance of different recommendation approaches based on RMSE, MAE, and Precision. The Collaborative Filtering model (SVD) yields an RMSE of 0.89 and an MAE of 0.68. The Hybrid Model, which integrates both techniques, shows improved performance with a lower RMSE (0.82) and MAE (0.59), along with a higher Precision of 0.61, demonstrating its ability to enhance recommendation relevance by leveraging the strengths of both methods.

VII. CONCLUSION

The movie recommendation system developed in this work represents a significant step toward creating a personalized, efficient, and user-centric platform. By combining collaborative filtering with content-based methods, the system effectively delivers highly relevant movie suggestions tailored to individual user preferences. Robust architectural design, extensive testing, and scalability planning have resulted in a high-performance solution capable of handling thousands of concurrent users. Key achievements include the development of a hybrid recommendation algorithm, integration with external APIs while maintaining system stability, and the creation of an intuitive user interface. These features, along with genre-based filtering and a responsive search function, significantly enhance user experience, showcasing the success of the system's design and implementation.

Future work will focus on further refining the system to adapt to emerging technologies and user needs. Enhancements will include incorporating graph-based algorithms to better capture complex user-

movie relationships and integrating real-time feedback mechanisms to dynamically adjust recommendations. Expanding multilingual support and broadening the scope to include international and niche content will make the platform accessible to a wider audience. Scaling the system to handle larger datasets and incorporating API integrations with popular streaming platforms will enhance its usability and deployment in real-world applications. These advancements aim to establish the system as a scalable and innovative solution in digital content delivery.

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