MOVIE RECOMMENDATION SYSTEM BASED ON MACHINE LEARNING USING PROFILING

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ABSTRACT

With the increasing amount of data available, recommendation systems are important for helping users find relevant content. This paper introduces a movie recommendation system that uses user profiles and machine learning techniques to improve the user experience by offering personalized suggestions. We tested different machine learning methods, including k nearest neighbors (KNN), support vector machines (SVM), and neural networks. We used several datasets, such as MovieLens and Netflix Prize, to check how accurate the recommendations were and how satisfied users were with them.

KEYWORDS

Recommendation System, Machine Learning, User Profiling user recommender system, datasets, deep learning

1. INTRODUCTION

This paper presents the design and implementation of a robust movie recommendation system that leverages advanced machine learning techniques and user profiling to deliver highly personalized suggestions. Recommendation systems play a critical role in enhancing user experience across digital platforms by filtering vast volumes of data to provide relevant content. The primary objective of this research is to address key challenges such as scalability, cold-start problems, and accuracy, which often hinder the performance of recommendation systems.

We begin by examining the background of recommendation systems, focusing on three primary approaches: content-based filtering, collaborative filtering, and hybrid filtering. Content Based filtering utilizes item attributes, such as genres and actors, to recommend similar items, while collaborative filtering leverages user-item interaction data to identify patterns and preferences. Hybrid filtering combines the strengths of both approaches, enabling improved performance and flexibility. This paper emphasizes the use of machine learning algorithms to enhance recommendation accuracy and scalability. Algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), and Deep Neural Networks (DNN) are implemented and compared to assess their effectiveness. Additionally, hybrid approaches are explored to leverage both collaborative and content-based filtering for improved accuracy and robustness. The importance of tailored movie recommendations is underscored, particularly in improving user satisfaction and engagement. Personalized recommendations not only reduce search effort but also increase content consumption by aligning suggestions with user preferences. The paper also highlights the role of preprocessing techniques, such as data cleaning, encoding, and vectorization, in preparing datasets for effective model training. Moreover, evaluation metrics including RMSE, MAE, and NDCG are employed to ensure reliable performance assessments.

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2. CONCEPT OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) is a transformative concept that has become a cornerstone of modern science and technology. At its core, AI involves designing and programming machines to emulate human-like intelligence and thought processes. This means teaching machines to perform tasks that typically require human cognition, such as learning, reasoning, problem solving, and decision-making. Through these processes, machines are not only able to execute complex tasks but also to evolve and improve their performance over time, mirroring the way humans adapt and learn.

AI's applications span a vast array of fields, contributing significantly to advancements across industries and enhancing the quality of life. In healthcare, AI aids in diagnosing diseases, predicting patient outcomes, and personalizing treatment plans. In transportation, it powers autonomous vehicles and optimizes traffic management. Similarly, in education, AI customizes learning experiences, making education more accessible and effective for diverse learners. AI also underpins innovations in fields such as finance, agriculture, cybersecurity, and entertainment, among others.

The integration of AI into these domains underscores its potential to drive progress and bring about substantial benefits for humanity. By automating repetitive tasks, analyzing vast datasets, and enabling insights that were previously unattain- able, AI continues to redefine the boundaries of what is possible in science and technology

2.1. Machine Learning in Artificial Intelligence

In the field of computer science, artificial intelligence (AI) is a widely recognized concept that is closely linked to machine learning. Machine learning refers to the ability of machines to acquire knowledge and adapt in a manner similar to human learning. Remarkably, this approach allows machines to process information and improve their performance over time, mimicking human cognitive functions.

3. SUGGESTED RECOMMENDATION MODEL

The adoption of a hybrid approach has shown considerable promise in the realm of recommender systems. By integrating diverse features and capabilities from various systems and technologies, hybrid models can potentially overcome limitations inherent in traditional methods. This approach, as we can see in the figure 1, fosters a more comprehensive solution by blending complementary techniques. However, to achieve a truly refined and highly effective recommendation model, further research and exploration are essential. This entails employing innovative feedback mechanisms and diverse methodologies to enhance system accuracy and user satisfaction. Traditional recommendation systems have predominantly relied on collaborative filtering. This method focuses on analyzing users' historical preferences and ratings to predict their future interests. While effective in certain scenarios, these earlier techniques primarily hinge on leveraging static user data, which can lead to limitations in adaptability and scalability.In contrast, modern recommender systems leverage advanced architectural frameworks, particularly those rooted in neural networks. The advent of deep learning-based recommendation systems marks a significant leap forward. These systems utilize artificial neural networks to process complex, multidimensional data, enabling them to deliver more sophisticated and precise predictions. Deep learning frameworks have opened up new avenues for handling dynamic user behaviors, contextual information, and large-scale datasets, thereby revolutionizing the landscape of recommendation technologies . [1]

