

Movie Recommendation System

A Project Work Synopsis

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Submitted by:

21BCS10510 Abdullah Khan

21BCS6732 Sahil Sharma

21BCS6698 Arman Bagthariya

Under the Supervision of:

Mr. Vineet Mehan



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CHANDIGARH UNIVERSITY, GHARUAN, MOHALI - 140413,
PUNJAB
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Abstract

Imagine a movie recommendation system that understands your unique tastes, suggests films you'll love, and explains why it chose them. That's what the NextGen Movie Recommendation System is all about. It uses smart technology to make finding the perfect movie effortless. You can customize your preferences and get real-time recommendations. Plus, your data privacy is our priority. It's the future of movie discovery – simple, smart, and enjoyable.

Keywords: Python, Pandas, Numpy, ast, Scikit-learn, Pickle.

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1. INTRODUCTION

1.1 Problem Definition

Our aim is to create a movie recommendation system that provides users with personalized movie suggestions, keeps recommendations up-to-date with their preferences, and ensures data privacy. The challenge is to use advanced algorithms to achieve precise recommendations while maintaining transparency in the choices made. This involves designing an intuitive user interface, integrating real-time data updates, and implementing explainable AI. The ultimate goal is to enhance the movie discovery experience for users while respecting their privacy and preferences.

1.2 Problem Overview

Our project, Smart Movie Suggestions, does just that. It uses clever technology to recommend movies personalized to your liking. No more endless scrolling or guessing – it's like having a movie expert at your fingertips. With a user-friendly interface and real-time updates, you'll discover great films effortlessly.

1.3 Hardware Specification

The hardware requirements for the project are as follows:

1. GPU
2. Memory
3. Storage
4. Devices
5. Internet Connection

1.4 Software Specification

The software requirements for the project are as follows:

1. Python

2. Jupyter Notebook
3. Machine Learning Frameworks
4. APIs
5. Databases
6. Cloud Services

2. LITERATURE REVIEW

2.1 Proposed System

Movie Recommendation system is an innovative solution designed to elevate the movie discovery experience. It commences with comprehensive data collection and meticulous preprocessing, guaranteeing data accuracy. Feature engineering extracts crucial movie attributes like genres, cast, crew, and keywords, augmented by natural language processing for deeper insights. The recommendation engine employs state-of-the-art machine learning and deep learning algorithms, fusing collaborative and content-based filtering for precision.

User experience is paramount, facilitated through an intuitive interface enabling customization of preferences, including genres and moods. Real-time data updates keep recommendations up-to-date, adapting to evolving trends and user behavior. Explainable AI (XAI) models provide clear explanations for each movie suggestion, bolstering user trust.

Privacy and security are core tenets, with robust measures to protect user data and comply with privacy regulations. User feedback continuously refines recommendation algorithms. Rigorous testing guarantees top-notch performance. Deployed on a robust server infrastructure, it's monitored for insights and regularly maintained to stay at the forefront of technology. In summary, Movie Recommendation system redefines movie discovery, offering precision, transparency, real-time relevance, and privacy protection, setting new standards in cinematic exploration.

2.2 Literature Review Summary

S.No	Authors	Year	Key Point	Description	Accuracy
1	Miyahara & Pazzani [1]	2000	CF, SBM	The authors developed a method to calculate a user's similarity between negative and positive user reviews independently.	Maximum classification accuracy of 71.6%
2	Thomas [2]	2004	CBF, latent semantic analysis	Collaborative filtering is a technology that is complementary to content-based filtering.	97.0%
3	Adomavicius, & Tuzhilin[3]	2005	CF, rating estimation methods	The authors include descriptions of different limitations of present recommendation techniques as well as more adaptable and unobtrusive sorts of recommendations.	Not mention
4	Pimwadee & Lina [29]	2005	Supervised and Unsupervised Classification	The authors introduced studies the use of machine learning and semantic orientation for movie review mining.	The accuracy of mining 100 reviews from using semantic orientation approach was 77%, which was quite good. The recall rate for positive reviews was 77.91%, and that for negative reviews was 71.43%.
5	Ruslan & Andriy [16]	2007	RBM, SVD, CF	The authors introduced define a class of generalised two-layer undirected graphical models. Boltz-mann with restrictions machines for tabular or count data modelling.	Not Mention
6	Sudhanshu & kanjar[7]	2020	CBF, RS, CF	The authors introduced with movietweets, one may ascertain current fads, popular opinion, and audience reaction.	PLCC=76%