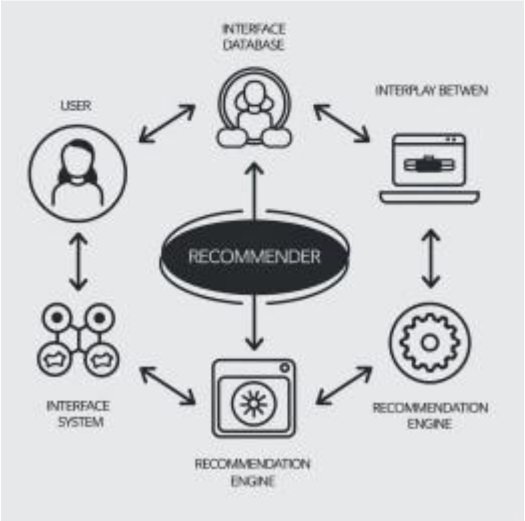

Figure 1. Recommendation Model.

4. Related Work

This section reviews prior work relevant to recommendation systems, highlighting approaches that incorporate machine learning and deep learning techniques. We examine methodologies, strengths, and limitations of these studies and explain how our proposed method builds upon these advancements.

4.1. Deep Collaborative Filtering via Marginalized Denoising Auto-Encoder

The article ”Deep Matrix Factorization Models for Recommendation” investigates the use of deep neural networks in matrix factorization techniques to enhance the quality of recommendations. Li et al. propose a method that combines explicit and implicit user feedback in a low-dimensional embedding space, allowing the system to capture more intricate user-item relationships. The approach was evaluated on large datasets, such as MovieLens and Amazon Music, using performance metrics like Normalized Discounted Cumulative Gain (NDCG).

In their experiments, Li et al. demonstrated that deep matrix factorization provides significant performance improvements over traditional matrix factorization methods by capturing non-linear interactions between users and items. The method leverages the deep architecture to represent complex user preferences more effectively. However, one limitation noted is the computational demand of training deep learning models, particularly for large-scale datasets. Despite this, the approach showed improved recommendation accuracy, particularly in settings with sparse data, making it a promising direction for advanced recommendation systems. [2]

4.2. Collaborative Filtering with Recurrent Neural Networks

This article examines how collaborative filtering can be reformulated as a sequence prediction problem and investigates the effectiveness of Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, in modeling sequential user interactions for recommendations.

By treating user-item interactions as ordered sequences rather than static data points, the study leverages the ability of LSTMs to capture temporal dependencies and long-term patterns, which are often overlooked in traditional approaches.

The performance of these deep learning models is compared against conventional methods, including k-nearest neighbor (kNN) and matrix factorization, which have been widely used in recommendation systems. Evaluations are conducted on two benchmark movie recommendation datasets—MovieLens and Netflix—to assess accuracy and predictive performance. The experimental results highlight the advantages of deep learning models, particularly their ability to handle complex, sequential patterns in user behaviour, demonstrating superior performance over traditional collaborative filtering techniques. [3]

4.3. Neural Collaborative Filtering

In this article, they developed a generalized framework using deep learning to directly model the user-item interaction matrix, rather than applying deep learning solely to auxiliary data.

The proposed approach completely replaces the matrix factorization approach, or expresses matrix factorization as a special case of the generic model proposed to generate latent user and item features. The proposed generic model is compared to state-of-the-art matrix factorization approaches, such as eALS and BPR, as well as baseline methods like ItemPop and ItemKNN, on the MovieLens and Pinterest datasets.