7	Fayyaz & Ebrahimian [28]	2020	Evaluation Metrics, CF, RS	This article provides review of the sorts of recommendation systems now available, along with their problems, restrictions, and commercial applications	Not Mention
8	Debashish & Chen[11]	2020	MF, DNN	The authors introduced the data recommended for the movie trailer Deep neural network models and matrixfactorization are both used to increase accuracy.	RMSE (MF=81%, DNN=79%)
9	Arno & Karen [14]	2021	Knowledge graph,CAMF, CF	The authors introduced for technically speaking, sentiment-based knowledge graphs that recommend movies have been shown to be effective.	Integrating a knowledge graph improves both accuracy and interpretability
10	Dabrowski & Rychalska [15]	2021	EMDE, top-k, Session based recommendation	The authors introduced using EMDE in top-k and session-based recommendation settings, fresh cutting- edge findings on numerous opendatasets in both unimodal and multimodal contexts are presented.	80%
11	Urvish & Ruhi [18]	2021	CF, RS	The author introduced Students, researchers, and fans will be able to develop more persuasive methods for MRS thanks to the combination of the extremely effective CF algorithm with other strategies.	The new item-based approach hadMAE of 72.0% whereas the traditional item-based approach had MAE of 73.9%
12	Harald & Linas [20]	2021	NLP, RS at Netflix	The author introduced recommendations have eventually muchimproved as evaluated by both offline and online metrics thanks to deep learning.	Not mention
13	Khademizadeh & Nematollahi [27]	2022	CFA, Associationrule	The author introduced numerous difficulties, including evaluation, collection acquisition procedures, and allocating funds for resources, could be addressed by applying analysis of the circulation data.	its training-set accuracy score wascalculated for the loan duration of 82.5 and the frequency of renewalsof 92%
14	Darban & Valipour[30]	2022	Deep learning Graph-based modelling, Autoencoder , Cold-start	The author introduced on recommendation accuracy; the technique (GHRs) performed better than several other existing recommendation algorithms. Additionally, the approach producedsignificant outcomes for the cold-start	80%

3. PROBLEM FORMULATION

Precision of Recommendations: The core challenge lies in developing recommendation algorithms capable of accurately predicting and suggesting movies to users. Given the vast and diverse content library, the system must analyze user preferences, historical data, and movie attributes to provide recommendations that resonate with individual tastes.

Scalability and Maintenance: As the movie library and user base grow, the system's scalability becomes paramount. It must handle increased data volume and user interactions without compromising performance. Ongoing maintenance ensures system reliability and stability.

Privacy and Data Protection: Protecting user data and privacy is non-negotiable. The system must adhere to strict data protection regulations, implementing robust security measures to safeguard user information throughout the recommendation process.

Privacy breaches are unacceptable.

Real-Time Adaptability: To stay relevant, the system needs to adapt recommendations in real-time. This entails tracking user behavior, monitoring industry trends, and incorporating newly released movies into the recommendation pool promptly. Ensuring that recommendations align with the ever-evolving movie landscape is crucial.

OBJECTIVES

The prime objectives of the project are as follows:

- Developing a recommendation system that surpasses existing solutions in terms of accuracy and personalization.
- Enhancing the user experience by providing insights into why a particular movie is recommended.
- Keeping recommendations up-to-date and relevant in the fast-paced world of entertainment.
- Maximize user satisfaction through continuous feedback and improvement.
- Create an intuitive user interface for effortless interaction and customization of

preferences.

- Implement explainable AI to provide users with insights into why a particular movie is recommended.

1. METHODOLOGY

- Data Collection & Preprocessing: Gather and clean movie data by collecting comprehensive movie information and ensuring its accuracy through data cleaning.
- Feature Engineering: Extract relevant movie features, such as genres, cast, crew, and keywords, to improve the precision of movie recommendations.
- Recommendation Algorithms: Implement Machine Learning (ML) and Deep Learning (DL) algorithms to power the recommendation engine, enhancing the accuracy of personalized movie suggestions.
- User Interface Design: Create an intuitive and user-friendly interface that allows users to easily customize their movie preferences and engage with the system effortlessly.
- Real-Time Data Updates: Continuously incorporate real-time data updates, including user behavior, industry trends, and new movie releases, to ensure that recommendations remain current.
- Explainable AI (XAI): Utilize Explainable AI models to provide clear explanations for each movie recommendation, fostering user trust and understanding.
- Deployment & Scaling: Deploy the system on robust infrastructure and ensure scalability to accommodate a growing user base and an expanding movie library.
- Monitoring & Maintenance: Continuously monitor system performance and data quality, promptly addressing issues and keeping the system up-to-date with the latest technological-advancements.

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