The proposed approach demonstrated consistent (statistically significant) improvements over all baselines on both datasets. [4]

4.4. Collaborative Filtering Algorithms Combined with Doc2Vec

The article ”Collaborative Filtering Algorithms Combined with Doc2Vec” explores the integration of Doc2Vec, a deep learning-based method, with collaborative filtering algorithms to enhance movie recommendation systems. By leveraging the PV-DM (Distributed Memory Paragraph Vector) and PVDBOW (Distributed Bag of Words Paragraph Vector) models, Doc2Vec analyzes movie synopses by converting words into vectors and identifying textual similarities. The study uses the MovieLens dataset, which includes over 20 million ratings and synopses for 22,172 films. Presented at the ITNEC 2019 conference, it demonstrates how combining natural language processing techniques with collaborative filtering improves recommendation accuracy.. [5]

4.5. Collaborative Filtering and Neural Networks

In the first set of experiments in this article, a model based collaborative filtering approach was used for prediction. They initially extracted the user’s historical movie ratings to calculate similarity between users, selected the top K neighbours with the highest similarity to the target user, and utilized these neighbours' ratings to predict the rating for a movie the target user had not yet watched. [6]

In Experiment 1, they assumed sufficient data on ratings was available and made predictions based on this ample rating data.

In Experiment 2, they utilized basic information about users and movies to predict scores in cases where sufficient rating data was unavailable. They hypothesized that neural networks should outperform traditional methods in this aspect. Therefore, in Experiment 2, they trained a neural network to predict ratings.

4.6. Towards a Deep Learning Model for Hybrid Recommendation

This work introduces a deep learning-based architecture for a hybrid recommendation system that effectively combines content-based and collaborative filtering approaches to deliver more accurate and personalized recommendations. The content-based component leverages the Doc2Vec model to create dense vector representations of user and item profiles, capturing semantic similarities and contextual relationships within the data. These vector embeddings are then fed into a classifier that predicts the relevance of items for specific users based on their preferences and past interactions. Complementing this, the collaborative filtering component utilizes the k-nearest neighbour (k-NN) algorithm to predict item ratings by identifying and analyzing patterns among users with similar preferences, enabling recommendations based on shared behavior. To integrate these two approaches, a Feedforward Neural Network is employed, learning an optimal combination of outputs from the content-based and collaborative models. This fusion leverages the strengths of both methods, addressing limitations such as data sparsity and cold-start issues often encountered in traditional recommendation systems. The proposed approach is rigorously evaluated on the MovieLens dataset, a widely used benchmark in recommendation system research, and demonstrates superior performance in terms of accuracy and relevance, highlighting its potential for scalable and real-world applications. [7]

5. METHODOLOGY

This section describes the development, implementation, and evaluation of a movie recommendation system using machine learning techniques. We provide details on the environment setup, datasets, algorithms used, experimental process, and results.

5.1. Simulation Environment

To implement and test our recommendation system, we utilized the following environment: a) Hardware Resources: Machines with Intel Core i7 processors, 16 GB RAM, and NVIDIA GPUs running Linux (Ubuntu 20.04) to accelerate the training of complex models such as deep neural networks.

5.2. Datasets and Preprocessing

Several well-known datasets were utilized for training and evaluation, ensuring diversity and robustness in the experiments. The Netflix Prize Data comprises over 100 million user ratings for various movies, making it an ideal benchmark for collaborative filtering algorithms and large-scale recommendation systems. The MovieLens 100k dataset contains 100,000 ratings along with user and movie metadata. Its compact size facilitates rapid experimentation and model prototyping. The Rotten Tomatoes dataset features user reviews combined with metadata, providing rich contextual insights for content-based filtering approaches. Additionally, the Movie Metadata dataset offers comprehensive information, including genres, actors, directors, and other attributes, enabling advanced content based recommendations. Data preprocessing involved multiple steps to prepare datasets for machine learning algorithms. Data cleaning removed duplicates, handled missing values, and standardized formats. Encoding transformed categorical attributes such as genres and user demographics into numerical representations using one-hot encoding and label encoding. Normalization scaled numerical features to ensure uniformity and prevent bias during training. For textual data, vectorization techniques like Word2Vec and TF-

IDF were employed to convert text into numerical vectors, capturing semantic relationships effectively. a) Preprocessing: Data preprocessing included cleaning (removing duplicates and missing values), encoding (transforming categorical attributes), normalization, and applying vectorization techniques such as Word2Vec for textual data.

5.3. Optimization of the Recommendation Process

To optimize the recommendation process, three machine learning methods were analyzed in detail:

1. K-Nearest Neighbors (KNN) Principle: Identifies similar movies based on user preferences using distance measures.

Distance formulas:

- Euclidean Distance

$$d(x, y) = \sqrt{\sum_{i=1}^{n} \left(x_i - y_i\right)^2} \qquad (1)$$

used for continuous data.

- Manhattan Distance

$$d(x, y) = \sum_{i=1}^{n} \left(x_i - y_i\right)^2 \qquad (2)$$

More robust against outliers.

2. Support Vector Machines (SVM) Principle: Classifies movies by creating a hyperplane that separates data in a multidimensional space.

Optimization function:

$$min \frac{1}{2} ||w||^2 \qquad (3)$$

$$subject\ to: \ y_i\left(w^T x_i + b\right) \geq 1 \qquad (4)$$

Where the coefficients w and b are the adjustable weight and bias respectively

Kernels used:

- Linear: Simple separation in the original space.
- Polynomial: Adds additional dimensions for nonlinear separations.
- RBF (Radial Basis Function): Transforms data into higher-dimensional space to handle complex relationships.

3. Deep Neural Networks (DNN)

Principle: Uses layers of neurons to capture complex relationships in data.

Architecture:

The figure 2 represent the architecture of our deep Multi-Layer Perceptron MLP

- **First hidden layer:** 192 neurons with ReLU activation: f(x) = max(0, x) (5) Promotes sparsity and fast learning.
- **Second hidden layer**: 300 neurons with *TanH* activation:

$$f(x) = max(0, x) \tag{5}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{6}$$

where x are the input features of the neuron in a neural network

Captures nonlinear transformations within a controlled range [-1, 1]. Optimization: Implemented with TensorFlow for optimal scalability and computational efficiency. features to enhance recommendation accuracy

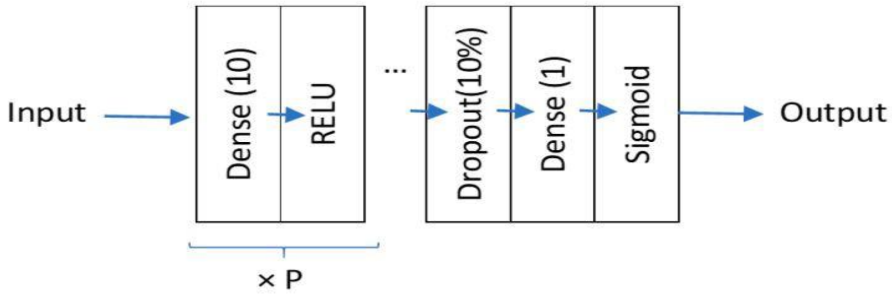

Figure 2. Diagram of the deep Multi-Layer Perceptron MLP used

5.4. Experimental Procedure

The experiments adhered to a structured methodology. Each dataset was divided into 80% training and 20% testing subsets to ensure fair evaluation. Models were trained using preprocessed data and optimized through hyperparameter tuning. Their performance was evaluated using three metrics: Root Mean Squared Error (RMSE), which assesses overall prediction accuracy, Mean Absolute Error (MAE), which measures the average deviation between predicted and actual values, and Normalized Discounted Cumulative Gain (NDCG), which evaluates the relevance of recommendations. This systematic approach enabled a thorough and reliable analysis of model effectiveness.ensured a comprehensive analysis of model effectiveness.

5.5. Experimental Results

These tables contain the results of our experiment with the Netflix Prize dataset and MovieLens100k.

Table 1. Performance on Netflix Prize Data

Model	RMSE	MAE	Execution Time (s)
KNN (Euclidean)	0.935	0.88	31.49
SVM (Linear)	0.845	0.80	104.33
Random Forest	0.810	0.78	150.12
DNN (TensorFlow)	0.760	0.76	136.28

Table 2 Performance on Movielens 100K

Model	RMSE	MAE	Execution Time (s)
KNN (Euclidean)	0.920	0.85	28.67
SVM (Linear)	0.810	0.79	97.44
Random Forest	0.770	0.75	125.39
DNN (TensorFlow)	0.735	0.74	110.22

5.6. Discussion

The experimental results highlight the strengths and weaknesses of each model. Advanced models such as Random Forest and Deep Neural Networks (DNN) achieved higher accuracy, as evidenced by lower RMSE and MAE values, due to their ability to capture complex patterns and interactions. Simpler models such as KNN and SVM provided faster execution times, making them suitable for scenarios requiring real-time predictions. The superior accuracy of DNNs can be attributed to their deep-layered architecture, which is capable of learning intricate patterns in the data. However, higher computational demands may limit their scalability for real time systems. Random Forest offered a balance between accuracy and computational cost, making it a viable choice for scalable applications. Hybrid filtering approaches demonstrated a 10% improvement in RMSE by combining collaborative and content-based filtering methods. This synergy provided robust performance, overcoming limitations of individual models and enhancing practical applicability. These findings emphasize the value of hybrid approaches, which combine accuracy and scalability, making them ideal for production-level system V.

6. Conclusion and Future Works

The study demonstrates the potential of combining traditional machine learning algorithms with advanced deep learning techniques and hybrid filtering approaches for recommendation systems. Key insights include the effectiveness of DNNs and Random Forests in achieving high accuracy, although they require careful consideration of computational resources. Simpler models like KNN and SVM remain valuable for scenarios where execution speed is prioritized. Hybrid approaches strike a balance between accuracy and scalability, making them well-suited for practical applications. Future work will focus on optimizing hyperparameters, exploring reinforcement learning techniques, and incorporating additional contextual features to further enhance recommendation performance.

6.1. Future Works

Looking forward, there are several promising directions for extending this work. One potential avenue is the integration of reinforcement learning techniques to dynamically adapt recommendations based on user feedback, enabling continuous improvement over time. Another area of interest involves leveraging graph-based neural networks to model complex relationships between users, items, and contextual features, enhancing the quality of recommendations. Furthermore, incorporating explainability methods, such as SHAP values or attention mechanisms, can provide insights into model decisions, fostering trust and transparency among users. Exploring multi-modal data sources, including images, audio, and video metadata, can further enrich content-based filtering approaches, opening possibilities for multimedia recommendation systems. Finally, scaling these models to handle real-time, large scale production environments through distributed computing frameworks like Apache Spark or Kubernetes clusters will be critical for practical deployment. These advancements will help build more adaptive, transparent, and scalable recommendation systems, addressing the evolving needs of modern applications.

REFERENCES

[1] F. Isinkaye, Y. Folajimi, and B. Ojokoh, "Recommendation systems: Principles, methods and evaluation," Egyptian Informatics Journal, vol. 16, pp. 261–273, 2015.

[2] S. Cao, N. Yang, and Z. Liu, "Online news recommender based on stacked auto-encoder," Proceedings of the 16th IEEE/ACIS International Conference on Computer and Information Science (ICIS), pp. 721–726, 2017.

[3] R. Devooght and H. Bersini, "Collaborative filtering with recurrent neural networks," Proceedings of the 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), pp. 1–10, 2016.

[4] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T. S. Chua, "Neural collaborative filtering," Proceedings of the 26th International World Wide Web Conference (WWW), pp. 173–182, 2017.

[5] G. Liu and X. Wu, "Using collaborative filtering algorithms combined with doc2vec for movie recommendation," Proceedings of the 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), pp. 1461–1464, 2019.

[6] L. Barolli, F. Amato, F. Moscato, T. Enokido, Y. N. Soe, Y. Feng, P. I. Santosa, R. Hartanto, and K. Sakurai, "Advanced information networking and applications, volume 1," 2012.

[7] G. Sottocornola, F. Stella, F. Canonaco, and M. Zanker, "Towards a deep learning model for hybrid recommendation," Proceedings of the 2017 IEEE/WIC/ACM

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Yacine Zerikat was Born in Oran in 1999, Yacine is a professional passionate about the field of data science and artificial intelligence. From a young age, he developed a strong interest in digital technologies and their impact on businesses and society. After obtaining his degree in a relevant field, system information gained significant experience working on various data science projects, particularly in developing recommendation algorithms and data analysis. His ability to transform complex data into actionable insights has allowed him to contribute to process optimization within organizations. In addition to his technical skills, Yacine stands out for his intellectual curiosity and constant desire to learn. He is also recognized for his ability to communicate effectively with multidisciplinary teams, thus facilitating collaboration between technical and non-technical departments.

Mokhtar Zerikat was born in Tlemcen (Algeria), on March 8, 1957. He received the B.S degree in electrical engineering and the M.S. and Ph.D degrees in electronics from the University of Sciences and Technology of Oran (USTO- MB), Algeria, in 1982, 1992, and 2002, respectively. Following graduation, he joined the university as a lecturer. He is currently a professor in electrical engineering department. He is engaged in research and in education in the area of automatic control systems. Actually he is Professor at Electrical Engineering Institute (National Higher Polytechnic School of Oran Maurice Audin). His current research includes electronics and embedded systems, High-performance motor drives, modeling and adaptive control systems and Artificial Intelligence Technology. He is regularly reviews papers for several journals in his area and recently active member of the Technology and Innovation Support Center (CATI).